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Distributed model-based nonlinear sensor fault diagnosis in wireless sensor networks

Chun Lo [a], Jerome P. Lynch [a,b,*], Mingyan Liu [a]

[a] Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, USA
[b] Civil and Environmental Engineering, University of Michigan, Ann Arbor, USA

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ABSTRACT

Wireless sensors operating in harsh environments have the potential to be error-prone. This paper presents a distributive model-based diagnosis algorithm that identifies nonlinear sensor faults. The diagnosis algorithm has advantages over existing fault diagnosis methods such as centralized model-based and distributive model-free methods. An algorithm is presented for detecting common non-linearity faults without using reference sensors. The study introduces a model-based fault diagnosis framework that is implemented within a pair of wireless sensors. The detection of sensor nonlinearities is shown to be equivalent to solving the largest empty rectangle (LER) problem, given a set of features extracted from an analysis of sensor outputs. A low-complexity algorithm that gives an approximate solution to the LER problem is proposed for embedment in resource constrained wireless sensors. By solving the LER problem, sensors corrupted by nonlinearity faults can be isolated and identified. Extensive analysis evaluates the performance of the proposed algorithm through simulation.

1. Introduction

Wireless sensor networks (WSNs) have been widely adopted in many engineering domains and applications including in structural monitoring [1], environmental monitoring [2], battlefield surveillance [3] and animal tracking [4]. Interest in WSNs is directly attributed to the benefits of not having to install wires in a system and to the mobility offered when untethered. For reliable system monitoring and subsequent data-based decision making, it is necessary to have accurate sensor measurements. However, in order to reduce the cost and size of wireless sensors, commercial off-the-shelf components are typically used in their design; these components can be vulnerable in harsh field settings. Given the fact that WSNs are usually deployed in demanding operational environments, wireless sensors are potentially more prone to failure than wired counterparts. Hence, automated sensor diagnosis algorithms that allow wireless sensors to self-diagnose errors in their measurements are direly needed.

A great deal of research has been conducted over the past decade to develop sensor diagnosis methods with many of them designed explicitly for WSNs. Sensor malfunctions can be classified into two broad categories: sensor failure and sensor faults. Sensor failure refers to a sensor's inability to report its data or to respond to user commands. The causes of sensor failure can be the breakdown of the hardware components or simply from the depletion of available power in the

* Corresponding author at: Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI 48109-2125, USA. Tel.: +1 734 615 5290.
E-mail addresses: chunlo@umich.edu (C. Lo), jerlynch@umich.edu (J.P. Lynch), mingyan@umich.edu (M. Liu).

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case of battery-operated sensors. The method of detecting failed sensors is to send a query to the sensor and to check whether the sensor responds. Highly efficient and accurate failed sensor detection algorithms have been published in recent years [5–7]. The second type of sensor malfunction is sensor fault, which refers to a situation where a sensor is able to report its observations but the reported data is corrupted. Sensor faults are significantly more difficult to detect than failure because investigation of the correctness of the reported observations (*i.e.*, measurements) is required. The process of sensor fault diagnosis can be classified into four steps: (1) detection (detecting whether there are any faulty sensors in the system), (2) isolation (determining which sensor(s) is(are) faulty), (3) identification (determining the type of faults that occurred) and (4) recovery (estimating the correct output of the faulty sensors). Most of the published studies only focus on the detection and isolation steps; comparatively, few have emphasized fault identification and recovery. The main approach being used for detecting sensor faults is to utilize analytical redundancies that exist in the system [8]. This general strategy assumes that sensors deployed to the same physical system should be correlated to some extent. This correlation can therefore be exploited for the diagnosis of sensor faults.

