Available online at www.sciencedirect.com

ScienceDirect

IFAC-PapersOnLine 49-28 (2016) 091–096

Marine Engine Centered Localized Models for Sensor Fault Detection under Ship Performance Monitoring

Lokukaluge P. Perera

Norwegian Marine Technology Research Institute (MARINTEK), Energy Systems and Technical Operations, Trondheim, Norway (e-mail: prasad.perera@marintek.sintef.no)

Abstract: Sensor fault detection under marine engine centered localized models of an engine propeller combinator diagram is presented in this study. The proposed approach consists of two detection levels to identify of sensor fault situations in an onboard data acquisition system of a vessel. Each parameter in ship performance and navigation data can have a realistic data range (i.e. a threshold relates to the variance), where the parameter can vary. If the sensor reads a value beyond this parameter range, then that data point is categorized as a sensor fault situation by the first fault detection level. However, some sensor faults are located within this data range and that cannot identify by this detection level. Such complex sensor fault situations are detected by the second fault detection level by considering the proposed localized models. These localized models are derived with respect to the operating regions of an engine-propeller combinator diagram, where the respective data points are clustered by Gaussian mixture models with an expectation maximization algorithm. Each data cluster is examined through principal component analysis and projected into the bottom principal component to identify such complex sensor fault situations. A data set of ship performance and navigation information of a selected vessel is used through these sensor fault detection levels and the successful results on identifying such sensor fault situations are also presented in this study.

Keywords: Sensor Fault Detection, Principal Component Analysis, Big Data, Statistical Data Analysis, Gaussian Mixture Models, Engine-Propeller combinator Diagram.

1. INTRODUCTION

Modern integrated bridge systems (IBSs) are equipped with various sensors and data acquisition (DAQ) systems to monitor vessel performance and navigation information. Those systems collect large quantities of ship performance and navigation data and analyze to observe optimal vessel operation and navigation conditions. However, these large scale data sets consist of various sensor related erroneous intervals and that may degrade the results of the respective data analyses. If such erroneous data intervals are detected in an early stage of the data handling process, that can be removed to improve the quality of the data set. Furthermore, the respective faulty sensors can also be detected in such situations and the required maintenance actions can be taken. That step eventually improves the quality of the collected data sets and the final results of the data analyses. This study proposes a sensor fault detection structure in an onboard DAQ systems of a vessel consisting of several fault detection levels.

There are several sensor fault detection approaches with respect to ship performance and navigation information under various DAQ systems are presented in the recent literature (Lajic and Nielsen (2009) and Lajic et al. (2009)). These studies often depend on various mathematical models that relate to ship kinematics and dynamics. However, the accuracy of such models can be challenged under various navigation situations and the respective model performance can also degrade under large scale data sets. A model learning methodology to detect sensor faults situations is considered in this study and that consists of identifying the respective mathematical models from the respective data set of ship performance and navigation information. Hence, this approach has the capability to handle large scale data sets and that is the main contribution of this study.

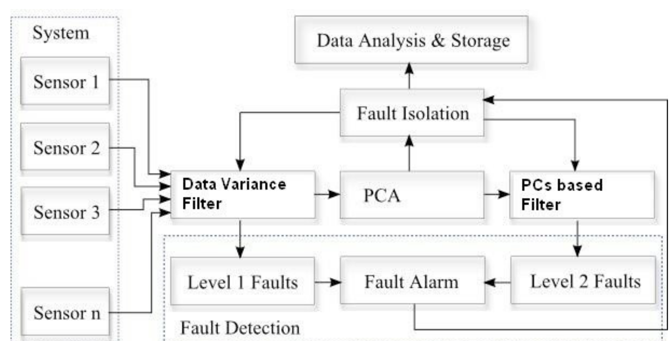

Fig. 1. Sensor fault detection structure

An overview of the proposed sensor fault detection structure is presented in Figure 1. This structure is developed by considering the respective studies of ship performance and navigation monitoring (Perera and Mo, 2016a, 2016b, 2016c, 2016d) and that consist of various data analysis and visualization tools and techniques. The figure consists of two

2405-8963 © 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.
Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2016.11.016

layers to identify of the respective sensor fault situations in an onboard DAQ system. The real-time data collected by the respective sensors transfer through these two layers. The first layer consists of a data variance filter (i.e. sensor faults level 1) that is attached to the respective fault alarm. The second layer consists of a principal components (PCs) based filter. Principal component analysis (PCA) (Sperduti, 2013) is used with the respective data set to derive this filter.

