

Adaptive Fault Diagnosis System for Nodes Using Wireless Sensor Networks

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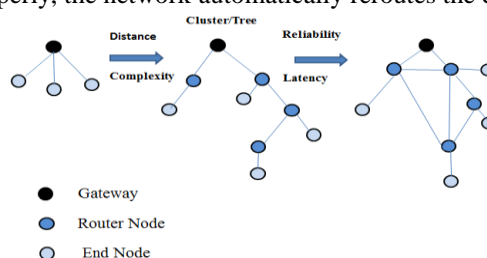
ABSTRACT: Cognitive approaches generally rely on machine learning techniques to configure the nominal state and create the faulty ones without requiring any a priori information about the fault signature or on fault time profile. a novel cognitive fault diagnosis framework for processes described by nonlinear dynamic systems that inspects changes in the existing relationships among sensors. The proposed framework is based on an evolving clustering algorithm that operates in the parameter space of time invariant linear models approximating such relationships. FDS, which extends the solution presented in, relies on a novel evolving-clustering algorithm (ECA) able to learn the nominal state of the process during an initial training phase create, update, and maintain the fault. A distributed localized faulty sensor detection algorithm technology used for evaluation of the proposed solutions reveals the node fault as well as the significant benefits obtained from the sensor networks.

I. INTRODUCTION

Wireless sensor networks have seen tremendous advances and utilization in the past two decades. Starting from petroleum exploration, mining, weather and even battle operations, all of these require sensor applications. One reason behind the growing popularity of wireless sensors is that they can work in remote areas without manual intervention. All the user needs to do is to gather the data sent by the sensors, and with certain analysis extract meaningful information from them. Usually sensor applications involve many sensors deployed together. These sensors form a network and collaborate with each other to gather data and send it to the base station. The base station acts as the control centre where the data from the sensors are gathered for further analysis and processing. In a nutshell, a wireless sensor network (WSN) is a wireless network consisting of spatially distributed nodes which use sensors to monitor physical or environmental conditions. These nodes combine with routers and gateways to create a WSN system.

The Wireless sensor network gateway, end nodes, and router nodes. Router nodes are much similar to end nodes in that they can store measurement data, but they also can be used to pass along measurement data from other nodes . The first, and most basic topology, is the star topology, in which each node maintains a single, direct communication link with the gateway. This topology is very simple but restricts the overall distance that our network can achieve.

The mesh network topology reduces this issue by extensively using redundant communication paths to increase reliability of the system. In a mesh network, nodes maintain multiple communication links back to the gateway, so that if a router node goes down or does not work properly, the network automatically reroutes the data through a different sets of path.



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II. EXISTING SYSTEM

Adaptive networks for fault diagnosis and process control. The use of adaptive (artificial neural) networks for fault diagnosis and process control is explored. Adaptive networks can be used as fault recognition systems, as adaptive nonlinear process models, and as controllers. Connection strengths representing correlations between inputs (alarms and sensor measurements) and outputs (faults, future sensor measurements or control actions) are learned using the LMS (Widrow-Hoff) rule and the backpropagation algorithm. The resulting system is a pattern recognizer which is able to learn nonlinear and logical relationships as well as linear correlations. Results are presented for two problems: diagnosing failures in a small model chemical plant, and controlling a highly nonlinear bioreactor. For the diagnosis problem, learning in adaptive networks given qualitative (alarm) and quantitative (sensor) data are compared, and the effect of noise is studied. The importance of nonlinear networks is demonstrated using simple problems which require context sensitivity and problems where optimal alarm thresholds are learned. Results using an adaptive model-based controller using two neural networks (one for the model and one for the controller) are presented and extensions to the standard layered feedforward network are suggested which greatly increase the utility of neural networks for process control.

Algorithm 1: FDS ECA (Evolving Clustering Algorithm):

We assume that a fault affecting θ_0 abruptly moves the process from a stationary state to a new stationary one (abrupt fault). A faulty state j is hence characterized by a mean vector θ_j and a covariance matrix S_j . The FDS stores the number n_j of vectors used to estimate θ_j and S_j and the latest time instant t_j , where $\hat{\theta}_i$ was associated to j .

$$m(\hat{\theta}_i, \Upsilon) = (\bar{\theta}_\Upsilon - \hat{\theta}_i)^T S_\Upsilon^{-1} (\bar{\theta}_\Upsilon - \hat{\theta}_i)$$

The distance between a parameter vector $\hat{\theta}_i$ and the center of a cluster can be computed by means of the Mahalanobis distance where $\Upsilon \in \{1, \dots, \varphi\}$. Since $_$ and $j \in$ are Gaussian clusters, a neighborhood centered in θ_Υ can be induced by containing those $\hat{\theta}_i$ s belonging to Υ with probability $1-\alpha_s$, where α_s is a given confidence level. More specifically, the spatial neighborhood is composed by those θ_s for which hold. $F_{p, n\Upsilon-p, \alpha_s}$ is the Fisher's distribution quantile of order $1-\alpha_s$ of parameters p and $n\Upsilon-p$. Similarly, a neighborhood is assigned to each cluster $\Upsilon \in \{1, \dots, \varphi\}$ and constitutes the core of the fault identification phase of the FDS (Lines 6 and 14). The FDS algorithm also contemplates the case of θ^I satisfying (3) for multiple clusters. In this case, θ^I is associated.

III. METHODOLOGY

FDS (Fault Diagnosis) Method :

Spatial confidence:

The spatial confidence α_s has been set to 0.03 (3). This parameter controls the rate of structural outliers generated by the FDS. Large values of α_s would create more compact clusters and be sensitive to new states, at the expenses of a larger outlier set. On the contrary, small values of α_s would reduce the number of outliers at the expenses of a reduced sensitivity in identifying new states.

Temporal Threshold:

The temporal threshold η_t has been set to one, meaning that cluster statistics in (8) are updated when two consecutive parameter vectors are inserted in the same cluster. Larger values of η_t update the cluster statistics with less restrictive conditions. $\eta_t = 1$ represents a conservative choice for this parameter.

Merging Confidence:

The merging confidence α_m has been set to 0.05. It represents the confidence of the hypothesis test designed to assess whether two clusters need to be merged or not.

Cluster Creation Confidence:

The cluster creation confidence α_c has been set to 0.1. It represents the confidence of the KS hypothesis test, meant to assess if a new cluster must be created by looking at the distribution of the parameter vectors.

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IV. CONCLUSION

This paper An evolving mechanism for cognitive fault diagnosis able to detect and cluster faults by characterizing the nominal state and the fault dictionary (initially empty) during the operational phase. The novelty of the proposed approach resides in the evolving mechanisms and the theoretically grounded framework that allows to work in the space of linear approximating models, even if the system under investigation is nonlinear. The cognitive approach allows us to characterize the faults during the operational phase by introducing clusters in the parameter vector space and updating them in an evolving manner. The experimental section shows the effectiveness of the proposed solution once compared with the existing clustering algorithm applied to both synthetic and real data. Results show the better ability of the proposed method over the ones present in the literature to correctly identify the states the process encounters over time.

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