Fault Detection and Diagnosis of Distributed Parameter Systems Based on Sensor Networks and Bayesian Networks

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Abstract: - This paper presents some considerations related to fault detection and diagnosis, using Bayesian networks, in the complex distributed parameter systems with time and space variables, where the intelligent wireless sensor networks are used as a distributed sensor. These miniaturized intelligent sensors may be placed in the area of multivariable distributed parameter systems and even with limited resources of energy, memory, computational power and bandwidth they may add to solve applications on a large space. Multivariable estimation techniques are easier to applied when a multi-sensor network is used. Bayesian networks bring their main characteristics as graphic models with a node topology and treating information by probabilistic inference. The usage of Bayesian networks is chosen considering the distributed parameter system as a system with continuous variable, but digitally surveyed in discrete time, the sensor placed to measure the time variation of system variables been affected by random noises. The paper presents as an application how Bayesian networks could be applied to fault detection and diagnosis in an on-line estimation of a dynamic model for distributed parameter systems, with exemplification in the case of the city road traffic.

Keywords: - Fault detection and diagnosis, distributed parameter systems, system identification, wireless sensor networks, Bayesian networks, city road traffic.

1 Introduction
Fault detection techniques serve to determine whether a fault has occurred in a system and fault diagnosis is to identify what component caused the failure [1, 2, 3]. In the last decades these tasks were done using different approaches, for complex systems with dynamic behaviour as the classical analytical methods, as principal component, parity relations, or methods from the system identification theory as parameter identification or state observers [4, 5, 6, 7]. Other methods based on artificial intelligence tools as fuzzy logic, neural networks and Bayesian networks, in a word – graphic models, were developed. Bayesian networks were introduced considering the dynamical systems with probabilistic events [8].

The intelligent ad-hoc wireless sensor networks are distributed sensor, which may be placed into the system, especially when we are dealing with distributed parameters systems, allowing measurement in well-chosen points of the system. Advances in scientific computation and developments in spatial sensor technology have enhanced the ability to develop modeling strategies and experimental techniques for the study of the spatiotemporal response of distributed nonlinear systems. Advances in hardware and wireless network technologies have created low-cost, low-power, multifunctional miniature sensor devices. These devices make up hundreds or thousands of ad hoc tiny sensor nodes spread across a geographical area. These sensor nodes collaborate among themselves to establish a sensing network [9, 10, 11].

Since for distributed parameter systems it is impossible to observe their states over the entire spatial domain, a possible solution is to locate discrete sensors to estimate the unknown system parameters as accurately as possible. The development of wireless sensor allows development of new methods and algorithms for identification of systems, especially in the case of distributed parameter systems [12, 13, 14, 15].

The strategy developed in this paper is based on the following assumption: system failures will be
detected using sensor nodes wherever is possible and using Bayesian networks for failures that can not be discover using distributed measurement. Moreover, Bayesian networks can be thought as a backup strategy to discover failures even when sensors may detect some of them.

In the last 5 years there were many paper published in the field of fault detection and diagnosis, based on sensor networks and Bayesian networks. Some of them are passed in a short review, with their main ideas, as it follows.

The paper [16] presents a method for fault detection on dynamic systems using Bayesian belief networks. Possible trends are identified for the variables in the systems that are monitored by the sensors. Fault trees are built to represent the causality of the trends and these are then converted into Bayesian network. Different networks developed for sections are connected together to form a unique concise network. If there are some deviations from the expected trends of the variables the updated probabilities are calculated which enables the obtaining of a list of potential causes for the system faults. The method was tested and validated on a water tank system.

In the paper [17] a Bayesian Network approach is proposed as a promissory data fusion technique for surveillance of sensors accuracy. The usefulness of that method is proven even in case when there is not enough feasible data to construct the model in traditional way. In presence of the data constrains an inversion of the causal relationship is suggested.

In the paper [18] initial developments for model-based fault-tolerant control are presented. A method based on the Kalman-filter by which fault detection and diagnosis are possible provided that an accurate model is available. That preliminary results are focused on the diagnosis step in the fault tolerant scheme.

In the paper [19] a serial sensor network is used to sense the current state a random vector of a generally nonlinear state-space model, time-dependent. A distributed Bayesian algorithm is presented for estimation in time and space, using only local communication between sensors. The demonstration is made on a target tracking problem.