PCA is a non-parametric method for extracting relevant information from a chaotic type data set, where the respective structure of the data set can be identified. The same structure can be used to reduce the size of the data set and that also improves the content visibility. This structure is considered as the new basis of the same data set and that consists of a linear combination of the original basis (i.e. the initial parameters of the data set). This new basis has the same dimensions as the original data set and represents by the respective principal components (PCs). Various parameter relationships (i.e. correlation, covariance, dependence etc.) can also be observed under PCA. The largest to smallest variance directions in a data set are represent from the top to bottom PCs. The top PCs consist of the most important information of the data set. Hence, the top PCs in a data set select to represents the entire data set in some situations, where the least important (i.e. the bottom) PCs are neglected (i.e. data compression).

It is also noted that erroneous data intervals can often be observed under the bottom PCs because such regions are projected far beyond the respective parameter variance values of the bottom PCs. Hence, a majority of sensor fault situations can often be detected by the bottom PCs as further described in the second level sensor faults (i.e. level 2). Then, the fault alarm executes the fault isolation procedure, where these erroneous data intervals should filter to improve the quality of the respective data set (Perera and Mo, 2016c). Finally, the cleaned data set will transfer for data analysis and storage facilities for further processing. These sensor fault levels (i.e. level 1 and 2) are further discussed in the following sections.

2. SENSOR FAULT DETECTION

Two sensor fault levels are introduced in this study: level 1 & 2. Two types of sensor fault situations are detected under level 1: i) the repeated data points and ii) the data points beyond the selected thresholds that relate to the variance values of the respective parameters. It is noted that sensor and DAQ systems may crate data intervals with repeated values (i.e. frozen data intervals) in real-time data handling processes (Perera and Mo, 2016a). These frozen data intervals are detected by observing the repeated data values and should remove from the respective data set. e.g. it is noted that wind sensors in vessels may repeat some data values due to high vibration conditions under rough weather navigation situations. In general, sensors should not repeat such values due to measurement noise and that often approximates to white Gaussian distributions. However, this type of faults (i.e. repeated data points) can occur either due to sensor or DAQ system faulty situations.

Each parameter in ship performance and navigation information has a realistic data range where the parameter can vary. This respective range can be derived either from maximum and minimum values or selected threshold values that relate to the variances of each parameter. If the sensor reads values beyond this parameter range, then those data points are categorized as sensor fault situations. This simple concept is used in this level to identify another sensor fault situation and that is categorized as the data variance filter. The respective parameters of ship performance and navigation information of a selected vessel are presented in Table 1. The table consists of minimum and maximum values of each parameter and these parameter ranges are used to identify sensor fault situations under the same fault level. However, appropriate threshold values can also be introduced to identify the decision boundaries that relate to the variance values (i.e. minimum and maximum values) of fault level 1.

	Parameter	Min.	Max.
1.	Avg. draft (m)	0	15
2.	STW (Knots)	3	20
3.	ME power (kW)	1000	8000
4.	Shaft speed (rpm)	20	120
5.	ME fuel cons. (Tons/day)	1	40
6.	SOG (Knots)	0	20
7.	Trim (m)	-2	6
8.	Rel. wind speed (m/s)	0	25
9.	Rel. wind direction (deg)	2	360
10.	Aux. fuel cons. (Tons/day)	0	8

Table 1: Ship performance and navigation parameters

More complex sensor fault situations undetected by level 1 are captured by level 2. This step is named as a PCs based filter designed under PCA as mentioned before. An overview of such filter design is presented in this section. A two sensor situation, where two parameters are measured by sensors in a DAQ system, is presented in Figure 2 to explain such complex fault situations. Two parameters that are measured by two sensors with a selected sampling period are denoted as Y_1 and Y_2. The actual parameter values with sensor noise are presented by the respective shaded regions in the Y_1-time and Y_2-time plots. The measured values (i.e. sensor measurements) are denoted by "x" in this figure. The respective variance for each parameter is presented in blue oval shapes (i.e. next to Y_1 and Y_2 axes) in each plot. Four sensor fault situations, beyond actual measurements, are introduced and denoted as e_1, e_2, e_3 and e_4. One should note that sensor faults e_1 and e_3 can be detected by fault level 1 because those two values are beyond the thresholds (i.e. relate to the variance) of each parameter. However, sensor faults e_2 and e_4 cannot be detected by fault level 1, therefore fault level 2 is introduced to capture such events. The respective data set without timestamp is presented in the Y_1-Y_2 plot and that is used for PCA.

It is assumed that both parameters have a positive correlation as presented in Figure 2 and this relationship is visible in the Y_1-Y_2 plot. Such parameter relationships among