Mälardalen University Licentiate Thesis
No.55

Diagnosis of Machines within Industry using Sensor Signals and Case-Based Reasoning

Erik Olsson

September 2005

MÄLARDALEN UNIVERSITY

Department of Computer Science and Electronics
Mälardalen University
Västerås, Sweden

ISSN 1651-9256
ISBN 91-88834-95-6
Printed by Arkitektkopia, Västerås, Sweden
Distribution: Mälardalen University Press

Abstract

Machines are not perfect; they sometimes fail to operate as intended. Such failures can be more or less severe depending on the kind of machine and the circumstances of the failure. E.g. the failure of an industrial robot can cause the hold-up of an entire assembly line costing the affected company large amounts of money each minute on hold. This kind of situation can be prevented by equipping machines with automatic condition-monitoring systems that continuously monitor their condition and instantly report the detection of a failure or an incipient failure. The nature of machine-monitoring and diagnosis lends itself naturally to Case-Based Reasoning. Case-Based Reasoning is a method in the discipline of Artificial Intelligence based on the idea of assembling experience from problems and their solutions as "cases" for reuse in solving future problems. Cases are stored in a case library, available for retrieval and reuse at any time. By collecting such sensor data as sound and vibrations from a machine and representing this data as the problem part of a case and consequently representing the measured corrective action as the solution to this problem, a complete series of the events of a machine failure and its correction can be stored in a case for future use. This thesis describes an innovative approach to this concept by using a combination of Case-Based Reasoning and wavelet analysis as a means of condition-monitoring and diagnosis of primarily industrial machines. For evaluation purposes this novel approach is implemented as a prototype system for the diagnosis of the status of gearboxes in industrial robots.

To my family

Preface

I would like to thank all the people who helped me making this thesis a fact. First of all I would like to thank my supervisor Peter Funk who has contributed with lots of ideas and valuable discussions. I would also like to thank my sponsoring company that made my research possible, foremost Mats Åhgren and my assistant supervisor Mats Jackson at ABB Robotics for their support and dedication in my work. I would also like to thank Rostyslav Stolyarchuk at the State Scientific and Research Institute of Information Infrastructure, Lviv, Ukraine, Marcus Bengtsson at Mälardalen University, Eskilstuna and my second assistant supervisor Ning Xiong at Mälardalen University, Västerås, for their cooperation and valuable ideas concerning the included papers. I would also like to thank Patrick Wehbi at ABB Robotics for his invaluable help concerning robot programming and sound recording.

Finally I would like to thank my family and my friends for making my life and work bearable!

Erik Olsson
Västerås, September 26, 2005

Publications

Publications included in the thesis

E. Olsson, P. Funk and N. Xiong. Fault Diagnosis in Industry Using Sensor Readings and Case-Based Reasoning. Journal of Intelligent & Fuzzy Systems, 15, pages 41–46, 2004.

E. Olsson. A Survey of Case-Based Diagnostic Systems for Machines. Seventh International Conference on Enterprise and Information Systems, pages 381–385. ICEIS, Miami, May 2005.

E. Olsson and R. Stolyarchuk. Dynamic Modeling and Sound (Noise) Diagnostics of Robot Gearboxes for Fault Assessments. Scandinavian Conference on Simulation and Modeling. SIMS, Trondheim, October 2005.

Publications not included in the thesis

E. Olsson, P. Funk and M. Bengtsson. Case-Based Diagnosis of Industrial Robots Based on Acoustic Signals. Proceedings of the European Conference on Case-Based Reasoning, pages 686–701. ECCBR, Madrid, August 2004.

E. Olsson and P. Funk. Diagnosis of Industrial Equipment using Case-Based Reasoning and Sound Comparison. Proceedings of the AILS-04 Workshop, pages 93–100. Lund, April 2004.

M. Bengtsson, E. Olsson, P. Funk and M. Jackson. Technical Design of Condition Based Maintenance System - A Case Study using Sound

Analysis and Case-Based Reasoning. Proceedings of the 8th Maintenance and Reliability Conference. Knoxville, May 2004.

Contents

I

Thesis

Chapter 1

Introduction

It is of great value to a production company in the growing global market of today to be able to automatically detect or predict a failure in its machines, either those in its production lines or those which it produces and offers to its customers. In either case, the failure of the machine might cost thousands of dollars in delayed or lost production or in damage to the company's reputation among buyers. To prevent this kind of breakdown, condition-monitoring systems can be used to aid the engineer in performing a diagnosis of the machine and in its repair.

A condition-monitoring system is able to assess the condition of a machine and report if any deviation from the standard mode of operation of the machine occurs or is likely to occur. Deviations can be increasing vibrations, rising temperatures, abnormal noise etc. Even though the benefits of this kind of systems are well known, they are still not widely accepted within industry. One basic reason for this might be the fear of investing much in the implementation of such a system without knowing exactly what the results will be [1]. E.g. it is well known that sensor faults can cause unwarranted stops in production but recent advances in research in the area of Artificial Intelligence (AI) have increased the reliability of this type of system. This thesis describes a novel approach that combines Case-Based Reasoning (CBR) and wavelet analysis in a decision-support system used for fault diagnosis of machines. For evaluation purposes, a prototype has been implemented and tested on gearboxes in industrial robots. The system can be used as a decision-support tool by engineers and it has been evaluated in an actual industrial setting at ABB Robotics in Västerås, Sweden.

CBR is a promising method for use in implementing a decision support system for fault diagnosis of machines. CBR uses a database containing problems experienced previously and the solutions to these, to solve new problems of a similar nature. [2]. The solutions can be collected from human experts or they can reflect previous search results in the case library. An example of an area in which CBR has been used is in medicine [3] where the symptom (the problem) and its diagnosis and treatment (the solution) are used as a case. The diagnostics of technical equipment such as industrial robots and the medical diagnosis of humans are analogous. When a robot fails to operate as intended it often shows unusual symptoms e.g. abnormal noises or shifting trends in driving current etc.

1.1 Outline of thesis

This licentiate thesis is organized as follows. Chapter 2 provides a background to the most important methods and techniques used in developing this thesis. Chapter 3 considers the area of case-based fault diagnosis of machines. It presents a short background, related work, motivation and contributions to this domain of applications. Chapter 4 summarizes the papers which form part of the thesis. The first part of the thesis is concluded in Chapter 5 and future work is suggested. The following three chapters contain complete versions of the included papers.

Chapter 2

Background

This chapter presents a short theoretical background to the work this thesis is based on. Section 2.1 gives a short introduction to the Case-Based Reasoning methodology and section 2.2 presents some theoretical explanations of the phenomena of gear noise.

2.1 Case-Based Reasoning

2.1.1 History of CBR

CBR is derived from instance-based learning which is a machine learning method [4]used in the artificial intelligence discipline. The technique of CBR had its theoretical origins in the mid 1970s and originally came from research in cognitive science [5]. It a feasible model of the reasoning process performed by our brain e.g. when we are subjected to stereotypical situations such as going to a restaurant or visiting a hairdresser. If a similar situation is encountered a second time, memories of these situations are already recorded in our brains and stored as scripts that inform us what to expect and how to behave. The original work in CBR was performed by Schank and Abelson in 1977. In 1983 Janet Kolodner developed the first CBR system designated CYRUS [6]. Cyrus was an implementation of Schank's dynamic memory model and contained knowledge, as cases, about the travels and meetings of a former U.S. Secretary of state. CBR has been known outside the research community since about 1990 when Lockheed began to use a CBR system named

CLAVIER [7] for the baking of composite parts in an industrial oven.

2.1.2 The Structure of Case-Based Reasoners

The designs of most CBR systems share some common features. The basic parts of the system are the case and the case library. The structure of cases can be very different, depending on the systems in which they are used but in general they all share some common parts:

- A problem description, generally a set of features.
- A solution to the problem

The features are used to match the case against other cases. They can be generic text, symbols, numerical values etc. The problem description is the reason for the existence of the case. It describes the problem to be solved. The solution describes how the problem has been solved when encountered in the past. The solution may be altered and adapted if the problem differs in any way from that described in the case. Cases are stored in a case library, commonly stored in a database with routines for storing, retrieving and manipulating cases.

