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REVIEW REPORT ON FAULT DETECTION IN SENSOR NETWORKS

Metodologias para processamento, redução e gestão hierarquizada de dados provenientes da observação automática de estruturas

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RELATÓRIO DE REVISÃO DE ESTADO DA ARTE SOBRE DETEÇÃO DE FALHAS EM REDES DE SENSORES

Resumo

As redes de sensores têm um largo espectro de aplicações, algumas das quais dizem respeito a estruturas críticas, como é o caso das redes de monitorização estrutural em engenharia civil. Contudo, os sensores, devido à sua natureza e às condições ambientais em que operam, estão sujeitos a falhas que, em ultima instância, podem comprometer a qualidade da informação indispensável para um controlo de segurança efetivo. Neste relatório é apresentada uma perspetiva sobre o desenvolvimento de estratégias de detecção automática de falhas e é feita uma descrição do estado da arte na aplicação de técnicas de aprendizagem estatística ao problema da validação de sensores.

Palavras-chave: Sensor, Validação, Detecção de Falhas

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Abstract

Sensor Networks are widespread across a large spectrum of applications. Some are even deployed in critical infrastructures, as is the case of Structure Health Monitoring networks. However the sensors, due to their nature and to the harsh environmental conditions in which they operate, are subject to faults that ultimately may compromise the quality of information essential for an effective safety control. This Review Paper gives a perspective on the development of automatic fault detection strategies and provides a literature review about the application of statistical learning techniques to the problem of sensor validation.

Keywords: Sensor, Validation, Fault Detection

Index

Figure Index

1 | Introduction

In the domain of Civil Engineering as the term Structure Health Monitoring (SHM, Figure 1) designates the set of actions aimed at the detection and diagnosis of abnormal situations during the exploration of major civil engineering works of art in order to ensure safety and reduce maintenance and inspection costs. For that purpose, it is necessary the installation in the monitored works of art of a large number of sensors, in a robust and autonomous way, according to the established observation plan. However, the sensors, due to their nature and to the harsh environmental conditions in which they operate, are subject to faults that ultimately may compromise the quality of the information essential for an effective safety control.

It is worth to note that in a metrological sense, the sensor is a device used in the measuring process that is directly affected by the mensuranda and, according to a predetermined law, generates a signal related to its magnitude. In the context of this report the term sensor is used a broader sense, comprising the sensor itself and all the other elements in the measuring chain.

In this review report we are always keeping in mind the possible application of the selected works in the context previously introduced. It is hoped that this study may contribute to the future development of innovative measurement Fault Tolerant Sensor Networks applied to Civil Engineering Structures, which may have potential application in the Structure Health Monitoring context.

