# Fault Diagnosis in Industry Using Sensor Readings and Case-Based Reasoning

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**Abstract.** Fault diagnosis of industrial equipments becomes increasingly important for improving the quality of manufacturing and reducing the cost for product testing. Developing a fast and reliable diagnosis system presents a challenge issue in many complex industrial scenarios. The major difficulties therein arise from contaminated sensor readings caused by heavy background noise as well as the unavailability of experienced technicians for support. In this paper we propose a novel method for diagnosis of faults by means of case-based reasoning and signal processing. The received sensor signals are processed by wavelet analysis to filter out noise and at the same time to extract a group of related features that constitutes a reduced representation of the original signal. The derived feature vector is then forwarded to a classification component that uses case-based reasoning to recommend a fault class for the probe case. This recommendation is based on previously classified cases in a case library. Case-based diagnosis has attractive properties in that it enables reuse of past experiences whereas imposes no demand on the size of the case base. The proposed approach has been applied to fault diagnosis of industrial robots at ABB Robotics and the results of experiments are very promising.

**Key Words:** case-based reasoning, fault diagnosis, feature extraction, signal filtering, wavelet analysis

## 1. Introduction

A fault is an abnormal state of a machine or a system such as dysfunction or malfunction of a part, an assembly, or the whole system. As machines become larger and more complex with industrial development, the costs and technical know-how required for system maintenance increases substantially. Fast and precise identification of faults and problems in equipments makes a crucial contribution to the enhancement of reliability in manufacturing and efficiency in product testing.

For monitoring purpose, streams of data are gathered by various sensors on-board equipments. Such sensor recordings can be regarded as evidence of origin for recognizing the working conditions of a machine (e.g. normal operation, loose rear wheel, damaged gear). Although experienced key persons can make proper judgment of failures by inspection of the measured signals in many circumstances, it would be fairly hard to do so by moderate staff. Trouble might arise when a fault occurs whereas the experienced personnel are not around due to some reasons like vacation and sickness to mention a few. Things turn still tougher with those sensor signals containing heavy measurement noise such that even skilled operators fail to distinguish faults without supporting tools.

Construction of automatic diagnosis systems based on Artificial Intelligence (AI) methods and techniques receives increasing attention for extending the capability of key personnel and reducing human costs connected with equipment maintenance. Expert systems [16] provide a useful means to acquire diagnosis knowledge directly from key personnel and transform their expertise into production rules. However, the knowledge acquisition and verification processes are difficult and complicated and sometimes experienced technicians even have no idea of how to express their strategies explicitly and accurately. Rule induction [6, 14] and neural network models [5, 10] are data mining methodologies that can be applied to find out fault classification knowledge using previous known examples. They show strong ability in discovering important knowledge from historic data but require a sufficiently large training set to ensure promising outcome and overcome the risk of over-fitting. Unfortunately, in many practical scenarios, merely a very low number of examples are available in support of machine learning.

Case-based reasoning [1] (CBR) offers another alternative to implement intelligent diagnosis systems for real-world applications [11]. Motivated by the doctrine that similar situations lead to similar outcomes, CBR fits well to classify the current new sensor signals based on experiences of past categorizations. The main strength lies in the fact that it enables directly reusing concrete examples in history and consequently eases the knowledge acquisition bottleneck. It also creates the opportunity of learning from experiences but skipping the step of data training such that the over-fitting problem no longer exists. We believe that CBR techniques are of particular application value for diagnosis in real industrial environments where the acquirement of adequate training examples in advance is mostly not realistic if not impossible.

This paper aims to investigate the utility of CBR techniques for diagnosis of industrial equipments based on streams of sensor recordings. The received signals are processed by wavelet analysis to filter out noise and at the same time to extract a group of related features that constitutes a reduced representation of the original signal. The derived feature vector is then compared with the known cases in the case library with its neighboring cases sorted out, and subsequently the new situation is classified by combining the outcomes of those similar cases retrieved. Our presented approach has been applied to fault diagnosis of industrial robots produced by ABB Robotics in Västerås (Sweden) and the preliminary results of evaluation are very promising.

The paper is organized as follows. Section 2 gives a general structure for fault classification starting from streams of sensor readings. Signal analysis and feature extraction is addressed in Section 3, followed by an outline of necessary details of performing case-based classification using extracted features in Section 4. Section 5 gives a case study applying the proposed approach to fault diagnosis of industrial robots and some experiment results are demonstrated. Finally the paper is concluded in Section 6 with a short summary and remarks.