The sensor fault detection schemes proposed in the literature can be further classified into two more categories: model-based and model-less methods. Model-based sensor fault detection methods rely on knowledge of the underlying system in the form of a model that offers analytical redundancies [9–13]. The system model can be acquired by the physical properties of the system (*i.e*., physics-based) or learned from the historical data of the system (*i.e*., data-driven). Data-driven methods are specially valuable when the system being monitored is too complex to be modeled analytically. The acquired system model then acts as a fundamental reference system for sensor fault diagnosis. For example, Da and Lin [9] and Kobayashi and Simon [10] both proposed a centralized sensor fault diagnosis method that uses a bank of Kalman filters to represent the system. Both methods assume that the system is linear with the system model formulated in a state-space form. For a network of N sensors, an N-Kalman filter system is established such that the ith Kalman filter is based on all but the ith sensor. Assuming that there is only one faulty sensor in the network, exactly one Kalman filter (out of the N Kalman filters) behaves differently from the others. Therefore, the faulty sensor can be detected and isolated. The difference between these methods is that Da and Lin's method measures the discrepancies on the sensor observations while Kobayashi's method measures the discrepancies on the state vector of the state-space model. In Xu et al. [12], a sensor fault diagnosis method based on artificial neural network (NN) models is proposed. A NN model is used to capture the correlations between a group of sensors based on the sensors' historical data. When one sensor (or a small number of sensors) becomes faulty, its output will be inconsistent with predictions of that sensor's output based on the other sensors' outputs. Dunia et al. [13] and Kerschen et al. [14] proposed a fault detection method based on Principal Component Analysis (PCA) models. Their studies assumed that the sensors are highly correlated and that their outputs can be captured in a more compact dimensional space (which is regarded as the principal components) than the original observation space. When the dynamics of a sensor's observations are not concentrated on the principal components, the sensor is regarded as potentially faulty. Dunia et al. [13] further analyzed how different types of faults affect the PCA residuals, thereby providing a tool to identify the fault types occurring in the faulty sensors. All of these model-based methods are centralized methods where a base-station has knowledge of the system model, collects observations from the sensors, and performs the fault diagnosis.

A challenge of model-based methods for fault detection in WSNs is that communication of data in the network consumes a large amount of energy. Due to the limited energy available at each wireless sensor, reduction of communication between sensor nodes is preferred. As a result, numerous studies have explored distributed fault diagnosis methods that generally require less data transmissions [15–18]. These methods tend to be model-less methods where a simple assumption is made: sensors in close proximity will observe similar signals. Because of this assumption, the diagnosis algorithm is usually easily formulated in a distributed fashion. For instance, Ding et al. [17] assumed that sensors in close proximity should have similar outputs. Therefore, their method has each sensor comparing its output with the mean output value of its neighboring sensors. If the sensor output is much bigger than that of its neighboring sensors, the sensor is regarded as faulty. Another model-less distributed method was proposed by Luo et al. [18] for event-detection WSNs. In this study, each sensor reports the occurrence of an event. Assuming sensor faults are stochastically unrelated, a final decision of the event state is made by a majority vote from the individual decisions of a group of sensors. Sensors that frequently give different results are considered to be faulty. The study also determined the optimal number of sensors in a group and the optimal threshold for majority voting based on the probability for a sensor to be faulty. Although these model-less diagnosis methods are distributive and have lower energy requirements, they also often impose limitations based on the assumptions made in their derivations.

In this study, a model-based distributed sensor fault detection method is proposed. The proposed method fills the gap between model-based centralized methods and model-less distributed methods. To fill this gap, the strategy presented will be tailored to search for a specific fault type. This allows the fault diagnosis algorithm to be capable of performing the first three steps: detection, isolation and identification. The proposed fault diagnosis algorithm specifically focuses on identifying non-linearity faults that exist in the sensor's transfer function. Non-linearity faults are a multiplicative error which means that the error is a function of the true signal. In this study, a sensor that suffers from a non-linearity fault (*i.e*., a nonlinear transfer function) has normal and abnormal operating regions. A sensor gives correct measurement when the true signal is within the normal region and gives distorted measurement when the true signal falls in the abnormal region. This is a common characteristic in many sensors. For instance, some sensors (*e.g*., amplifiers) suffer from nonlinear distortions when the input signal is close to their operating limits. Piezoelectric sensors also observe a large (undesired) gain in their transfer function when the input signal gets close to the sensors' resonant frequencies [19]. Nonlinearities can also be introduced