Finding the Odd-One-Out in Fleets of Mechatronic Systems using Embedded Intelligent Agents

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Abstract

With the introduction of low-cost wireless communication many new applications have been made possible; applications where systems can collaboratively learn and get wiser without human supervision. One potential application is automated monitoring for fault isolation in mobile mechatronic systems such as commercial vehicles. The paper proposes an agent design that is based on uploading software agents to a fleet of mechatronic systems. Each agent searches for interesting state representations of a system and reports them to a central server application. The states from the fleet of systems can then be used to form a consensus from which it can be possible to detect deviations and even locating a fault.

Introduction

Reliability, availability, quality and total life cycle cost are crucial factors for commercial mechatronic systems. To secure up-time new methods have to be found that extend the boundaries of what is feasible with embedded fault detection and diagnostic algorithms. One of the major challenges in today's maintenance planning is to have system status monitoring algorithms that can tune themselves, can be implemented in embedded control units with low computational resources and that can handle the system variant problem, i.e. easily adapt to new variants of the mechatronic system.

For maintenance prediction functions the goal is algorithms that can predict and monitor the system health status at such an early stage that presumptive faults with related secondary faults can be avoided with little impact on up-time. The methods used today are well developed for specific faults and systems, which often require expert knowledge; pre defined models or functions for specific faults. The models are typically based on thorough knowledge of the system, either by measurements or by first principals. Furthermore, these diagnostic models must be maintained and updated along with new variants. The computational resource limitations in the mechatronic system leads to that only a subset of problems can be handled in the diagnostic algorithm (based on consequences of the problem and computational load). Isermann provides an extensive description of different diagnostic methods (Isermann 2006).

However, improved up-time requires that most potential problems are found by the diagnostic algorithms, not only the pre-selected and prioritized ones. A new method is required (as a complement to the existing methods) that can improve up-time and enable predictive maintenance planning that works without profound (expert) knowledge of the system and with low computational requirements on the embedded control unit. Using a fleet of systems has been shown to be a possible path for detecting and isolating unexpected faults in e.g. the production stage of vehicles (Zhang et al. 2009).

In this paper we present a method based on wireless communication technology and self-learning methods. The method builds on a similar idea as the VEDAS system (Kargupta et al. 2004), but incorporates an automatic search for "interesting" parameters. On-line model parameters are derived on embedded control units and the parameters are communicated to a central server where the transmitted data describe the actual system behavior (the transmitted data can be seen as a low dimensional representation of the system behavior). Model parameters from similar systems can then be compared at the central server to find systems with odd parameters. Those systems can then be classified as possibly faulty system.

Strategy for Intelligent Agent Based Fault Detection

There are three steps in the proposed procedure; (1) searching for "interesting" relations on the internal network of a mechatronic system, (2) using the found relations for detecting deviations; and (3) locate the actual fault on the deviating system.

Searching for interesting relations

The first step involves searching for representations of a certain systems state. This can be realized by uploading a search-agent to an embedded control unit in each of the available mechatronic systems. The agent can there search for "interesting" relations on the internal data buses. In general, relations that do not appear to be random can potentially be interesting relations to monitor. The relations can be modeled in the agent using e.g. linear models, auto-encoders or self-organizing maps. Judging if a relation appears to be non-random can e.g. be done using correlation coefficients or fitness errors in the case of linear models, and spread (distortion) measures in the case of a clustering technique.

If the agents find interesting relations then they report them back to a central server application. The application will then select some of the found relations depending on the "interestingness", e.g. fitness error. The configuration for the selected relations is then sent to all mechatronic systems for continuous fitting (adaptation) of their model parameters, and they then regularly send the parameters back to the central server application using wireless communication.

The point with sending relationships between signals between the mechatronic systems and the back-office server, rather than raw data, is that this requires much less wireless traffic.

Detecting deviations in found relations

When the mechatronic systems are continually fitting the model parameters of the interesting relations, it is possible to monitor the parameter values in the central server application. The purpose is to detect deviations in model parameters, e.g. using a cross-validation technique. In essence, this means that a model parameter set for one system (returned from one of the mechatronic systems) is tested if it belongs to the group of model parameters from the other systems. The group can consist of the model parameters of all the other systems or a subset of all systems. The test procedure is then repeated for all the systems, to calculate the probability that a system belongs to the distribution given by the group (all the other systems). A low probability for belonging to the group indicates a deviating system, which can potentially be a faulty system. The underlying assumption here is that most of the monitored systems have normal (non-faulty) functionality.

The approach requires finding a suitable metric and distribution estimation method for the model parameters. For linear models, we have previously used a single Gaussian model for modeling the distribution and Mahalanobis distance as a metric (Byttner et al. 2009). If the models are principal component subspaces then an angle based similarity measure is more suitable (Rögnvaldsson et al. 2008); if the models are self-organized maps then a different distance may be appropriate (Svensson, Byttner and Rögnvaldsson 2008).

Fault localization on systems with deviating model parameters

The transmitted data from the on-line models can be used to locate the cause of the problem. The limited amount of information in the transmitted parameters can be used to build a fault dictionary that learns to tie specific parameter combinations to specific faults. This can be done, e.g., by connecting the service histories of the vehicles to the observed time trace of signal relations.

Another way to find the cause of the problem is to use simulation models of the system to replicate the behavior of the system, by adapting the model to the model parameters transmitted from the real system. This means that the simulations can be run off-board and only the relations between signals are compared between the simulation and the real system. At the central server the available computational power is large, which enables the usage of advanced models. This also allows easier maintenance and upgrading of the fault isolation hardware.

Summary

With increased requirements on managing up-time and to secure that service is done when actually needed there is a need to monitor individual systems health conditions. A method has been proposed where embedded intelligent agents are used for learning how similar systems behave through deriving on-line model parameters and transmit them to a central server for analysis and comparison with similar systems. By comparing each system's model parameters with the norm (defined by the other system parameters) possible faulty systems can be detected.

The method essentially tries to build a self-learning system that incorporates the exploratory data analysis that a human expert performs when learning about a problem. In its current form the explored relationships are very simple, yet effective, but we envision that it can be expanded with more complex models for the relationships. The core idea is to have a collaboratively learning group of systems.

We believe that a method like this (which is based on self-learning methods and comparison between similar systems) has potential to improve mechatronical system monitoring, by providing a way to predict and locate presumptive faults and to be used as a method for predictive maintenance.

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