## 2. Fault Diagnosis Based on Sensor Signals

Abnormality of industrial machines can be reflected by some key states during their operation. Using sensor technology it is possible to detect and measure the values of these system states and their profiles. We can then process and analyse the collected sensor recordings in order to find out hidden symptoms. The system can, based on the symptoms, reason about the class of fault associated with the machine or make prediction about what potential problem is likely to occur in a near future. A general system structure for this purpose is illustrated in Fig. 1, which includes signal filtering, feature extraction, and pattern classifier as its important components.

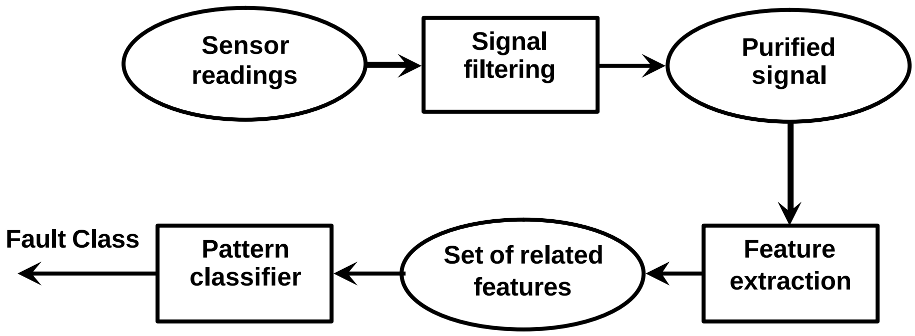


**Fig. 1.** Fault diagnosis based upon sensor signals

Signal filtering is used to purify original sensor readings by removing the noises contained in the signals such that more reliable diagnosis results will be warranted. Usually there are two kinds of noises involved in the perceived signals; one is measurement noise due to intrinsic imprecision of sensors and the other is external noise caused by disturbance from surroundings and which is added to the sensor data received. Signal recovery from external background noise has been well dealt with by applying signal processing methods like wavelet analysis and time domain averaging (see [8, 9]). The reduction of measurement errors is outside the scope of this paper, but interested readers can refer to sensor fusion systems in which Bayesian based filtering approaches such as Kalman filtering [3] and particle filtering [7] merit to be used to obtain more accurate estimates of related states.

Feature extraction is purported to identify characteristics of the sensor signals as useful symptoms for further analysis. This stage is critical for fault diagnosis in many industrial applications in which the underlying system is dynamic. If so, the measurements of a state generally change with the time rather than constantly staying at a static level. This means that the observations of the system are continuously varying which makes it hard to handle them directly in diagnosis. In order to supply the pattern classifier (in Fig. 1) with a moderate number of inputs for effective analysis and reasoning, representative features from the sensor signals have to be extracted. Our point is that for many tasks the collection of extracted features ought to be adequate to give a concise and complete description of the condition of the system to diagnose.

Regarding fault classification a number of different methodologies can be considered. Expert systems were developed in support of gathering, representing and utilizing human expert knowledge for problem solving but they suffer from the knowledge acquisition bottleneck. Regression functions fit themselves into defining linear classification boundaries using a low number of attributes as function variables. For complex diagnosis situations with non-linear boundaries and many relevant features a classifier based on artificial neural network might be a good choice. Nevertheless the success of neural network functioning is conditioned upon the prior training of the network with sufficient examples, which unfortunately are not guaranteed in quite a few industrial environments. In contrast CBR has the advantages of entailing no training beforehand but still exhibiting the ability for incremental learning if new useful cases are properly injected into the case library. This motivates us to develop a case-based classifier of fault patterns in this paper. We believe that applying CBR techniques for diagnosis is a strong candidate to deal with certain industrial problems with a high feature dimension but few known samples as support.

## 3. Case-Based Classification Using Extracted Features

As mentioned before, the measurements from a dynamic industrial system constitute time-varying data streams that are not suitable for immediate usage. Hence we need to "dig out" representative features hidden in the signal profiles prior to fault classification. The features extracted are delivered to the fault classifier as a probe case. According to the domain from which features are derived we can distinguish between two categories of features: time-based features and frequency-based features.