The paper [20] uses artificial intelligence and signal processing for online fault detection and identification. Some thermocouple sensor faults are taken in consideration, using a statistical analysis. A self organizing map is used to classify.

The paper [21] presents a distributed adaptive scheme for detecting faults in wireless sensor networks. Each sensor nodes makes a local decision, based on the comparisons of its own readings with those of adjacent sensors, in a fault detection cycle, adjusting some parameters of the detection algorithm. The scheme is demonstrated by simulation for a high number of sensors.

2. System Components

The complexity and sophistication of the present generation of distributed parameters systems stimulate the necessity for robust online monitoring and diagnosis methodologies. Besides the major objective of system optimal control, there is an obvious need for monitoring the state of the system, reliably detecting of abnormal behaviors and diagnosing the potential failures. Numerous approaches have been applied for dealing with these types of problems, but none of them has been reported as a panacea, due to their well-known limitations. The conventional model-based representations for diagnosis, monitoring and control are affected in most of the real world cases by computational intractability and numerical convergence problems. The qualitative and probabilistic reasoning mechanisms, even with their lack of accuracy in the representation and the uncertainties introduced by the reasoning framework can cope with some of these problems even when complex system dynamics is involved. The remarkable advancements associated to the artificial intelligence research domain have been the foundation of various techniques that can be efficiently applied in the fault detection and diagnosis for various types of systems. Such a method has proved the enormous potential represented by the Bayesian networks [22, 23, 24]. A Bayesian network (also called belief network or directed acyclic graphical model) is a probabilistic graphical model that symbolizes a series of random variables and their conditional independencies. Being used to describe and handle uncertain knowledge, Bayesian networks are graphical models (directed acyclic graphs) where their nodes represent random variables (e.g. observable quantities, latent variables, unknown parameters or hypotheses) and their edges characterize probabilistic dependencies.
between nodes. In other words, a Bayesian network is a mechanism that automatically applies Bayes theorem to complex problems. Bayesian networks appeared as a research topic in the '80s and are effectively utilized in fault detection and diagnosis since the '90s. Bayesian networks are used to represent knowledge and, on the other hand, they are used as efficient reasoning methods. For this, a learning process (inference) is required. Many interesting aspects of diagnostic models can be represented using dynamic Bayesian networks framework. It allows a natural encoding of the representation of higher-order system dynamics, and also, that many interesting types of failures can be modeled logically, including burst faults, parameter drift, and measurement errors. The advantages implied by the use of probability models such as Bayesian networks are obvious in the field of fault detection and diagnosis. A Bayesian network is in fact a complete model of the system. Based on this model, the state of the system, including its malfunction states, can be tracked due to a probability distribution over potential system states and the set of the measurements gathered until then. This belief state distribution is an accurate representation of the best possible beliefs based on all obtainable evidence. This tracking through belief states of the system includes inside it the likelihood of different types of failures, as well as a distribution over the significant system parameters. Numerous questions that have confronted conventional system diagnosis methods (ranking probable failures, handling of multiple synchronized failures, and robustness to parameter drift, etc.) can be tackled using probabilistic tracking frameworks. Bayesian networks are complex probabilistic diagrams that systematize a mixture of domain expert knowledge and observed datasets by mapping out cause-and-effect relationships between key variables and encoding them with numbers that signify the amount in which one variable is probable to influence another. In order to understand the philosophy applied in the development of a Bayesian network we considered as a starting point the Bayes theorem expressing the conditional and marginal probabilities of two events \( \alpha \) and \( \beta \), where \( \beta \) has a non-vanishing probability:

\[
P(\alpha/\beta) = \frac{P(\beta/\alpha) \cdot P(\alpha)}{P(\beta)} \tag{1}
\]

The meaning of every term in the theorem is described below: 1. \( P(\alpha) \) is the prior probability (marginal probability) of the event \( \alpha \), without any information about the event \( \beta \), 2. \( P(\alpha/\beta) \) is the conditional probability of the event \( \alpha \), given the event \( \beta \), 3. \( P(\beta/\alpha) \) is the conditional probability of the event \( \beta \), given the event \( \alpha \), 4. \( P(\beta) \) is the marginal probability of the event \( \beta \), acting like a normalizing constant.