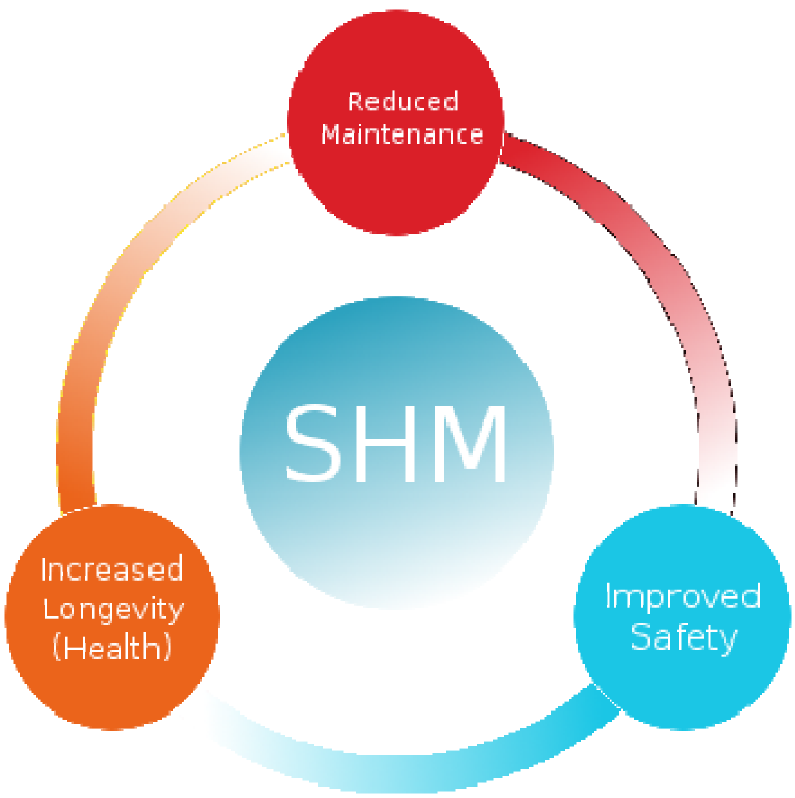

Figure 1 - Structure Health Monitoring

2 | Automatic Fault Detection

Since the beginning of the 1960's, the industrial processes had a huge increase in their degree of automation, due both to more demanding performance requirements and to free human operators of repetitive, tedious and often dangerous tasks. As a consequence, the need for appropriate tools for automatic detection of faults, diagnostic and monitoring has been strongly felt since [1].

2.1 Terminology

In the context of an industrial application, a fault is perceived as a non-permitted deviation of a characteristic property that leads to failure of the system or manufacturing facility to fulfill the purpose for which it was designed [1].

Although some effort has been made by the scientific community to establish a common terminology ([1],[3],[4]), the peculiarities of multidisciplinary topics involved often lead to terminologies that are not unique.

2.2 Development of automatic fault detection strategies

The development of strategies for automatic fault detection took place in the early 1970's and has been receiving increasing attention worldwide, both in theory and application ([5],[6]). This development was (and still is) stimulated mainly by the automation trend toward greater complexity and increased demand for greater availability and safety of control systems. A strong impetus also comes from the development of powerful techniques of mathematical modeling, state estimation and parameter identification that became feasible with the progress of computer technology [7].

2.2.1 Linear observers

The first strategies for automatic fault detection were based on linear observers, operating in linear systems [8]. One of the first books on the subject was published in 1978, on fault detection and diagnosis in chemical and petrochemical processes [9].

2.2.2 Analytical redundancy

A great deal of work has been developed using the paradigm of analytical redundancy by exploiting well-established techniques in automatic control as parameter estimation and state. These techniques are summarized in [10]. The idea of replacing hardware redundancy by analytical redundancy originated in MIT [11], which was developed for fault detection filters that generate directional residuals for FDI (Fault Detection and Isolation). That approach was known has Beard-Jones fault detection filter.

2.2.3 Statistical approaches

In parallel with the development of Beard-Jones fault detection filter, statistical approaches were also developed in the early 70's,. In [11] Peschon & Mehra introduced a general procedure for FDI using Kalman filters. The faults are diagnosed by statistical tests of whiteness, mean and covariance of the residuals.

Later a strategy was developed for fault diagnosis using a generalized likelihood ratio test (GLR) in a residual generated by a Kalman filter ([13],[14]).

In [8] Willsky presented key concepts of analytical redundancy FDI-based models, with emphasis on stochastic systems and detection of jumps. Following this line, Baseville in [15] treated the problem of detection, estimation and diagnosis of changes in the dynamic properties of signals and systems, with particular emphasis on statistical methods for detection, to provide a general framework for detecting changes in signals and systems.

The development of statistical approaches was later summarized by Tzafestas & Watanabe in [16]. In this publication, other approaches as knowledge-based techniques were also discussed.

The fundamental methods and developments of the statistical approach can be found in [17],[18] and [19]. The approach of adaptive filter with multiple model is one of the statistical approaches, which involves the testing of multiple hypotheses of residuals generated by a bank of Kalman filters ([20],[21] and [22]). New developments and applications were introduced in [23],[24] and [25]. The statistical methods based on the use of Principal Components Analysis have also received attention from the scientific community [26],[27],[28].