A Case-Based Reasoner operates with the case library as the central part of the system. When a new problem occurs the case-based reasoner:

1. Retrieves the appropriate case from the case library.
2. Reuses the retrieved case in the current situation.
3. Revises the retrieved case if needed.
4. Retains the revised case in the case library.

This cycle enables the Case-Based Reasoner to improve it's ability to solve problems over time as more and more cases are stored in the case library.

A new problem is matched against cases previously stored in the case library and those most similar are retrieved from the library. A solution is suggested based on the retrieved case(s) that represents the closest match to the new case. If the proposed solution is inappropriate it will probably need to be revised, resulting in a new case that can be retained in the case library. Figure 2.1 depicts the CBR cyclical process applied to the classification and diagnosis of sensor data.

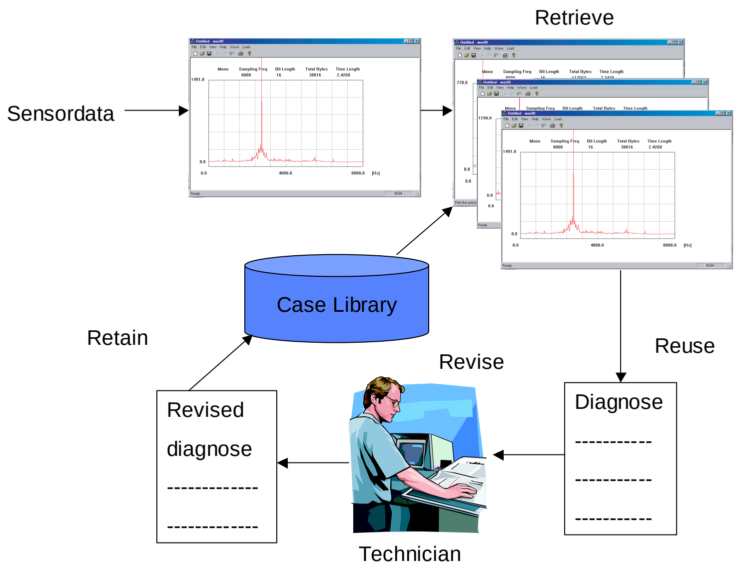

Figure 2.1: The CBR process.

2.1.3 Case Retrieval

To retrieve cases similar to a new problem the system needs a matching function able do identify such similar cases. Most often, cases are retrieved by some kind of similarity measurement. The similarity measurement is based on certain selected characteristics and enables the quick retrieval of appropriate cases from the case library. E.g. in a machine diagnosis system, these features might be the type of machine, specifications of the machine, various extracted sensor data from the machine etc.

The similarity measurement calculation usually results in the retrieval of cases not identical with the new case but separated by a certain "distance". A common technique used when calculating the distance measurement is the nearest neighbor retrieval. The formula for the nearest neighbor distance calculation is shown in 2.1.

$$Similarity(N, R) = \sum_{i=1}^{n} w_i \times f(N_i, R_i) \tag{2.1}$$

where

N is the new case
R is the retrieved case
n is the number of features in each case
i is an individual feature from 1 to n
f is a similarity function for attribute i in cases N and R
w is a weight that controls the importance of attribute i

As shown in 2.1 weights can be used in the retrieval process to discern features that are more or less important in the retrieval process. By weighting certain attributes, the nearest neighbor calculation can be made more realistic.

2.1.4 Adaptation

When a case is retrieved, the CBR system will try to reuse the solution it contains. In many circumstances this solution may be appropriate. But if the proposed solution is inadequate, the CBR system might try to adapt the proposed solution. Adaptation means that the system tries to transform the proposed solution (if close enough) to a more appropriate solution suited for the new case. In general there are two kinds of adaptation procedure in CBR:

- Structural adaptation
- Derivational adaptation

Structural adaptation begins with the original solution and adapts this by the application of adaptation rules and formulas. Derivational adaptation derives a new solution from the rules or formulas that created the original solution. In this method, the rules that created the original solution must be saved in the case.

Today, most CBR systems do not use adaptation. They simply reuse the solution suggested by the closest matching case. If any adaptation is needed, this is performed manually

2.2 Gear Noise

Operating gears generate noise by the meshing of gear teeth. The noise is transmitted to the shafting, bearings and transmission housing. The transmission housing then acts as a loudspeaker and radiates the noise to the surrounding environment. The noise is in most cases caused by a imperfect engagement of the gear teeth. This imperfect action results in non-constant angular velocities caused by the dynamic forces at the gear teeth which in turn excite vibrations in the gear blanks and shafting. The gear housing walls normally prevent noise from the gear blanks reaching the human ear. The most significant transmission path of the noise is through the transmission housing.

Figure 2.2 depicts the first part of a drive train of an axis in an industrial robot. It consists of a driving and a driven shaft.

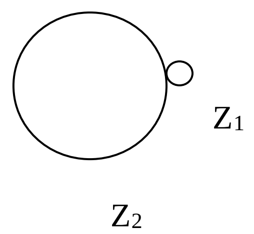

Figure 2.2: A part of a simple drive train.

The gear ratio i of Figure 2.2 can be calculated as:

$$i = \frac{Z_2}{Z_1} \tag{2.2}$$

where

Z_1 =number of teeth of the driving gear (pinion)
Z_2 =number of teeth of the driven gear

The primary shaft rotational frequencies can be calculated using the following formulas [8, 9]:

$$f_{s1} = \frac{N_1}{60} \tag{2.3}$$

$$f_{s2} = \frac{N_2}{60} = f_s 1 \frac{Z_1}{Z_2} \tag{2.4}$$

$$f_m = f_{s1} Z_1 \tag{2.5}$$

where

f_{s_1} = driving shaft frequency, Hz
f_{s_2} = driven shaft frequency, Hz
f_{m_1} = gear mesh frequency, Hz
N_1 = driving shaft speed, rpm
N_2 = driven shaft speed, rpm

The shaft and meshing frequencies can also be seen in the bands and sidebands of a Fast Fourier Transform spectrum (see Figure 2.3). The sidebands can be calculated from the gear mesh and shaft frequencies with the following formula:

$$f_{sb} = f_m \pm n f_{s1}, f_m \pm n f_{s2} \tag{2.6}$$

Figure 2.3 depicts a Fast Fourier Transform (FFT) [10] of a sound recording of the gear train of which the gear wheels described above form a part. From this FFT, it is possible to obtain information about the gearbox status by analyzing the noise peaks in the frequency spectrum.

The noise peak at around 600 Hz corresponds to the meshing frequency of the driving gear. This frequency can be calculated using formula 2.5 by inserting the rotational frequency of the driving shaft which was 43 Hz and the number of teeth on Z_1 which was 14:

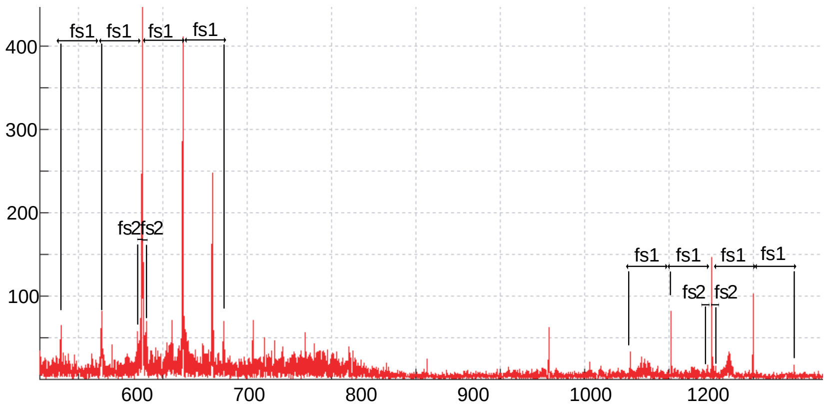

Figure 2.3: An FFT noise spectrum from an industrial robot.

$$f_m = f_{s1} Z_1 = 43 * 14 = 602Hz$$

As depicted in 2.3, the shaft frequencies can often be read from the sidebands; fs_1 corresponds to the driving shaft rotational frequency and fs_2 corresponds to the driven shaft rotational frequency. Harmonics occur at integer multiples of the fundamental frequencies. The first harmonic can be seen at the right in the figure at 1200 Hz. The same sidebands occur in the harmonic(s).