A Bayesian network architecture, appropriate for setting relationships among a large number of nodes/variables, is graphically represented by a directed acyclic graph that efficiently encodes the joint probability distribution (2) for a large set of variables (3).

\[
P(X) = \prod_{i=1}^{n} P(X_i | Parents(X_i))
\tag{2}
\]

\[X = \{X_1,...,X_n\}\tag{3}\]

where: \( n \) represents the number of nodes included in BN and \( Parents(X_i), i = 1 \) represents the set of parents (nodes that have an influence over the child node) of the node \( X_i \).

After the modeling stage, the Bayesian inference is used to update the network statistical knowledge based on current observations and the Bayes theorem. Inference can be defined as the stage in which the probability of each value of a node in a Bayesian network is computed when other variables’ values are known. Between several different inference algorithms adapted for Bayesian a network, a decent choice can be the one called the junction tree algorithm, which is appropriate for any arbitrary Bayesian network.

And now, let’s see how inference stage is done: Presuming that we identify certain values for one or more of the variables in the network. If one variable has an observed value, the probabilities for the other variables have to be revised by computing the updated probability distribution for any variable based on the already established values of the other variables.

Wireless sensor networks are extremely distributed systems having a large number of independent and interconnected sensor nodes, with
limited computational and communicative potential. The sensors are deployed for data acquisition purposes on a wide range of locations. The sensors are smart, small, lightweight and portable devices, with a communication infrastructure intended to monitor and record specific parameters like temperature, humidity, pressure, wind direction and speed, illumination intensity, vibration intensity, sound intensity, power-line voltage, chemical concentrations and pollutant levels at diverse locations. They are low cost and low energy devices, realized in nanotechnology. The sensor networks have different structures: the star networks, with a central data collection point, or the mesh networks are networks in which sensors can communicate with each other. A sensor has the following hardware: radio node, antenna, on-board board microprocessor contains code for managing mesh network. As hardware development board it contains pins for sensor connection, microprocessor for handling signal, power supply, serial port, radio node plugs onto top of board. The sensor contains software on board for data acquisition, signal processing, embedded programming, embedded C language, messages format up to user. In the network there is a base station, sometimes called access point, acting as a controller and also as a key server. It is assumed to be a laptop class device and it is supplied with long-lasting power. In this architecture, a number of base stations are already deployed within the field. Each base station forms a cell around itself that covers part of the area. A versatile architecture is SENMA - SEnsor Network with Mobile Access architecture.

The distributed parameter systems, opposed to the lumped parameter systems, are systems whose state space is infinite dimensional. An object whose state is heterogeneous has distributed parameters. Such a system is described by partial differential equations. Partial differential equations are used to formulate problems involving functions of several variables, such as the propagation of sound or heat, electrostatics, electrodynamics, fluid flow, elasticity. Also, other processes as medical diseases [8, 22] or city traffic may be seen as distributed parameter systems. The example from our case study is done on the last case.

3 Case study

In a fault detection strategy, sensor networks (a physical network) and Bayesian network (a model) can work synergically to provide better diagnosis. Currently, city road traffic control is an important problem in large towns. The permanent enlargement of the number of vehicles, cyclists and pedestrians in the city traffic can not be stopped, the only answer to massive decongestion being the development of new infrastructure along with the implementation of efficient large-scale intelligent control systems. Preventing traffic jams is very important nowadays for the environment and also for the economy and the Intelligent Transport Systems (ITS) are essential for traffic safety and road traffic decongestion.

Fig.1. Map of the roads and intersections

The development of large-scale dynamic control strategies in this domain is the only solution with rapid impact to road traffic decongestion. Such
complex control systems are subject to failures that must be carefully solved. The present case study tries to discover failures in the traffic lights operation in a small central area of Timisoara (a group of three connected intersections – see the map presented in Fig. 1).

Traffic lights, which may also be known as stoplights, traffic or semaphore, are signaling devices positioned at road intersections, pedestrian crossings and other locations to control competing flows of road traffic. Their presence in intersections is almost unavoidable in crowded city crossroads and can be imagined as actuators in a control closed-loop perspective over traffic control. Each state of the traffic lights determines a traffic probability in every direction. These probabilities are also depending on the time of the day, day of the week, the weather conditions, and so on.