2.2.4 Parameter estimation

One of the other approaches developed for FDI was the parameter estimation [29][30]. This approach is directly based on system identification techniques. In the review paper [10] Isermann showed that the fault diagnosis process can be obtained through the estimation of process parameters of non measurables state variables, and gave a generalized framework for FDI based in process models and non measurable quantities [1][31]. In [32] Isermann & Freyermuth studied FDI online systems using a combination of parameter estimation and heuristic process knowledge. Later several papers were published using this approach [33][34][35][36][37].

2.2.5 Further information about the FDI state of the art

The FDI state of the art is described in books [38][39], and review papers [31],[40], [41]. Many books provide a clear picture of developments in the field [7],[40],[42], [43], [44], [45], [46] and [47].

2.3 Model Based FDI

Currently it is accepted as standard procedure for FDI based on models that it consists of two steps [48][49] :

- Generation of residuals,
- Decision-making (including evaluation of the residuals)

In most of the publications it can be seen that the majority of the approaches are based on mathematical models of the system. Such models can be of two types [50]:

- Models based on first principles
- Input-output (data-driven) models

While the model based on first principles is obtained through differential equations that represent the physical behavior of the system components, the input-output (also designated has data-driven) model is constructed using system identification techniques [31],[51],[52],[53].

Although in general, analytical models based on first principles allow a greater depth in diagnosis, they require a difficult and laborious modeling, especially for non-linear cases.

On the other hand the input-output model is a powerful tool for dealing with the problem of modeling so as to serve fault diagnosis [50][54].

In addition to the conventional techniques for identification, mainly for non-linear cases, methods to infer these models have been developed through: neural networks [55][56]; fuzzy clustering [57][58][59]; and immune networks [60][61][62]. In this case, the main issue in fault diagnosis is the classification of patterns corresponding to different fault situations. In this approach, after joining residuals into clusters, two main issues – known as the problem of the validity of the cluster – need to be addressed regardless of the clustering technique used:

i) How many clusters are present in the data, and

ii) which is the quality and validity of the clustering [58].

3 | SENSOR VALIDATION

The fault detection and diagnosis (FDI) when applied to sensors is usually designated as sensor validation [1]. However, although less frequently, other name is also common in the literature regarding this topic, and is referred as signal validation [63],[64].

Almost all the techniques of fault detection and isolation (FDI) described in the literature can be applied to sensor validation [1].

Although fault detection can not usually depend on the physical redundancy of system sensors, due to cost and inefficiency inherent in the replication of the entire sensor system, tools can be designed to explore the redundancy of physical sensors in parts of the system where it exists [1].

As in fault detection and isolation (FDI) at the process level, in the validation of sensors one can compare the results of measurements of system sensors with mathematical models that describe the static and dynamic relationships between the measurements, supported in the techniques of fault detection based on models, and the possibility, in the event of a fault to provide an estimate (during a finite time window) of the missing measurements [1]. However, using this approach, care must be taken to distinguish errors in the sensors from faults in the process or control system. Since a failure in the process may result in abnormal readings from the sensors, the developed algorithms may report a faulty sensor. The use of a higher layer in the diagnostic system must consider this situation [75].

Virtually, any suitable machine learning technique can be applied using the model based FDI framework since the residual generation can be seen as a regression problem and decision-making as a classification problem. Obviously the classification problem can also be performed directly from the data without the computation of residuals or a separate fault detection step [66]. However, depending on the concrete situation, difficulties could be found since a representative training set, characterizing all the faults on the system, or the probabilistic distribution of the data, could be difficult to obtain.

In the literature various approaches exist for performing data-based fault detection, which can be divided basically into three main groups [67]:

- <u>Classification-based fault detection</u>: different system conditions representing faulty cases define different fault classes due to their appearance in the corresponding recorded data (fault patterns); also the faulty-free case represents one class; these classes are learned by training data and are applied whenever a new data point needs to be assigned to a class. The major disadvantage of this approach is that all kind of faults and their corresponding appearance in the data need to be known a-priori and therefore new faults cannot be detected very often (only in the case that its pattern is luckily similar to an already known pattern of another fault). This disadvantage can be somewhat overturn using one class classification [68], or novelty detection methods [69] .
- <u>Signal-based fault detection in intelligent sensors</u>: can be seen as a single channel check approach where dynamic sensor data is analyzed with respect to the occurrence of peaks,

drifts or other unnatural behaviors in their corresponding signal curves. As commonly no interactions in form of redundancy or correlation analysis between other sensors are taken into account, no wide-spread system failures can be detected within this approach.