2.2.1 Transmission Error

In most cases, the dominant source of noise is vibration due to transmission error (geometric inaccuracies) introduced during the manufacture of the gear. Transmission error is defined as [8]

”the difference between the actual position of the output gear and the position it would occupy if the gears were perfectly conjugate”

2.2.2 Gear Tooth Impacts

Gear tooth impacts occur when there are tooth deflections or spacing errors in a gear. This will result in a premature contact at the tooth tip causing an impact between the gears. These impacts can cause large frequency noise levels and also shorten the life of a gear due to reductions in gear tooth fatigue life.

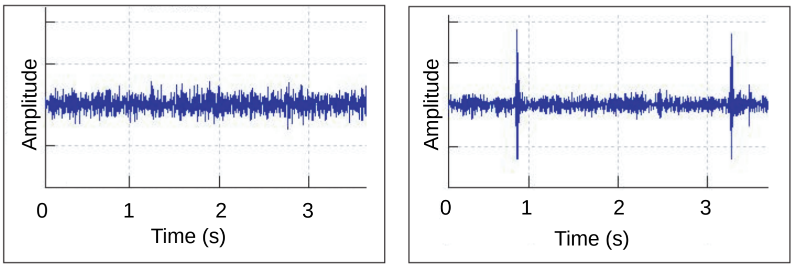

Figure 2.4: A normal and a faulty recording from an industrial robot.

Figure 2.4 shows two recordings of the axes of an industrial robot; a recording of a normal axis at the left and a recording with an abnormality at the right. As can be seen in the figure, the normal recording is smooth and steady, containing no prominent peaks. The faulty recording at the right resembles the normal recording except for two very prominent peaks. These peaks are the results of impact noises due to a notch in one of the gear wheels in the gearbox. In paper A, these peaks were extracted as features and classified in a case-based approach. Impulse noises are not always detectable in an FFT spectrum [11]. Under these circumstances wavelet analysis might be more successful.

By measuring the time t between two repeating noise impulses the shaft speed can be obtained (see 2.3 and 2.4) using the formula:

$$f = \frac{1}{t} = \frac{N}{60} \tag{2.7}$$

2.2.3 Gear Play

Excessive play between two mating gears can result in undefined rattling impulse noises. These noises can occur when an instant torque is applied to the output shaft of the gearbox or when the driving shaft changes its direction of rotation. Figure 2.5 depicts a filtered sound recording of a rattling gearbox of an industrial robot.

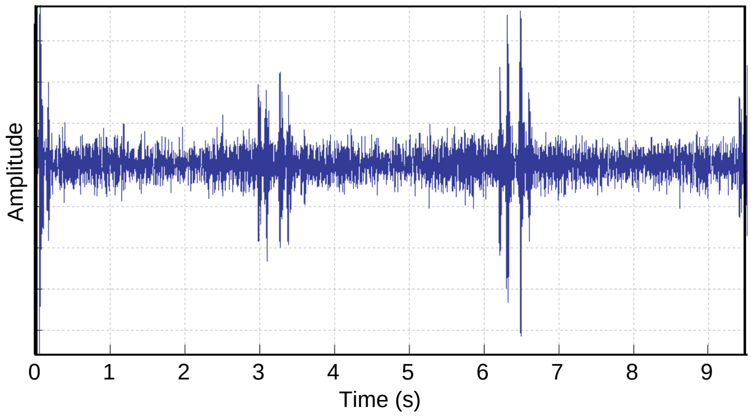

Figure 2.5: Filtered noise with play fault.

It can be difficult to determine which part of the gearbox causes such rattle. It is not always straightforward and in this case, the experience of experts is very valuable.

2.2.4 Friction

Increased friction between two mating gears is a potential source of increased vibration. The meshing action between two gears is characterized by a combination of rolling and sliding. The sliding forces between two gear teeth as they mesh will increase with increased friction resulting in increasing gear noise.

2.3 Diagnostic Methods

2.3.1 Time Domain Averaging

In transmissions with multiple reductions, time domain averaging provides a means of isolating each gear in the transmission line. This method requires an external synchronization pulse from the input shaft. The pulse is connected to the data sampling unit. Each gear tooth meshing noise can be calculated with reference to the rotation of the input shaft and the gearbox ratio.

2.3.2 Frequency Bandwidth Analysis

The noise signal from a gearbox must be processed before any important information related to the gear wheels can be extracted from it. A common way to achieve this is to calculate an FFT. FFT produces a noise spectrum of the calculated signal in which it is possible to identify gear meshing and shaft rotation components (see figure 2.3). Another method of frequency analysis is wavelet analysis. Wavelet analysis [10] is an effective tool for transforming analogue sensor signals to a frequency spectra. It has been shown to be more effective than FFT under heavy background noise conditions. [12].

2.4 Recapitulation

One of the main ideas behind this thesis is to introduce various sensor signals e.g. the above described recording of noise from faulty gearboxes into the Case-Based Reasoning cycle described in section 2.1. In chapter 3, a framework for this is presented and in paper A, a prototype system inspired by this framework is tested using these sound recordings.

Chapter 3

Case-Based Fault Diagnosis of Machines

In this chapter the application of case-based fault diagnosis of machines in industry is described with respect to background, motivation, related work and contribution.

3.1 Background

Manual diagnosis of machines has been performed as long as machines have existed. Automatic diagnosis of machines began to appear first when suitable computers became available in the 1970's. Computer-aided diagnosis of machines has many advantages and can be an effective cost-saving investment for companies [1].

Most machinery failures give a warning in advance before they occur. This warning is usually a physical condition which indicates that a failure is about to occur [9].

Table 3.1 lists some common machine monitoring parameters and their associated sensors.

A typical diagnosis system consists of some of the sensors listed in table 3.1 which output are fed to an analysis system. Figure 3.1 depicts

Table 3.1: Monitoring Parameters

Parameter	Sensor
Temperature	Temperature detector
Vibration	Accelerometer
Sound	Microphone
Electrical current	Ammeter, voltmeter

a schematic figure of a selection of some of the OSA-CBM [13] standard modules that form a typical analysis and fault monitoring system [14].

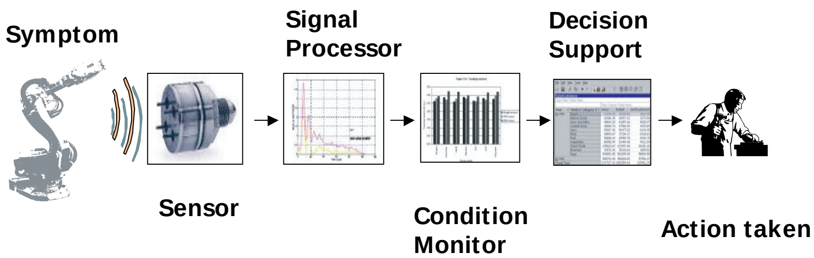

Figure 3.1: Four of the OSA-CBM standard modules for machine monitoring.

The modules in figure 3.1 (from left to right) are:

- Sensor Module: The sensor module provides the system with monitoring data (see table 3.1)
- Signal Processing Module: The Signal Processing Module receives sensor data and processes the data with e.g digital filters such as FFT, wavelet transform etc.
- Condition Monitor Module: The primary purpose of the Condition Monitor is to generate alerts based on preset operational limits
- Decision Support Module: The primary purpose of the decision support module is to generate recommended actions with respect to the condition of the system

When implementing such a system, computers are used in almost all of the above described modules. Computers are used for signal processing, condition monitoring, decision support and presentation of collected sensor data. In paper A a prototype system based on some of the modules in Figure 3.1 is implemented and tested on a gearbox of an industrial robot. This system uses CBR for decision support.