Time-based features are extracted from the profile of signal values with respect to time. Typical features of this kind can be peak value, start time, overshoot, rising time, mean value, integral, standard deviation, etc. In practice what features to derive from the time domain is commonly ad-hoc and problem dependent. An example of using time-based features for case-based circuit diagnosis is illustrated in [13].

Frequency-based features characterize sensor signals according to their amplitudes under significant frequencies. As many fundamental signal analysis methods are available to yield frequency spectra, we seem to have more solid basis for extracting features based on frequency than for deriving time-based features. We thus adopt frequency-based features as descriptors of condition parts of cases in our research. Generally a vector of frequency-based features is formulated as

$$FV = \left[ Amp(f_1), Amp(f_2), \cdots, Amp(f_n) \right] \tag{1}$$

where $Amp(f_i)$ denotes the function of amplitude which depends on frequency $f_i$ and $n$ is the number of frequencies in consideration.

Wavelet analysis [2] is an effective tool of transforming analogue sensor signals to frequency spectra. It has been shown to perform better than Fourier transform under circumstances with heavy background noise [9]. Technical details of wavelet analysis for feature extraction are discussed in [12], therein a comparative study was also performed between wavelet analysis and Fourier transform demonstrating the superiority of the wavelet approach in producing high quality features for case-based classification.

## 4. Case-Based Classification Using Extracted Features

After the features have been extracted from sensor signals, we perform case-based reasoning to make classification of the current fault using known cases in the case library. Fig. 2 gives an overall illustration for this procedure, which consists of the following two steps:

1. Retrieval: compare the feature vector with the known cases in the library by means of similarity calculation and subsequently select the *k* nearest cases exhibiting the highest similarity degrees;
2. Solution fusion: determine the fault class associated with the current feature vector in terms of both the classes of the retrieved cases and their similarity values with respect to the probe case.

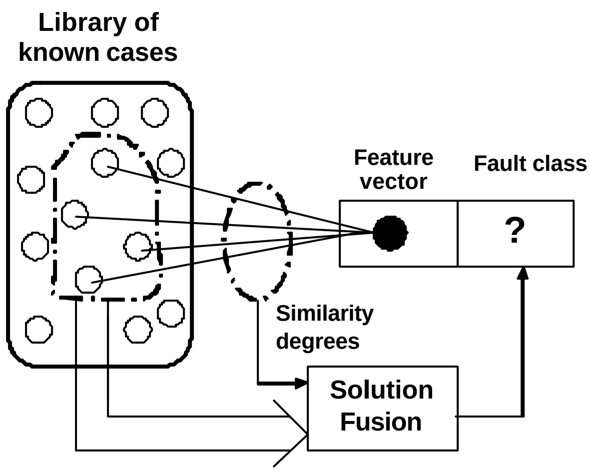


**Fig. 2.** Case-based fault classification

Given a feature vector $Y = (y_1, y_2, \ldots y_n)$ its similarity degree with case $C$ in the case library is defined as

$$Similarity(Y,C) = \sum_{i=1}^{n} w_i \times \left(1 - \left|norm(y_i) - norm(c_i)\right|\right) \qquad (2)$$

where $w_1, w_2, \ldots, w_n$ are attribute weights reflecting different importance of individual features, $c_i$ represents the $i$th feature of case $C$, and $norm(y_i)$ and $norm(c_i)$ denote the normalized values of $y_i$ and $c_i$ respectively.

In the step of solution fusion we can easily judge a fault class if all the retrieved cases have that class as their outcomes. Otherwise voting is launched among the classes that exist in the retrieved cases. For every such class $B_j$ we calculate its voting score as

$$VS(B_j) = \sum_{P \in Rs} \begin{cases} Similarity(Y,P), & if \quad P \quad has \quad class \quad B_j \\ 0 & otherwise \end{cases} \qquad (3)$$

where $Rs$ denotes the set of retrieved cases and $P$ is the current feature vector. Finally the fault is classified into the class that has the largest voting score.

## 5. Application to Fault Diagnosis for Industrial Robots

As a case study we applied the proposed approach to diagnosis of industrial robots manufactured by ABB Robotics in Västerås, Sweden. The prototype system developed for this purpose is shown in Fig. 3. Sound signals are gathered from the robot to be tested via a microphone device and then transmitted to the computer for pre-processing. The pre-processing is tasked to filter out or remove unwanted noise as well as identify period information from a sound profile. Subsequently sound features are extracted from the frequency domain and they are assembled into a feature vector as a condensed representation of the original sound signal. Classification of the feature vector is performed based upon previously classified sound descriptions in the case library. The experiments have shown that this system is able to successfully diagnose faults in an industrial robot based on a low number of previous examples.