- Model-based fault detection: multi-dimensional models or some of their parameters are trained from simulated, historic or online measured data and used as reference situation characterizing functional dependencies between measurement variables for the faulty-free case. The drawback for this approach is that if systematic failures occur in the train data (when no simulated data is available, of course), wrong models are trained, which get useless for fault detection. Besides, a fault isolation strategy has to be appended in order to identify the faulty variables amongst faulty-free ones, all integrated in complex high-dimensional models.

3.1 Model-based sensor fault detection

In [70] Conde proposes a method based in Relevance Vector Machines (RVM) to generate residuals. The residuals are classified as faults if a predefined threshold based in the estimated prediction confidence interval was exceeded (similarly to using a Shewhart control chart). The RVM method was shown to have better performance (as in similar previous cases) than Artificial Neural Networks (ANN) also considered in the work.

In [64] a Pattern Recognition and Artificial Neural Networks techniques are proposed to the signal validation problem. The approach is based on the use of a pattern recognition algorithm (ISODATA) which drives nine specialized supervised networks, each network being trained to provide accurate outputs only in a limited and restricted operational region.

A minimum mean square error (MMSE) approach to the sensor fault detection problem can be found in [71].The MMSE estimation is applied to the time history data to detect additive faults (drifiting and bias) a Shewart chart is used to monitor the mean of the log-ratios, whereas multiplicative faults (gain and precision degradation) are detected by applying a univariate S chart to monitor the change in the variance of the log-ratios. Using this approach either a single or multiple sensors can be estimated from the remaining sensors if training data from the functioning sensor network are available. Both spatial and temporal correlation of the sensors can be used.

In [65] a hierarchical Bayesian space-time (HBST) modeling is used to model the phenomenon of interest, and then uses maximum a posteriori selection to identify a set of trustworthy sensors. It is claimed that compared to an analogous linear autoregressive system, the method proposed can achieve excellent fault detection when the HBST model accurately represents the phenomenon.

3.2 Classification-based sensor fault detection

In [72] a method is proposed using Hidden Markov Models (HMMs) to capture the fault-free dynamics of an environment and the dynamics of faulty data. The method performs a structural analysis of these HMMs to identify the type of data and system faults affecting sensor measurements.

In [73] an algorithm is proposed for detecting anomalies in time series data inspired by the negative-selection mechanism of the immune system, witch discriminates between self (normal data patterns) and other (deviation exceeding an allowable variation).

In [74] it is claimed that the use of a modified version of an Artificial Immune Network (A2INET) algorithm can achieve a classification model that is substantially immune to the drift of the sensors. To investigate the quality of the Artificial Immune System, two standard classifiers, such as the k-Nearest Neighbors (k-NN) and the Partial Least Square-Discriminant Analysis (PLS-DA), have been considered.

Approaches based in Bayesian Networks to sensor validation can be found in [66], [75] .

Data Mining approaches to the sensor validating problem can be found in [76],[77],[78].

3.3 Signal based sensor fault detection

Taking into account that the output signal of the sensors has specific properties in the time domain and in the frequency domain and that in the event of a fault therein such properties change, Yung & Clarke in [79] first used this approach, known as local sensor validation, witch uses detection of anomalies in the measurement for validating sensor. This technique matches the field of process fault detection that uses fault detection with signal models, in which a mathematical model is built for the signals under analysis, and the characteristics of the signals read are extracted and compared with the nominal value [1]. In recent publications relating to the detection of anomalies in the measurement descriptions can be found of techniques for *in situ* calibration verification, measurement of response times of the measuring instruments, test cables in sensor network, and noise test diagnostics [80], as well as techniques based on the theory of signal processing and statistical approach [63].

