Building and Environment 46 (2011) 970–979

Contents lists available at ScienceDirect

Building and Environment

journal homepage: www.elsevier.com/locate/buildenv

A novel model-based fault detection method for temperature sensor using fractal correlation dimension

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A R T I C L E I N F O

Article history:
Received 16 July 2010
Received in revised form
7 September 2010
Accepted 31 October 2010

Keywords:
Fault detection
Fractal correlation dimension
Noise
Temperature sensor
Air handling unit

A B S T R A C T

The direct residual-based fault detection method compares the difference between measured and estimated data of a process variable. Its correct fault detection rate is low due to the noise in measured signals. A novel method using fractal correlation dimension (FCD) is developed, in which FCD deviation is adopted instead of direct residual. The method is validated by detecting fixed and drifting bias faults generated in supply air temperature sensor of air handling unit (AHU) system. The setting of three main parameters including embedding dimension, time delay parameter and length scale, is investigated to find out the influence on calculating FCD values. The results show that it is more efficient to detect relatively small bias fault under noise conditions, although it needs a period of time to collect measured data. As a promising and practical tool, a hybrid fault detection technique combining FCD with direct residual should be conducted in further investigation to identify the generated fault under inevitable noise conditions.

1. Introduction

As the key components in heating, ventilation and air conditioning (HVAC) systems, sensors provide the basic information for operation and control system. It is very important to maintain an accurate and reliable operation without any faults in sensors. Unfortunately, sensor fault may occur in sensing device or its electronic components after long-term operation [1]. The common sensor faults can be classified as four different categories including fixed bias, drifting bias, precision degradation and complete failure [2]. All of them may decrease the control efficiency of controller, and result in poor operation or the invalidation of advanced optimal strategies.

Dozens of different methods have been applied to detect faults and their major differences are the knowledge used for formulating the diagnostics. The state-of-the-art fault detection and diagnosis (FDD) methods can be divided into four categories, including redundancy related [3], quantitative model-based [4–6], qualitative model-based and process history based [7] methods. Each method possesses some strengths as well as some weaknesses and suitability [8], and none is generic and perfect for any desirable cases. Only a few have actually been employed in FDD implementations although a number of physical models were developed for HVAC systems over the decades.

According to the engineering literatures, some of the FDD methods directly compare the residuals or deviations between measured and estimated values, and these tools can be defined as direct residual-based methods. For the widespread use of these methods, a crucial step is the ability to develop an accurate reference model of the equipment or system characterizing its fault-free operation [9–12]. Then, such a model can detect faulty operation by tracking the residuals or deviations between measured and estimated performance, and by identifying fault occurrences when these deviations exceed pre-selected thresholds.

There are some reference models to acquire the accurate fault-free parameters. Using the first law of thermodynamics with steady-state mass or energy conservation, a robust fault diagnosis method [13] can examine and minimize the sum of squared deviations over a period. This method is validated to evaluate soft sensor faults (biases) for temperature sensors and flow meters in central chilling plant. Other mathematical models including black-box multivariate polynomial methods, specifically radial basis function and multilayer perceptron, the generic physical component model [11,12], artificial neural network [14], rough set approach [15], transient pattern analysis [16] and others, are used to get deviations for well suited automated FDD in HVAC equipments and systems.

Residuals or deviations are always obtained by data processing of measured variable [17] about the actual process. This processing

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doi:10.1016/j.buildenv.2010.10.030

Nomenclature

$C(r)$	Correlation integral function
D_C	Fractal correlation dimension
H	Heaviside step function
m	Embedding dimension
n	Length of the time series
n_m	Number of the coordinate vectors
r	Length scale
r_{ij}	Radius
$t_{sup,a}$	Supply air temperature (°C)
ΔD_C	Deviation of fractal correlation dimension
Δt	Sample interval
Greek symbols	
τ	Time delay parameter
Subscript	
max	Maximum
meas	Measured
min	Minimum
est	Estimated

contains the limited value checking of directly measurable signals, the analysis of these signals, and the process analysis by using mathematical process models together with characteristic values, state variables or deviations. Rossi and Braun [18] also describe a common way to distinguish between the preprocessing whose features are extracted to represent the system state including generating deviations, filtering data, and classifying to analyze the extracted features for FDD.

The direct residual-based methods, however, have some weaknesses in fault detection. In practice, some inevitable noise may decrease the correct fault detection rates. Further, under noise conditions, the specified thresholds may impact on faulty or fault-free decision so significantly that it is very difficult to set a perfect value. If the threshold is far beyond noising ranges, the methods could not identify fault symptoms or state fluctuations especially when the faults present unobvious effects on the measured parameters. As to a small threshold, however, some influences, such as the error of data filtering, the disturbance of external environment and the time delay from measuring equipments, will be impossible to prevent. In this case, the methods may call good processes faulty and lead to large false alarm rates.

The fault detection method using fractal correlation dimension (FCD) algorithm [19] may cover the deficiency of direct residual-based method. FCD measures the probability of two points chosen at random. Within a certain distance between these two points, how this probability changes is examined with the distance increasing. As a non-linear signal processing tool, the FCD algorithm employs a dimension value to represent the curve variation of the original time series. The FCD value contains the characteristic information which includes the important fractal theories such as the self-similar characteristic and fractal dimension, and the curve variation refers to the time-dependent variation in the parametric curves. FCD could reflect the irregular or non-stationary nature of signals, and even the operational state of equipment or system. To extract the FCD of feature vector will be beneficial to detect or identify the faulty characteristic signals.

In this study, the principle of FCD is formulated and a novel FCD-based method is developed to detect fault generated in AHU supply air temperature sensor. The multiple-point fast Fourier transformation (FFT) algorithm is used to filter noise and the novel method is validated by detecting fixed and drifting bias faults. Besides, three main parameters are investigated to get the desirable FCD values.

2. Principle of FCD

In fractal geometry, the fractal dimension is a statistical quantity to indicate how completely a fractal appears to fill space. There are many specific definitions of fractal dimension. Partly due to the ease of implementation, FCD algorithm is widely used in practice. FCD algorithm is a measure of the dimensionality of the space occupied by a set of random points.

Usually, the practical measured data are irregular signals to display fractal characteristics at certain scales. As one of the achievements of chaos theory, an attractor is a set towards which a dynamical system evolves over time. The points can get close enough to the attractor, and an attractor can be a point, a curve, or even a complicated set with a fractal structure. If the system operation deviates from the fault-free state, the corresponding attractors, as well as the consequent FCD, will change. To put it in another word, the changes of system state will induce different FCD, which implies the changing state for system. Thus, fractal characteristics can use an FCD value to depict structural characteristics from irregular signals.

By using Grassberger and Procaccia (GP) algorithm [20], the phase space reconstruction can be available from the observed one-dimensional time series, and the FCD value representing dynamical system attractor can be calculated from the observations of phase time series. The curves for $\ln C(r)$ versus $\ln r$ can be plotted based on GP algorithm. By regulating the values of m and τ until the slope of the curve's linear part is almost invariable, the slope of this linear part is calculated by a least-square fit.

The time series can be described as

$$\{X_i\}, i = 1, 2, \cdots, n \tag{1}$$

where n is the length of time series.

The idea of chaotic dynamics reconstruction technique stems from the embedding theorem which regards a one-dimensional chaotic time series as the compressed information of a high dimension space [21]. m denotes the embedding dimension, and there are m points of data in each phase space. Then, the phase of spatial data can be represented as a series of points in an m-dimensional space and the jth scalar time series can be recorded as

$$x_j(m,\tau) = \left(x_j, x_{j+r}, \cdots, x_{j+(m-1)\tau}\right), \quad j = 1, 2, \cdots, n-(m-1)\tau \tag{2}$$

where τ is the time delay parameter and $\tau = k\Delta t$.

According to the method mentioned above, the time series with n points of data is divided into n_m groups.

$$n_m = n-(m-1)\tau \tag{3}$$

where n_m is the number of the points or coordinate vectors in the fractal set.

The m-dimensional hypersphere radius, is represented by Euclidean distance.

$$r_{ij}(m,\tau) = \left|x_i(m,\tau) - x_j(m,\tau)\right| = \sqrt{\sum_{k=0}^{m-1}\left(x_{i+kr} - x_{j+kr}\right)^2} \tag{4}$$

The center of a hypersphere can be defined as and the radius as. For each i with fixed value, a radius can be calculated from the