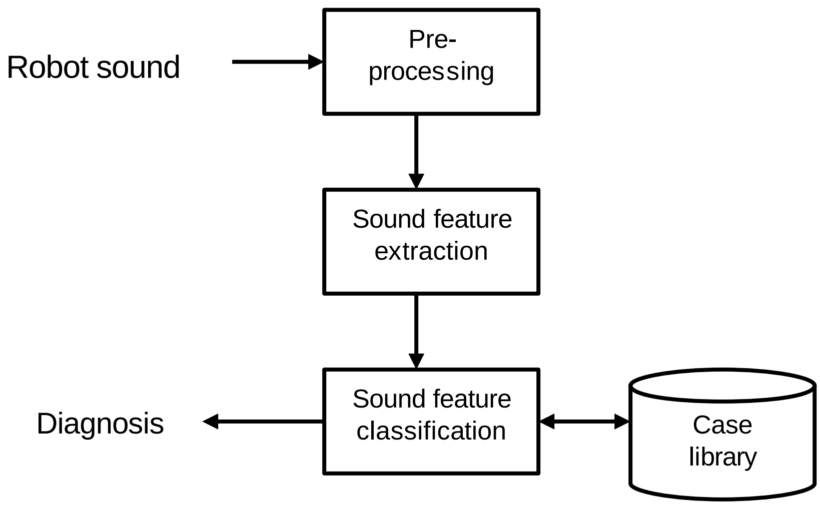


**Fig. 3.** Schematic outline of the prototype system

It is worth mentioning that the above prototype system has some similarities with the Open System Architecture for Condition Based Maintenance (OSA-CBM) [15]. That architecture suggests that a Condition Based Maintenance (CBM) system be divided into seven modules [4] including sensors, signal processing, condition monitoring, diagnosis, prognosis, decision support, and presentation. The system presented here in this paper has microphone as sensor module and pre-processing & feature extraction steps as signal processing module in correspondence to the OSA-CBM architecture. In addition, the case-based classification in Fig. 3 also serves condition monitoring by detecting and identifying deviations in sound profiles.

### 5.1 Pre-processing and Feature Extraction

Sounds of robots in industrial environments typically contain unwanted noise from background. A robot fault is often indicated by the presence or increase of impulsive elements in the sound. The detection of these impulsive sound elements can be hard. This is owing to the various sporadic background noises prevalent in industrial environments and they are added to the received sound signals. Before the attempt of classification, the sound from the robot has to be pre-processed in order to remove as much unwanted noise as possible. In Fig. 4 the two pre-processing steps are shown which are termed as period extraction (left box) and time domain averaging (right box).

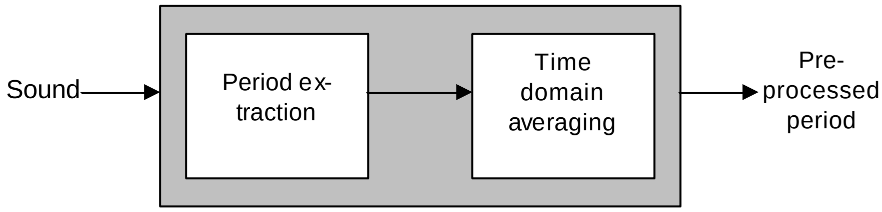


**Fig.4.** Pre-processing of sound data in the prototype system

In order to obtain time information about the robot arm movement, period has to be detected from the sound profile. A period refers to the duration within which the robot arm rotates from the start position to its destination. Commonly sounds from the robot are recorded in a time span with a few periods. Each period for the robot arm movement is characterised by a continuous sound followed by a short time of silence. After getting period information a mean length for periods is calculated from a number of successive periods of the robot sound, thereby eliminating sporadic impulsive elements from unwanted sources and enhancing repeating impulse sound normally related with robot faults.

After identifying period information a set of important features must be extracted from the sound signal within a single period. Wavelet analysis is applied herein to find out such features for sound classification. In a related paper [12] we experimentally verified that, under certain circumstances of strong background noise, wavelet outperforms Fourier transform in supplying distinguishable feature vectors between different faults for case-based classification.