In [81] a combined wavelet and Support Vector Machine (SVM) approach is proposed. The time-series filtered data are passed through mother wavelets and several statistical features are extracted. Then these features are classified using SVM to detect anomalies as short fault (SF) and noise fault (NF).

In [82] a similar approach is proposed. The frequency domain features (shape statistics) are extracted from the data to characterize a spectrum for sensor fault detection purpose. The shape statistics include the centroid, the standard deviation, the skewness, and the kurtosis. Then a classification tree is used for classification.

In [83] a method is proposed for integrated sensor validation and fusion scheme based on the nonparametric kernel statistical estimator (smoother) Nadaraya-Watson.

A multi-scale principal component analysis (MSPCA) approach to the sensor validating problem can be found in [84]. MSPCA simultaneously extracts both, cross correlation across the sensors (PCA approach) and auto-correlation within a sensor (wavelet approach).

In [85] a sensor fault diagnosis model is established by chaos particle swarm optimization (CPSO) algorithm and support vector machine (SVM). In the study, wireless sensor is employed as research object, and four fault types of wireless sensor including shock, biasing, short circuit and shifting are applied to test the diagnostic ability of CPSO-SVM compared with particle swarm optimization support vector machine (PSO-SVM), and error back propagation Neural Network (BPNN) diagnostic methods. Ten features are extracted as input data of CPSO-SVM from experimental data (the article does not mention which features), and the four fault types of a wireless sensor are used as output data of CPSO-SVM. A Radial Basis Function (RBF) Kernel is used. Three CPSO-SVM classifiers are applied to recognize the four fault types each specialized in separating one kind of fault type from the remaining types. The diagnostic results obtained show that CPSO-SVM has higher diagnostic accuracy of sensor than PSO-SVM and BP neural network.

Although applied to fault diagnosis of a gearbox, in [86] a diagnosis model is proposed based on wavelet support vector machine (WSVM) with immune genetic algorithm (IGA) optimization. The WSVM uses a wavelet kernel function applied to the SVM classifier. Moreover, the feature vectors for fault diagnosis are obtained from vibration signal that is preprocessed by empirical mode decomposition (EMD). It is claimed that, compared with other ordinary method, such as canonical WSVM model, canonical RBF-SVM model and RBF neural network, the proposed method has more excellent characteristics and better generalization performance.

3.4 Qualitative Fault Diagnosis

The quantitative fault diagnosis based on symptoms generates models based on the analytical knowledge of the process. However, in many cases, such information is not sufficient to indicate the location and magnitude of the failure and, in addition, it may be necessary to use a qualitative knowledge-based approach [16],[33],[34],[88]. With this qualitative approach it is intended to transfer the existing knowledge of the system for supervision methodology and thereby develop expert systems for diagnosing faults [31][89][35][36][41][90]. This approach may also be used to develop models in order to do a qualitative sensor validation [1].

In [91] different techniques are reported for sensor fault detection, disambiguation, and mitigation. It presents an expert system that uses a combination of object-oriented modeling, rules, and semantic networks to deal with the most common sensor faults, such as bias, drift, scaling, and dropout, as well as system faults. The paper also describes a sensor correction module that is based on fault parameters extraction (for bias, drift, and scaling fault modes) as well as utilizing partial redundancy for dropout sensor fault modes). The knowledge-based system was derived from the results obtained in a previously deployed Neural Network (NN) application for fault detection and disambiguation. The paper includes a sensitivity analysis that compares the results previously obtained with the NN. It concludes with a discussion of similarities and differences between the two approaches and how the knowledge based system provides additional functionality compared to the NN implementation.

4 | Conclusion

Any suitable machine learning technique can be applied to the sensor validation problem since the residual generation can be seen as a regression problem and the decision-making as a classification problem. The classification problem can also be performed directly from the data without the computation of residuals or a separate fault detection step. This review highlights that an effective tool for sensor validation should use a balanced combination of the several techniques above mentioned. Depending on the type of approach used, the system will have best results in detecting specific types of faults. On this type of systems, a suitable method for sensor validation can be achieved through the fusion of different validation techniques in a sensor knowledge-based framework.

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