3.2 Motivation

CBR is an attractive AI method for building machine diagnosis systems. The methodology of CBR lends itself naturally to the fault diagnosis of machines by representing the sensor data as the problem and the repair action as the solution. CBR uses an existing database with known problems and their solutions to solve new problems that are similar to the known problems [2]. The solutions can be collected from human experts or they can reflect previous search results in the case library. The CBR system stores the information gained which can be retrieved at any time for future use.

We have concentrated our research on a machine diagnosis system used in the end-test of industrial robots. Mechanical faults in industrial robots often show their presence through abnormal acoustic signals coming from the gearboxes. Correct diagnosis of the robot sound may be a very critical part of the end-test. An incorrect diagnosis of the sound can result in the delivery of a faulty robot to the customer. Manual diagnosis based on sound requires extensive experience and usually such experience takes a long time to acquire. The experience acquired is also difficult to preserve and transfer and is often lost if the personnel concerned leave the task of testing. CBR is very suitable for this kind of industrial application. Implementing this technique in industrial applications preserves experience that would often be lost if skilled personnel leave their employment.

3.3 Related Work

Case-based maintenance and diagnosis systems began to evolve after 1994. Case-based diagnosis systems are installed most frequently in helpdesks, one example being Case Advisor [15], the first commercial helpdesk application that utilized CBR. Case-based systems for machine diagnosis remain a new area, most systems existing today being prototypes on a research level. CheckMate [16] is one example of a case-based diagnosis system implemented for use in an industrial environment. It was implemented in order to aid technicians in repairing industrial printers. A survey that includes some other case-based diagnostic systems for machines is given in paper B.

3.4 Contribution

The contributions of this thesis are:

- A method that allows the reuse of experience in machine diagnosis by assembling the symptom, diagnosis, corrective action and follow-up of a machine failure as a case
- A method for classifying cases in sparsely populated case libraries
- A novel combination of Case-Based Reasoning and wavelet analysis for fault diagnosis

Chapter 4

Paper Contributions

This thesis includes three papers inserted in chronological order. All papers were written within the frames of the EXACT project [17] initiated in 2003. The first paper, *Fault Diagnosis in Industry using Sensor Readings and Case-Based Reasoning* is largely based on my master's thesis. The paper contains additional research results and is largely rewritten to follow the style of a journal publication. It was published in the Intelligent & Fuzzy Systems Journal, volume 15, number 1, 2004. Paper B, *A Survey of Case-Based Diagnostic Systems for Machines* was originally a paper written in a science theory course. It was later submitted and accepted at the Seventh International Conference on Enterprise and Information Systems (ICEIS 2005), held in Miami, Florida. The last paper in this thesis (paper C), *Dynamic Modeling and Sound (Noise) Diagnostics of Robot Gearboxes for Fault Assessments*, has (at the time of writing this) been accepted for presentation at the Scandinavian Conference on Simulation and Modeling (SIMS 2005) to be held in Trondheim, Norway.

4.1 Paper A

Paper A presents an innovative approach to the fault diagnosis of industrial robots by using sensor signals (sound recordings) combined with CBR. The end-testing of industrial robots plays a very important part in the assembly line of the robot factory at ABB Robotics in Västerås, Sweden. As a part of this end-test the robots are set up and an automatic run-in program is executed. The robot is driven back and forward in all its degrees of freedom during this run-in cycle. The run-in cycle is primarily used for the run-in of the robot gearboxes but it also functions as a check to ensure that the robot is fully operational and without defects in its gearboxes, electric motors, cables etc. This paper represents an approach to the automatic detection of any problems during this cycle by means of sound recording and CBR; sound from the gearboxes is recorded during the run-in cycle. A system that inputs this sound, extracts features from it and uses CBR as a means of making a diagnosis on the basis of the sound recording is outlined. Such a system has many advantages as compared with a manual analysis performed by the testing personnel. It not only performs a diagnosis of the gearbox but also enables the storage for reuse of experience gained in machine diagnosis by connecting the symptom, diagnosis, corrective action and follow-up of the machine by packaging as a case.

Erik Olsson is the main author of the paper and Peter Funk contributed with valuable ideas and comments. Ning Xoing added to the paper with expert knowledge in Fuzzy systems and sensor fusion.

4.2 Paper B

Paper B is a survey of certain systems that use CBR for fault diagnosis of machines. With only five systems considered, it is not a broad survey but it attempts to focus on "pure" CBR systems with a well documented CBR-part. All systems but one are documented in the ECCBR and ICCBR proceedings. The systems are compared to each other with respect to their CBR-implementations such as case storage, case representation, case retrieval and adaptation of retrieved solutions. It is concluded in the paper that case-based fault diagnosis systems for machines are still quite unusual on the public market and most existing systems are still on a research level but also that CBR and its application to fault diagnosis of machines is a promising area for future research.

Erik Olsson is the single author of this paper.

4.3 Paper C

This paper builds upon previous work on the classification of sound recordings from industrial robots. The paper presents a model of a gearbox of an industrial robot. The model was made with the Modelica mechanical library using Dymola graphical tools. The model was used for simulation of the gearbox and was run under different load conditions in order to detect correlations between vibrations on the force level extracted from the model during simulation and previously obtained sound recordings from real gearboxes. These vibrations were projected onto the sound recordings with a statistical vibration diagnostic parameter known as the Crest Factor.

Erik Olsson and Rostyslav Stolyarchuk contributed equally to this paper. Rostyslav, from the State Scientific and Research Institute of Information Infrastructure, Lviv, Ukraine worked as a guest researcher at Mälardalen University during the time this paper was written. The authors are listed in alphabetical order.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

This thesis presents a CBR approach towards the condition monitoring and diagnosis of machines. This is achieved with the aid of various sensor readings and a relevant feature identification and extraction process based on those sensor signals. The approach enables the collection of valuable sensor data from machines on a regular basis for use for condition monitoring and for storage for future use. As previously mentioned, the main contributions of this thesis are:

- A method that enables the reuse of experience in machine diagnosis by assembling the symptom, diagnosis, corrective action and follow-up of a machine failure as a case
- A method for classifying cases in sparsely populated case libraries
- A novel combination of Case-Based Reasoning and wavelet analysis for fault diagnosis

5.2 Future work

Future work proposed includes:

The adoption of further sensor signals for use in the classification process and the extraction of relevant features from these. Those to be considered include time- and frequency-based features extracted from e.g. sound data, current data, vibration data etc.

The development of an automatic weighting system. Instead of manual weighting, an automatic weighting algorithm can be adopted that automatically adjusts the weights as required, e.g. [18] presents an approach to automatic weighting.

Continued work on an automatic diagnosis system for machines that implements and tests important results from this research such as relevant feature extraction, automatic weighting, fast and correct case retrieval etc.

Bibliography

[1] M. Bengtsson, E. Olsson, P. Funk, and M. Jackson. Technical design of condition based maintenance system - a case study using sound analysis and case-based reasoning. *Proceedings of the 8th Maintenance and Reliability Conference*, 2004.

[2] A. Aamodt and E. Plaza. Case-based reasoning: Foundational issues, methodological variations, and system approaches. *Artificial Intelligence Com*, 7:39–59, 1994.

[3] M. Nilsson and M. Sollenborn. Advancements and trends in medical case-based reasoning: An overview of systems and system development. *Proceedings of the 17th International Flairs Conference (Flairs'04)*, May 2004.

[4] T. Mitchell. *Machine Learning*. McGraw Hill, 1997.

[5] I. Watson. *Applying Case-Based Reasoning: Techniques for Enterprise Systems*. Morgan Kaufmann, 1997.