The case study presumes the deployment of a wireless sensor network containing traffic sensors for both vehicles and pedestrians. The wireless traffic sensors are deployed in intersections (Fig. 2) and along the roads.

Each traffic sensor reports the traffic values from its coverage area to the base station. The base station is imagined to be a laptop-class device having access to long-lasting energy power and, by this, being able to execute complex algorithms that require important computational power.

On the base station we developed a Bayesian network that monitors, together with the sensor network, the state of the controlled system. For this reason, the Bayesian Network contains nodes for each state of the intersections traffic lights situation, including the failure-state when the traffic lights are not working (in this case the traffic is governed by other road signs that should be posted close to the traffic lights defining who has the priority). Based on probabilities encapsulated in our Bayesian network (Fig. 3) and based on the measurements provided by wireless sensor nodes, the failure states (no traffic lights working in that particular intersection) are discovered immediately and appropriate action can be taken.

The inference may be done based on the equation (4).

The working data of the network is acquired by a traffic study on a period of several months, in different areas and different weather conditions. The network has 40 variables/nodes and 88 connections, which are describing the interdependences. The relations parents [-sons are bidirectional. The characteristics and the senses are presented in Fig. 3.

For the case study of a decision with a Bayesian network, determining with approximation the number of cars, which are crossing the streets we are presented the following results.

In Fig. 4 we are presented the average distribution for some groups of hour in a day (7:00-9:00, 9:00-15:00, ..., 24:00-7:00).

In Fig. 5 we are presented the maximum distribution for different weather conditions as: 1-sun, 2 – rain, 3 – fog, 4 – ice.
\[
P(C_1, \ldots, C_{17}, ev_1, \ldots, ev_9, dv_1, \ldots, dv_4, dv_7, dt_8, int_1, int_2, int_3, int_1_{-b}, int_2_{-b}, int_3_{-b}, indice_{nr \_tot}) = \\
P(nr \_tot | C_1, \ldots, C_9)P(indice | int_1, int_2, int_3)P(int_3_{-b} | int_3)P(int_2_{-b} | int_2)P(int_1_{-b} | int_1) \\
P(int_3 | C_9, C_8, C_7, dt_8, int_1)P(int_2 | C_13, \ldots, C_{10}, C_6, C_5, C_4)P(int_1 | int_2, dt_4, C_3, C_2, C_1) \\
P(dv_8 | C_9, int_1)P(dv_7 | C_7)P(dv_4 | int_2)P(dt_3 | C_3)P(dt_2 | C_2)P(dt_1 | C_1) \\
P(C_9 | C_{14}, \ldots, C_{17}, ev_9)P(C_8 | C_{14}, \ldots, C_{17}, ev_8)P(C_7 | C_{14}, \ldots, C_{17}, ev_7) \\
P(C_6 | C_{14}, \ldots, C_{17}, C_{12}, ev_6)P(C_5 | C_{14}, \ldots, C_{17}, C_{11}, ev_5)P(C_4 | C_{14}, \ldots, C_{17}, C_{10}, ev_4) \\
P(C_3 | C_{14}, \ldots, C_{17}, ev_3)P(C_2 | C_{14}, \ldots, C_{17}, ev_2)P(C_1 | C_{14}, \ldots, C_{17}, ev_1) \\
P(C_{13})P(C_{12})P(C_{11})P(C_{17})P(C_{16})P(C_{15})P(C_{14})P(ev_9)P(ev_8)P(ev_7) \\
P(ev_6)P(ev_5)P(ev_4)P(ev_3)P(ev_2)P(ev_1)
\]

\[ (4) \]

Fig. 4. The average distribution

Fig. 5. The maximum distribution

4 Conclusion

In this paper a short survey of fault detection and diagnosis in distributed systems based on sensor networks and Bayesian networks is presented. In introduction some related work is reviewed. The main concepts of developing Bayesian networks and sensor networks with application at distributed parameter system monitoring are presented. A case study on a city traffic control is developed. It structure, the main inference equation and some distribution in time are presented.

References:


