# Chapter 15
# Generating Indicators for Diagnosis of Fault Levels by Integrating Information from Two or More Sensors

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## ABSTRACT

*Diagnosis of fault levels is an important task in fault diagnosis of rotating machinery. Two or more sensors are usually involved in a condition monitoring system to fully capture the health information on a machine. Generating an indicator that varies monotonically with fault propagation is helpful in diagnosis of fault levels. How to generate such an indicator integrating information from multiple sensors is a challenging problem. This chapter presents two methods to achieve this purpose, following two different ways of integrating information from sensors. The first method treats signals from all sensors together as one multi-dimensional signal, and processes this multi-dimensional signal to generate an indicator. The second method extracts features obtained from each sensor individually, and then combines features from all sensors into a single indicator using a feature fusion technique. These two methods are applied to the diagnosis of the impeller vane trailing edge damage in slurry pumps.*

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## INTRODUCTION

Fault diagnosis is of prime importance to the safe operation of rotating machinery in various industries such as mining, power, and aerospace. It provides information on the health condition of a machine, based on which preventive maintenance or other actions can be conducted to avoid consequences of severe damage or failure. There are mainly three tasks in fault diagnosis (Bocaniala & Palade, 2006): fault detection, fault isolation and fault identification. The first task (fault detection) is to determine whether a fault occurs or not. The second task (fault isolation) is to determine the location of a fault and to specify the fault type. The third task (fault identification) is to estimate the severity of a fault. The first two tasks are also called fault detection and isolation (FDI). They are the first steps in fault diagnosis and have been widely studied in the literature (Bocaniala & Palade, 2006; Jardine et al., 2006). The third task provides detailed information on a fault and gains more and more attention. For the convenience of description, fault identification is referred as the diagnosis of fault levels in this chapter.

One important characteristic of fault levels is the inherent ordinal information among different levels. For example, "a severe fault" is worse than "a medium fault", and even worse than "a slight fault". This makes the diagnosis of fault levels more complicated than the diagnosis of fault types (Lei & Zuo, 2009b; Zhao et al., 2011b). Having ordinal information is an important characteristic of fault levels. Thus keeping the ordinal information is a necessity for the diagnosis of fault levels. One way to achieve this is to generate an indicator reflecting the fault propagation. If such an indicator is obtained, the fault propagation can be tracked by monitoring the value of this indicator and the fault level can be easily estimated by comparing the value of this indicator with pre-determined thresholds. How to generate such an indicator is a challenging problem.

Vibration analysis is widely used for fault diagnosis, in which various features can be obtained to express the health information on machines. The indicator that can be used for the diagnosis of fault levels must signify the propagation of a fault. In another word, the indicator must monotonically vary with the fault levels. This requirement makes many traditional features unqualified as an effective indicator. Previous researches have shown that different features are sensitive to different stages of fault propagation. For instance, kurtosis, crest factor and impulse factor are sensitive to the existence of sharp peaks (impact faults), especially at the initial stage of a fault. But they will decrease to the value of a normal case as the damage grows (Tandon & Choudhury, 1999). Li and Limmer (2000) studied some statistical features' correlations with gear tooth wear, including RMS, FM0, FM4 and NA4 (Sait & Sharaf-Eldeen, 2011), and found that these features showed little change during most of the gear life.

In order to obtain an indicator for fault levels, various techniques have been used, which can be generally classified into two groups. The first group resorts to an assessment model which is obtained through machine learning techniques such as neural network (Jay, 1996) and hidden Markov model (Ocak et al., 2007). An indicator is generated using the assessment model. Li and Limmer (2000) built a linear auto-regression model based on normal vibration data, and then applied this model to vibration data over the gear's life. The distance (prediction error) between the model output value and the monitored vibration data was used as an indicator for gear damage levels. Qiu et al. (2003) employed Self Organizing Map (SOM) to build a model for bearing health assessment. An indicator evaluating the distance between the new input data and best matching unit of the SOM was extracted. Pan et al. (2010) built an assessment model based on training samples including normal and failure data using fuzzy c-means. The subjection of tested data to the normal

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