[6] J. Kolodner. *Case-Based Reasoning*. Morgan Kaufmann, 1993.

[7] B. Mark. Case-based reasoning for autoclave management. *Proceedings of the Case-Based Reasoning Workshop*, 1989.

[8] D. P. Townsend. *Dudleys Gear Handbook - The Design, Manufacture and Application of Gears*. Mc-Graw Hill, 1992.

[9] A. Barber. *Handbook of Noise and Vibration Control. 6th Edition.* Elsevier Advanced Technology, 1992.

[10] E. Beckenstein G. Bachman and L. Narici. *Fourier and wavelet analysis*. Springer, 2000.

[11] E. Olsson, P. Funk, and M. Bengtsson. Case-based diagnosis of industrial robots based on acoustic signals. *Proceedings of the European Conference on Case-Based Reasoning*, pages 686–701, 2004.

[12] J. Lin. Feature extraction of machine sound using wavelet and its application in fault diagnosis. *NDT&E International*, 34:25–30, 2001.

[13] M. G. Thurston. An open standard for condition-based maintenance systems. *AUTOTESTCON Proceedings*, pages 401–415, 2001.

[14] M. Bengtsson. Condition based maintenance system technology - where is development heading. *Proceedings of the 17th European Maintenance Conference*, 2004.

[15] Sentenitia Software Inc. Case advisor.

[16] P. W. Grant, P. M. Harris, and L. G. Moseley. Fault diagnosis for industrial printers using case-based reasoning. *Engineering Applications Artificial lntelligence*, 9:163–173, 1995.

[17] P. Funk and M. Jackson. Experience based diagnostics and condition based maintenance within production systems. *COMADEM 2005, The 18th International Congress and Exhibition on Condition Monitoring and Diagnostic Engineering Management*, August 2005.

[18] N. Xiong and P. Funk. Construction of fuzzy knowledge bases incorporating feature selection. *Special issue of the Journal Soft Computing*, 12 2005.

II

Included Papers

Chapter 6

Paper A: Fault Diagnosis in Industry Using Sensor Readings and Case-Based Reasoning

E. Olsson, P. Funk and N. Xiong. Fault Diagnosis in Industry Using Sensor Readings and Case-Based Reasoning. Journal of Intelligent & Fuzzy Systems, 15, pages 41–46, 2004.

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

6.1 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 [1] 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 [2, 3] and neural network models [4, 5] 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 [6] (CBR) offers another alternative to implement intelligent diagnosis systems for real-world applications [7]. 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 6.2 gives a general structure for fault classification starting from streams of sensor readings. Signal analysis and feature extraction is addressed in Section 6.3, followed by an outline of necessary details of performing case-based classification using extracted features in Section 6.4. Section 6.5 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 6.6 with a short summary and remarks.

6.2 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 Figure 6.1, which includes signal filtering, feature extraction, and pattern classifier as its important components.

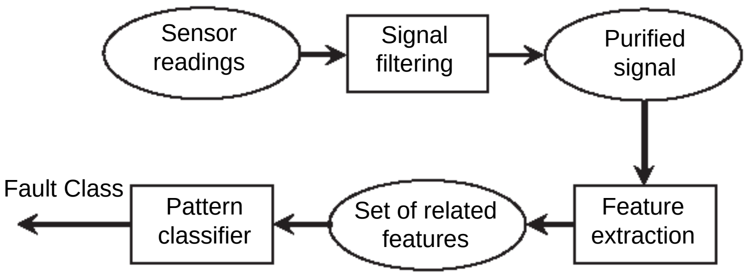

Figure 6.1: Fault diagnosis based upon sensor signals.

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 [10] and particle filtering [11] 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 Figure 6.1) 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 nonlinear 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.

6.3 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 [12].

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

$$FV = [Amp(f_1), Amp(f_2), ..., Amp(f_n)] \tag{6.1}$$

where $Amp(f_1)$ denotes the function of amplitude which depends on frequency f_i and n is the number of frequencies in consideration.

Wavelet analysis [13] is an effective tool of transforming analogue sensor signals to a 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 [14], wherein 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.

After the features have been extracted from the sensor signals, we perform case-based reasoning to make a classification of the current fault using known cases in the case library. Figure 6.2 gives an overall illustration of 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.

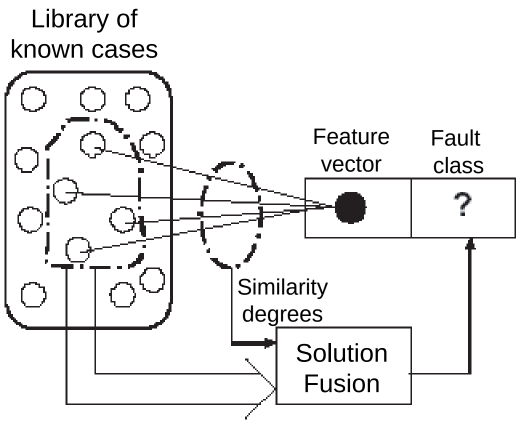

Figure 6.2: Case-based fault classification.

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

$$Similarity(Y, C) = \sum_{i=1}^{n} w_i \times (1 - |norm(y_i) - norm(c_i)|) \tag{6.2}$$

where $w_1, w_2, \ldots, w_n$ are attribute weights reflecting different importance of individual features, c_i represents the ith 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

$$VS(B_j) = \sum_{P \in Rs} \begin{cases} \text{Similarity(Y,P), if P has class } B_j \\ \text{0 otherwise} \end{cases} \tag{6.3}$$

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.

6.4 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 Figure 6.3 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.

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 [16] 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

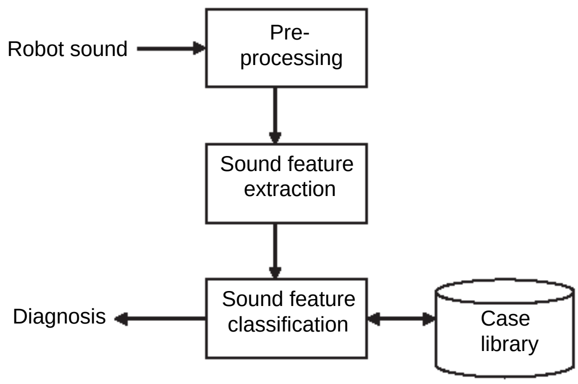

Figure 6.3: Schematic outline of the prototype system.

Figure 6.3 also serves condition monitoring by detecting and identifying deviations in sound profiles.

6.4.1 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 Figure 6.4 the two pre-processing steps are shown which are termed as period extraction (left box) and time domain averaging (right box).

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 characterized 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 eliminat-

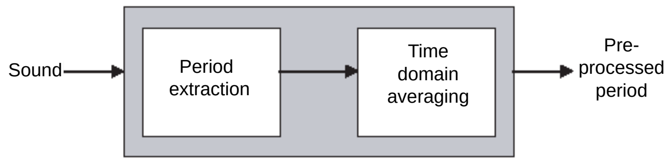

Figure 6.4: Pre-processing of sound data in the prototype system.

ing 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 [14] 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.

6.5 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 [13] 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 6.1 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 6.1: 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 Figure 6.5 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%.

6.6 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:

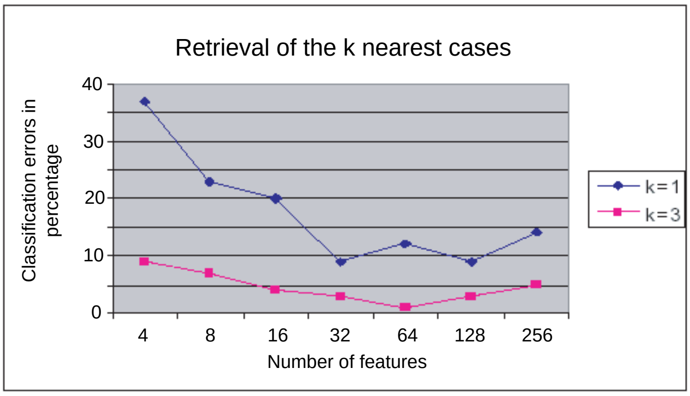

Figure 6.5: Relation between classification performance and the number of features.