## 6. Sound Classification and Results

Sounds from 24 healthy robots and 6 faulty robots were collected to enable case-based classification of conditions of robots. Two types of faults need to be recognized in the experiments hereafter called Fault 1 and Fault 2. A notch on the big gear wheel in the gearbox causes Fault 1. This fault is hearable and is characterized by a low frequency impulse sound in the middle of the rotation of the axis. Fault 2 is caused due to a slack between the gear wheels in the gearbox and can be heard as bumps at the end of each rotation.

A feature vector is assembled with peak wavelet coefficients taken from different depths in a wavelet package tree [2] and it is then matched with the previously inserted cases in the case library. The prototype system demonstrated quite good performance by making right judgements in 91% of the all tests (see further down). Table 1 displays a ranked list of the three best matching cases in the case library according to the similarity values calculated. As can be seen from the table, a previously diagnosed notch fault recording is deemed to be the most similar case thereby making the strongest recommendation to classify the probe situation into notch fault. The cases ranked the second (case #12) and the third (case #4) are descriptions classified as normal in the case library. This list of the most similar cases can be presented to human operators as decision support.

Table 1: A ranking of the most similar cases for the sound profile

| Case name | Similarity | Case ranking |
|---|---|---|
| Notch fault #2 | 98% | 1 |
| Normal case #12 | 84% | 2 |
| Normal case #4 | 83% | 3 |

We also investigated the classification accuracy in relation with different feature vector sizes in order to assess the smallest number of features that still produce good classification performance. The diagram in Fig 5 indicates the relation between the classification error rate and the number of features. The upper curve in the figure shows the results when only top 1 case was considered for solution fusion. The curve below in the diagram shows the classification results when the top three cases were considered. When only the nearest case was considered, the system produced a classification rate of 91%. When the three nearest cases were considered, the classification rate of the system rose to 99%.

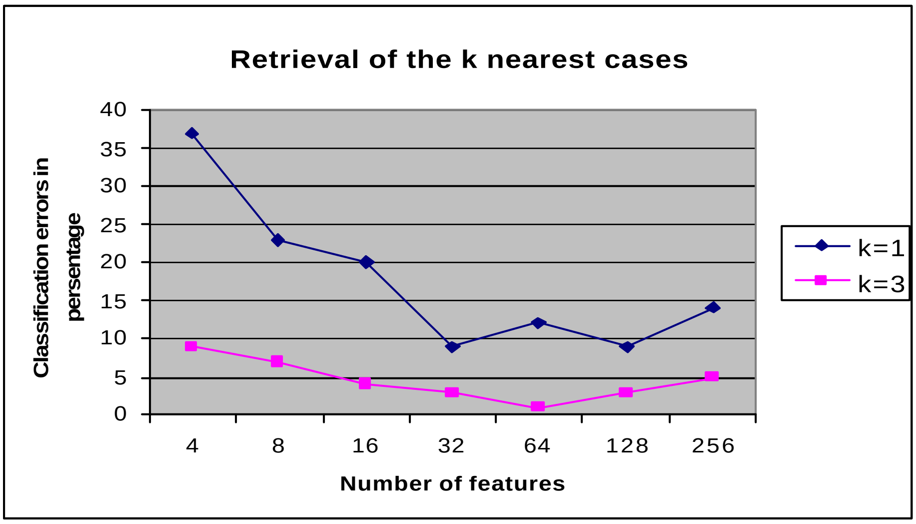


**Fig. 5.** Relation between classification performance and the number of features

## 7. Conclusions

This paper presents a new approach to fault diagnosis of industrial equipments using case-based reasoning and sensor data. Wavelet analysis is advocated as an effective means to remove noise and extract a set of good quality features. The assembled feature vector serves as condition description of a case. Case-based fault classification gives considerable benefits in numerous practical applications. They include:

It fosters experience reuse and sharing in the sense that classified signal descriptions from different sources can be easily added to a common library.

- It does not require a complete case library for functioning properly. As no training of known cases is needed, there exists no over-fitting risk any more.

- It enables improving classification performance as long as newly classified signal descriptions are injected into the case library.
- It entails case retrieval, giving intermediate results that are user-friendly and offer a sort of decision support for human operators in diagnosis.

## Acknowledgement

This research is part of the ExAct project, funded by The Swedish Foundation for Strategic Research (ProViking) and ABB Robotics, Volvo, SKF and Svenska Underhållsföretagen (SCEMM).

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