Chinese Journal of Aeronautics, (2015), 28(3): 874–882

Chinese Society of Aeronautics and Astronautics
& Beihang University

Chinese Journal of Aeronautics

cja@buaa.edu.cn
www.sciencedirect.com

A fault tolerant model for multi-sensor measurement

Li Liang [a,*], **Shi Wei** [b]

[a] *Information and Ecommerce Institute, University of Electronic Science & Technology of China, Chengdu 610054, China*
[b] *China Gas Turbine Establishment, Mianyang 621703, China*

Received 28 April 2014; revised 8 January 2015; accepted 13 March 2015
Available online 21 April 2015

KEYWORDS

Cointegration;
Fault tolerant;
Measurement;
Multi-sensor;
Turbine engine

Abstract Multi-sensor systems are very powerful in the complex environments. The cointegration theory and the vector error correction model, the statistic methods which widely applied in economic analysis, are utilized to create a fitting model for homogeneous sensors measurements. An algorithm is applied to implement the model for error correction, in which the signal of any sensor can be estimated from those of others. The model divides a signal series into two parts, the training part and the estimated part. By comparing the estimated part with the actual one, the proposed method can identify a sensor with possible faults and repair its signal. With a small amount of training data, the right parameters for the model in real time could be found by the algorithm. When applied in data analysis for aero engine testing, the model works well. Therefore, it is not only an effective method to detect any sensor failure or abnormality, but also a useful approach to correct possible errors.

1. Introduction

Multi-sensor systems are widely applied in complex environments to measure signals in many places. Altitude Test Facility of China is a huge laboratory for aircraft engines, where hundreds of sensors for many purposes are put inside an engine during testing. In each cross-section of the engine, there are several uniform linear sensor groups, e.g., seven sensors for temperature, five sensors for pressure and two sensors for vibration. When any unusual event happens, at least one sensor's signal inside the engine would be abnormal. Therefore, by comparing the outputs from the sensors, engineers can find out the possible fault. Usually, there are two reasons for an abnormal signal. One happens when a sensor itself breaks down, and the other happens when something around a sensor goes wrong. The traditional signal processing models to fit a test signal are auto-regressive and moving average (ARMA) model and wavelet etc. However, their performances are not satisfactory for non-stationary signals. That is why the multi-sensor approach is becoming popular in many scenarios especially in engine testing.[1–4] The redundant data from multiple sensors can improve both robustness and accuracy.[5,6]

The aim of this study is to establish a fault tolerant mechanism by investigating the relationship among the output signals of these engine testing sensors. When one signal deviates too far from its normal position, we can identify it and give

* Corresponding author. Tel.: +86 28 83201114.
E-mail address: liliang@uestc.edu.cn (L. Li).

Peer review under responsibility of Editorial Committee of CJA.

Production and hosting by Elsevier

http://dx.doi.org/10.1016/j.cja.2015.04.021
1000-9361

an alarm. Meanwhile, we can restore a deviated signal to the right position in which it "ought to be". A fault tolerant multi-sensor system is indispensable when one sensor undergoes impairment or when an unusual event such as oil leak happens.[7–9] The output of one sensor could be substituted by a combination of the outputs of others in the same sensor group, in case that there is something wrong around this sensor. In this paper, a novel approach is presented that can repair the signal from an abnormal sensor.

There are many papers discussing the data fusion and relationship among sensors in a multi-sensor architecture. In engine testing, each sensor in a sensor group works individually and independently, and it is impossible to put different sensors in exactly the same place. Therefore, there must be some difference between the outputs of any two sensors in the same sensor group no matter how close they are. Some papers use an absolute value of the difference as the distance between the outputs of two sensors, while more others use a relative value as the distance by considering their covariance.[10–13] One of them uses an "arcot" function to limit the distance within 0 to 1, and one uses the Minkowski distance.[14] All the papers above have attempted to find a reasonable relationship for two signals and use their distance for data fusion.

All the papers above did provide some useful techniques, however, they have two drawbacks. Firstly, their methods attempt to reconcile the difference by using a non-existent "center". It is thought that noises and drifts make signals deviate from a right pathway and this pathway is the "center" for all the signals. Meanwhile, the goal of data fusion is thought to find this center (right pathway) that all the signals ought to have taken, so most of the sensor fusion papers have used different methods to obtain the weights by Eq. (1), with v_i the value and w_i the weight of signal i.

$$E = \sum_{i=1}^{n} w_i v_i \tag{1}$$

Usually, E is the so-called "center value", and a signal that has a shorter distance from others is assigned a heavier weight in Eq. (1). Theoretically, this might be true, but it is not true in reality. Due to limitations in size, each sensor has to be put in different locations. Each sensor measures its source in its own location individually, and consequently, each output signal goes its own way. Therefore, we believe there is no center or "right pathway" for all the different sensors. One cannot tell where the right pathway suitable for all the sensors is. We believe that the relationship among sensors can be exploited for signal correction or amendment, but there is no center. Secondly, many researchers do not treat signals from sensor groups as time series. In their researches, monitoring of gas turbine engines uses either snapshot data at a time instant from various sensors or a window of time series data from selected sensor observations.[15] Thus, in data fusion, engine studies only compare the signals from different sensors at time t, and ignore the signals at time $t-1$, $t-2$, $t-3$ and so on. Therefore, in multi-sensor engine testing, time series analysis is usually not applied. Actually, the signals at time t usually are more relevant to the signals at previous times. With previous time information, people can find and handle fault propagation in an aircraft engine test.[16] In this paper, we try to build the following model for an n-sensor group as Eq. (2).

$$S_i^t = f\left(S_{\text{others}}^t, S_k^{t-1}, S_k^{t-2}, \ldots\right) \quad i = 1, 2, \ldots, n; \; k = 1, 2, \ldots \tag{2}$$

where $f(\cdot)$ is a transform function; S_i^t is the output of sensor i at time t; S_{others}^t represents the outputs of other $n-1$ sensors excluding sensor i at time t; S_k^{t-k} represents the outputs of all sensors at time $t-k$.

Fig. 1 shows the sensor signals from a seven-sensor group, in which seven sensors (named sensor 1, sensor 2, ..., sensor 7, respectively) are put on a cross-section of T23 in a jet engine. It is obvious that the signal from sensor 3, goes very high and is apparently abnormal. Is there any way to find the path that the signal of sensor 3 ought to have taken? Or whether we can restore the "original signal" of sensor 3? The studies which do not use time series analysis, provide no answers. So we will try a brand new way in this study. To repair the signal from sensor 3, we have to find a model that one signal can be substituted by others. In the following sections, a statistical method will be used to discover the possible relation between sensor signals which will be used to build a mathematical model.

When dealing with non-stationary signals such as those in Fig. 1, people tends to use difference calculation to make them "stationary", such as ARIMA. However, this way conceals the trend of the signal data. In many cases, the data after difference calculation has nothing to do with the original ones. Therefore, it is not easy to explain the phenomena as we lose the important information hidden in the original data.

Cointegration is an important statistical method to describe the relation among multiple time-series data.[17] In the cointegration model, one signal could be replaced by others. Cointegration was first used in explaining economical phenomena, and now its application has extended into many other fields. Though cointegration is not used so often in engineering, some papers can still be found. Kaufmann et al.[18] used cointegration for two sensors to analyze the relation between the solar zenith angle and advanced very high resolution radiometer data. Pan and Chen[19] used cointegration for four sensors in car engine testing. Lu and Chen[20] used cointegration for four sensors in a hydraulic flap servo system. In those studies, cointegration means a linear combination of variables and eliminates the stochastic trend in data, so for multivariable, especially non-stationary signals, cointegration is a powerful tool.

In this paper, cointegration is applied on sensor signals in engine testing. As it is very difficult to identify the pattern of

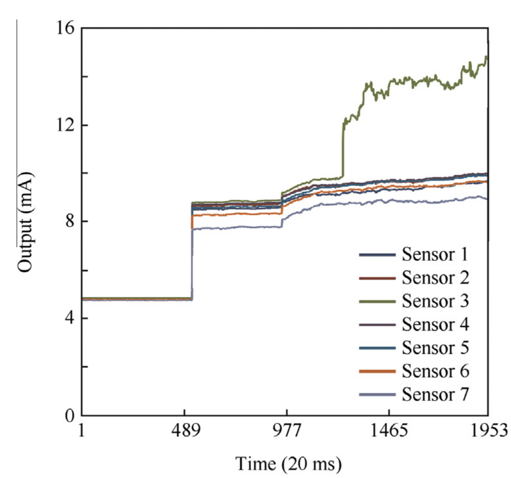

Fig. 1 Signals from seven-sensor group with sensor 3 signal abnormal.