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.

6.7 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 Underhllsfretagen (SCEMM).

Bibliography

[1] Y. Zhang et al. Fuzzy production rule based expert systems. *Fuzzy Sets and Systems*, 44:391–403, 1991.

[2] P. Clark and R. Boswell. Rule induction with cn2: Some recent improvements. *Proceedings of the European Working Session Learning*, pages 151–163, 1991.

[3] J. R. Quinlan. *C4.5: Programs for Machine Learning*. Morgan Kaufmann, 1993.

[4] J. P. Bigus. *Data Mining with Neural Nets*. McGraw-Hill, 1996.

[5] R. P. Lippmann. An introduction to computing with neural nets. *IEEE ASSP Mag*, 4:4–22, 1987.

[6] A. Aamodt and E. Plaza. Case-based reasoning: Foundational issues, methodological variations, and system approaches. *Artificial Intelligence Com*, 7:39–59, 1994.

[7] M. Nilsson, P. Funk, and M. Sollenborn. Complex measurement in medical applications using a case-based approach. *Workshop Proceedings of the International Conference on Case-Based Reasoning*, pages 63–73, 2003.

[8] S. K. Lee. and White P. R. The enhancement of impulse noise and vibration signals for fault detection in rotating and reciprocating machinery. *Journal of Sound and Vibration*, 217:485–505, 1998.

[9] J. Lin. Feature extraction of machine sound using wavelet and its application in fault diagnosis. *NDT&E International*, 34:25–30, 2001.

[10] Y. Bar-Shalom and X. Li. *Estimation and Tracking: Principles, Techniques, and Software.* Artech House, 1993.

[11] A. Marrs N. Gordon and D. Salmond. *Nonlinear and Nonstationary Signal Processing.* Cambridge University Press, 2001.

[12] C. Pous, J. Colomer, and J. Melendez. Extending a fault dictionary towards a case-based reasoning system for linear electronic analogue circuits diagnosis. *Proceedings of the European Conference on Case-Based Reasoning*, pages 748–762, 2004.

[13] E. Beckenstein G. Bachman and L. Narici. *Fourier and wavelet analysis.* Springer, 2000.

[14] E. Olsson, P. Funk, and M. Bengtsson. Case-based diagnosis of industrial robots based on acoustic signals. *Proceedings of the European Conference on Case-Based Reasoning*, pages 686–701, 2004.

[15] M. G. Thurston. An open standard for condition-based maintenance systems. *AUTOTESTCON Proceedings*, pages 401–415, 2001.

[16] M. Bengtsson. Standardization issues in condition based maintenance. *Proceedings of the 16th International Congress on Condition Monitoring and Diagnostic Engineering Management*, pages 651–660, 2004.

Chapter 7

Paper B: A Survey of Case-Based Diagnostic Systems for Machines

E. Olsson. A Survey of Case-Based Diagnostic Systems for Machines. Seventh International Conference on Enterprise and Information Systems, pages 381–385. ICEIS, Miami, May 2005.

Abstract

Electrical and mechanical equipment such as gearboxes in an industrial robot or electronic circuits in an industrial printer sometimes fail to operate as intended. The faulty component can be hard to locate and replace and it might take a long time to get an enough experienced technician to the spot. In the meantime thousands of dollars may be lost due to a delayed production. Systems based on case-based reasoning are well suited to prevent this kind of hold in the production. Their ability to reason from past cases and to learn from new ones is a powerful method to use when a failure in a machine occurs. This enables a less experienced technician to use the proposed solution from the system and quickly repair the machine.

Keywords: Case-Based Reasoning, Fault Diagnosis, Artificial Intelligence, Machine Learning, Neural Networks.

7.1 Introduction

This paper addresses case-based reasoning (CBR) (Aamodt, Plaza. 1994) systems used for diagnosis of machines. The paper is intended to give the reader a survey of CBR systems in this area. The particular systems in this survey were chosen because of their well-documented CBR-part [1] and their application in the area of machine diagnosis. All systems in this survey were created or reported after about 1999 and are published in major Proceedings and Journals such as the ECCBR and ICCBR Proceedings and Journal of Intelligent and Fuzzy Systems.

The paper is structured as follows: Section 7.2 gives an overview of five CBR diagnostic systems for machines. Section 7.3 discusses and compares features of the systems. Section 7.4 gives a brief conclusion of the systems.

7.2 The Systems

This section describes five CBR systems for diagnostics of machines. The first system is a diagnostic system for locomotives. It collects fault codes from locomotives and uses them for off-board locomotive diagnosis. The second system diagnoses electric circuits. It uses measurement data from the circuit as features and matches them with similar cases. The proposed solution is then adapted to the new case. The third system monitors the health of satellites by looking for anomalies in the down linked data from the satellite. The fourth system diagnoses industrial robots with the aid of acoustic signals. The fifth system uses a combination of a neural network and CBR to diagnose induction motors.

7.2.1 ICARUS A Diagnostic System for Locomotives

Locomotives are large and complex machines that are very difficult and expensive to repair. Due to their complexity, they are often best served and repaired by their manufacturer. The manufacturer often have a long time service contract with their customers and it is important for the manufacturer to reduce the service costs as much as possible.

ICARUS [2] is a case-based reasoning tool for off-board locomotive diagnosis. Locomotives are equipped with many sensors that can monitor their state and generate fault messages. ICARUS is designed to handle the fault codes that are generated by the locomotives.

Each fault code is saved in a fault database. Connected to each fault is a repair log taken from a repair database. The fault log combined with the repair log is a case in ICARUS.

Most repair logs contains a fault cluster. This means that many small faults occur before a repair is performed. The cluster of faults is used as features for case matching. Each cluster is assigned a weight between 1 and 0. The value of the weight is set to represent a clusters ability to isolate a specific repair code. If a cluster is connected to only one repair code its weight will be 1. If a cluster is connected to evenly distributed repair codes in the case base its weight will be lower. Clusters below a certain weight threshold will be assigned zero weights.

The weights are used in the matching formula. The degree of likeness between a new case and as stored case is calculated as:

$$\frac{\left[\sum w_c\right]^2}{\left[\sum w_s\right]\left[\sum w_n\right]} \tag{7.1}$$

where

w_c = weights in common clusters between stored and new case
w_s = weights of clusters in stored case
w_n = weights of clusters in new case

The repair code associated with the case with the highest degree of likeness is the retrieved case.

The system vas validated with a case base consisting of 50 repair codes. Each repair code was associated with 3-70 cases. Each case was removed from the case base and matched to all other cases in the case base. If the repair code of the case was in the top three nearest neighboring cases, the match was considered as a success. As a result the overall accuracy of the system was 80%.

7.2.2 Diagnosis of Electronic Circuits

Diagnosis of electronic circuits is based on the analysis of the circuit response to a certain input stimuli. Input signals are generated and measurements are acquired in certain nodes of the circuit. A traditional way of doing this is to use fault dictionaries. Fault dictionaries are based on selected measurements on faulty systems. The comparison is performed by a nearest neighbor calculation and the closest case is taken as a diagnosis. The problem with fault dictionaries occurs when a new fault is found that cannot be matched with the ones already stored in the dictionary. To deal with this a case-based approach is suitable to be able to automatically extend the dictionary with new faults as they occur [1].

The case consists of two parts. Part one is the numeric part that contains the case identification number and the measurements taken from the circuit. The second part contains information about the fault diagnosis.

Table 7.1: Case Structure. The Measurement Part.

Case id	Measure1	Measure2	...	MeasureN
Case i	M1	M2	...	MN

Table 7.2: Case Structure Fault Part

Class	Comp.	Deviation	Hierarchy
Class	Comp.	X%	$M_i L_i$

The class corresponds to the class of component that is diagnosed. The components are divided into different classes if they have different accepted deviations from their normal value. E. g. +/-10% can be an accepted deviation for a class of components. The component field contains the component location. The deviation field contains the measured deviation of the component. The hierarchy field contains a description of witch level in the circuit hierarchy the components is.

A normalized Euclidian distance function is used to retrieve the cases from the case base and the k nearest neighbors where k=3 is retrieved. The solution is adapted to the new case by transformational reuse [3]. A learning algorithm is then applied to decide whether the case should be saved as a new case in the case base or not. E.g. if the diagnosis is correct there is no need to retain the new case in the library. But if the retrieved cases produce a misclassification of the new case, the case might be added to the case base according to the results of the learning algorithm.

The system has been tested with the DROP4 [4]and the All-KNN learning algorithms. All cases are also equipped with weights to improve the classification.

A measurement on a circuit is performed resulting in the k=3 nearest neighbors in table 7.3.

Table 7.3: An Example of Case Retrieval.

	M1	M2	M3	Comp	Devi
New Case	0.6	0.7	0.2	C_1	75
Neighbor1	0.6	0.7	1.1	C_1	23
Neighbor2	0.7	0.4	1.3	C_1	24
Neighbor3	0.7	0.4	1.3	C_2	11

Neighbor 1 and 2 has the same component as the new case but the deviation is smaller in both cases. Neighbor 3 has a different component. The new case will be selected as a component C1 because of its similarity in the measurements. The deviation is far from normal so the case will be introduces in the case base.

The system has been tested on a filter circuit that is commonly used as a benchmark for electronic circuits. The filter consists of several capacitors and resistors. The average result with the All-KNN retain algorithm was 89% and the average result with the DROP4 retain algorithm was 88%.

7.2.3 Satellite Diagnosis

Satellites are monitored from the ground using down linked data (telemetry). The case-based diagnosis program can be resembled as an expert apprentice. The program remembers the human experts actions along with the context that is defined by the down linked data. It then attempts to make its own diagnosis when similar data appears in another occasion [5].

The features in the case are not state values taken at a certain point of time. Because of the telemetrys streaming values the features are instead trends extracted from the streaming data flow. The length of the trend is different for different parameters. The table below shows a sample case with two parameters:

Table 7.4: structure of a satellite case (problem part).

Case id	Length of time series	Sampling rate	Lower bound	Upper bound
1234	1000	45	-3	10
2345	2000	60	0	10

A case is constructed from the streaming data at a time called the case point. A case is constructed looking back from the case point a certain length of time. The attribute values are picked using a window of the same length as the sampling rate. For each window only one average value is saved as representing that window. The length of the time series corresponding to an attribute is l/s were l is the length specified in the case schema and s is the sampling rate.

The distance between two time series R, W is calculated by dividing the time series into smaller sequences R_i, W_i. An Euclidian distance calculation between each R_i, W_i is performed and a global distance d_g is calculated from all the obtained distances between the time series sequences:

$$d_g(R,W) = \frac{1}{k}\sum_{i=1}^{k} d_i(R_i,W_i) \quad (7.2)$$

The system notifies the user if a new case is considered interesting. The new case is considered interesting it two ways:

1. A similarity threshold determines if the new case should be considered as an anomaly. If the similarity of all the retrieved cases is below that threshold the case is considered to be an anomaly and the user is automatically notified.
2. If some of the retrieved cases are above the first threshold. Another threshold determines if the new case is similar enough to some other case in the case base that is previously diagnosed as an anomaly. If so the system will notify the user of the type of anomaly. In both situations the user is able to give feedback to the system.

7.2.4 Diagnosis of Industrial Robots

Mechanical fault in industrial robots often show their presence through abnormal acoustic signals.

At the factory end test of industrial robots a correct classification of the robot is very critical. An incorrect classification of a faulty robot may end up in the factory delivering a faulty robot to the customer.

The industrial robot diagnosis system uses case-based reasoning and acoustic signals as a proposed solution of recognizing audidable deviations in the sound of an industrial robot [6].

The sound is recorded by a microphone and compared with previously made recordings; similar cases are retrieved and a diagnosis of the robot can be made.

Features are extracted from the sound using wavelet analysis [7]. A feature in the case is a normalized peak value at a certain frequency. The case contains peak values from many frequencies. The case also contains fields for information of the robot model and type of fault (if any). There is also room to enter how the fault was repaired. Table 7.5. displays a part of the case structure.

Table 7.5: A part of the case structure for robot diagnosis.

Serial Number	Type	Fault	Diagnosis and Repair	Features 1-n
45634	4500	2	...	...

Cases are retrieved using a nearest neighbor function that calculates the Euclidian distance between the new case and the cases stored in the case library. A list with the k nearest neighbors is retrieved based on the distance calculations. The system learns by adding new cases to the case base. A technician enters the diagnosis and repair action manually in each case.

The system has been evaluated on recordings from axis 4 on an industrial robot. Sounds from 24 healthy robots and 6 faulty robots were collected to enable case-based classification of the condition of the robots. The prototype system demonstrated quite good performance by making right judgments in 91% of all tests.

7.2.5 Induction Motor Fault Diagnosis

Induction motors are very common within industry as prime movers in machines. Induction motors has a simple construction and are very reliable. But working in a tough environment driving heavy loads can introduce various faults in the motors. A system for fault diagnosis of induction motors is presented here. The system has interesting features such as a neural network combined with a case-based reasoning system [8].

A case consists of 6 categories of features and 20 variables. Among the variables are measurement positions, rotating frequency components and characteristic bearing frequencies. The case also includes the type of machine to be measured, the symptom, the corrective action etc.

The system uses an ART-Kohonen neural network [9]) (ART-KNN) to guide the search for similar cases in the case base.

CBR is used to select the most similar match for a given problem. The advantage with the ART-KNN compared to other neural networks such as the Kohonen Self Organizing Map [10] is that it can learn new knowledge without losing old knowledge. When a new case is presented to the system the ART-KNN learns the new case in one of two ways:

1. If the similarity of the new case compared to the cases already learned by the network is below a certain threshold; the similarity coefficient. The network learns the case by adding new nodes to its layers.
2. If the similarity of the case is above the threshold, the network learns the case by adjusting its old nodes to resemble the new case.

Cases are then indexed in the case base by clusters of features in the ART-KNN. The indexed cases are then matched against the new case with a standard similarity calculation.

The system has been tested with measurements from an AC motor in a plant. The motor had a rotor fault witch resulted in high levels of noise and vibration. The system was trained with 60 cases containing different motor defects such as bearing faults, rotor damages and component looseness.

The system retrieved two previous cases from the case base together with results from a modified cosine matching function. The retrieved cases both indicated a bearing fault. The average result of a test of all cases in the case base was 96,88%.

7.3 Discussion

When comparing different case-based reasoning systems with each other one must focus on the features that are shared by all case-based reasoners.

Below is a comparative discussion of five common problems that has to be faced when implementing a case-based reasoner and how they are solved in each system. The problems are as follows:

1. Feature extraction and case representation.
2. Case retrieval and indexing.
3. Case reuse.
4. Case revision and retain.
5. Case base maintenance.

1. ICARUS uses combinations of fault codes as features because that is the way a locomotive signals its faults. A repair action on a locomotive is also very expensive, thus several faults must be combined before a repair action can be executed. Often machines cannot provide such fault codes. Instead features such as filtered measurements from different kinds of sensors are used. This is the situation for the electronic circuit diagnosis system, the induction motor diagnosis system, the satellite diagnosis system and the industrial robot diagnosis system. They all collect single measurements or time series measurements, e.g. current, vibration, acoustic signals, streaming telemetry data etc. The data collecting sensors can be an integrated part of the object or an external portable measurement device.

The basic case representation is similar for the systems in this survey. The three basic components of the case are the features, the problem description and the repair action. Sometimes the repair action is implicit in the fault description. As in the electronic circuit diagnosis system, the repair action is equal as to replacing the faulty component.

2. The case retrieval process most commonly uses some kind of distance calculation combined with weights to calculate a distance between the new and stored cases. The k nearest neighbours to the new case is then retrieved. This kind of retrieval is used in all systems except the induction motor diagnosis system and the satellite health diagnosis system. The satellite health diagnosis system uses two similarity thresholds; one for anomaly detection and one for event detection. The induction motor

diagnosis system uses a neural network to first index relevant cases in the case base. After that a straightforward k nearest neighbour distance calculation is performed to calculate the distance between the indexed cases and the new case.

3. All systems in this survey implements the reuse phase by suggesting the diagnosis extracted from the retrieved k nearest neighboring cases. The satellite diagnosis system also has a threshold for sorting out irrelevant cases not to be considered for reuse. In addition to this form of reuse the circuit diagnosis system uses adaptation [3] by transforming the past solution of the k=3 nearest neighbors to an appropriate solution for the new case. The new solution is then inserted into the new case as the proposed solution.

4. The simplest form of retaining is to just add the new case in the case base. The industrial robot diagnosis system uses this kind of retaining (the robot diagnosis case base is then manually investigated by an experienced technician in order to remove irrelevant cases and provide relevant cases with more diagnostic information). To few removals of cases can in time cause problems with an overfilled case base making the system perform less well. Most system implements some kind of user interaction before a case is retained. This is performed in the satellite diagnosis system and in ICARUS by letting an experienced technician decide whether the case is relevant or not. The retaining process can be extended by calculating if the new case has any ability to improve the future diagnosis of the system. The simplest form is to look if a similar case already exists in the case base. If it does, there is no need to retain the case. The circuit diagnostic system also incorporates a machine-learning algorithm that calculates the ability of the case to improve the performance of the system.

5. Most systems in this survey are only prototypes and have not yet implemented any automatic maintenance process of the case memory. The circuit diagnosis system implements a confidence factor [11] to prevent bad cases from spoiling the performance of the system. The case base is maintained by removing cases when the performance of the case drops below a certain confidence index.

7.4 Conclusions and Further Work

This paper has briefly described five intelligent machine diagnostic systems that use case-based reasoning as their primary approach to problem solving. Case-based reasoning is still new in the area of fault diagnosis of machines and most systems in this survey are still prototypes. Some parts of the CBR process seem to be implemented to a higher extent than others in the systems. E.g. feature extraction and case retrieval seems to be fully implemented but adaptation is not widely implemented. Also, automatic maintenance of the case memory seems not to be implemented in the majority of the systems in this survey.

Bibliography

[1] C. Pous, J. Colomer, and J. Melendez. Extending a fault dictionary towards a case-based reasoning system for linear electronic analogue circuits diagnosis. *Proceedings of the European Conference on Case-Based Reasoning*, pages 748–762, 2004.

[2] A. Varma. Icarus: Design and deployment of a case-based reasoning system for locomotive diagnostics. *Third International Conference on Case-Based Reasoning*, pages 581–596, 1999.

[3] A. Aamodt and E. Plaza. Case-based reasoning: Foundational issues, methodological variations, and system approaches. *Artificial Intelligence Com*, 7:39–59, 1994.

[4] D. Wilson and T. Martinez. Reduction techniques for instance-based learning algorithms. *Machine Learning*, 38:257286, 2000.

[5] K. K. Penta and D. Khemani. Satellite health monitoring using cbr framework. *Seventh European Conference*, 21:732–747, 2004.

[6] E. Olsson, P. Funk, and N. Xiong. Fault diagnosis in industry using sensor readings and case-based reasoning. *Journal of Intelligent & Fuzzy Systems*, 15:41–46, 2004.

[7] E. Beckenstein G. Bachman and L. Narici. *Fourier and wavelet analysis*. Springer, 2000.

[8] T. Han B. Yang and Y. Kim. Integration of art-kohonen neural network and case-based reasoning for intelligent fault diagnosis. *Expert Systems with Applications*, 26:387395, 2004.

[9] G. A. Carpenter and S. Grossberg. The art of adaptive pattern recognition by a self-organizing neural network. *IEEE Transactions on Computers*, 21:77–88, 1988.

[10] T. Kohonen. *Self-organizing maps.* Springer-Verlag, 1995.

[11] D. W. Aha, D. Kibler, and M. Albert. Instance based learning algorithms. *Machine Learning*, 6:3766, 1991.

Chapter 8

Paper C: Dynamic Modeling and Sound (Noise) Diagnostics of Robot Gearboxes for Fault Assessments

E. Olsson and R. Stolyarchuk. Dynamic Modeling and Sound (Noise) Diagnostics of Robot Gearboxes for Fault Assessments. Scandinavian Conference on Simulation and Modeling. SIMS, Trondheim, October 2005.

Abstract

Some gear faults in industrial robots can during operation be recognized as abnormal noise peaks coming from the gearbox. A library of such recordings has been assembled in order to automate fault diagnosis of the robots. A computer records sound from the gearbox and compare the new recordings with recordings stored in the library. The result of the comparison is a diagnosis of the condition of the robot. This paper proposes an extension of the sound library by incorporating model based reasoning. A dynamic model of the gearbox in the drive system has been constructed and gear vibrations on the force level are extracted from the model. These vibrations are projected onto the sound recordings with a statistical vibration diagnostic parameter known as the Crest Factor (CF).

8.1 Introduction

A case-based prototype system that makes a diagnosis based on recordings of noise from an industrial robot has previously been implemented [1]. The prototype system analyzes the recordings using Fast Fourier Transform (FFT) [2] for feature extraction and case-based reasoning [3] to make a diagnosis of the condition of the gearbox of the robot.

Gearbox dynamics often has a strong impact on the performance of the system vibrations. In this paper we use the Modelica.Mechanics.Rotational Library [4] to simulate gearbox torques, especially for the output shaft with an applied payload. The simulations were then compared with sound recordings from one normal and two faulty gearboxes.

It is difficult to simulate gearbox effects and to get a reasonable agreement between the measurements and the dynamic simulation. To solve this problem we represented the simulation results and sound recordings by means of the Crest Factor (CF) [5]. CF is defined as the maximum value of a signal normalized by the RMS value. CF aids the comparative study between noise measurements of normal and faulty gearboxes as well as providing a mean to compare these noise measurements against the simulation results measured on the input and output shaft of the model.

The gearbox model is created in Dymola and is characterized by tooth contact stiffness, backlash and efficiency. The model has a correct representation of the relation between force and vibration. Several parameters can be altered in order to produce different simulation results. The results of the simulation represent an oscillation of torque on the input and output shaft of the gearbox model.

In the majority of cases the regular vibrations and noise effects in the gear sets have been predicted theoretically as well as experimentally by measurements. The theoretical description of the gear noise phenomena has been based mainly on force analysis of multibody models undergoing non-linear tooth and bearing contact conditions, inertia masses and the influences of the applied excitation torques. Those directions are highly complicated and involve problem identification, a mathematical formulation and numerical methods. To reduce the gearbox simulation problem to its simplest form we can use modern software e.g. the Dymola tools and Modelica Mechanical Library [4, 6].

8.2 Sources of Gear Noise

An ideal gearbox with rigid equally spaced gears, accurate teeth and good lubrication would transmit minimal noise and vibrations. All kinds of deviations from this ideal gearbox cause an increase in vibrations and noise. In the majority of cases the source of noise and vibrations is transmission errors introduced during manufacture. These errors can e.g. be geometry inaccuracies and eccentricities which both result in impact noises [7]. Other sources of impact noises can be gear rattle. Gear rattle is caused by a combination of backlash and unloaded gears. Friction and pitting due to gear fatigue is also a source of noise [8].

Most modern techniques for gear diagnostics are based on the vibration signal picked up by an accelerometer from the gearbox casing. The vibration signal is normally filtered by time synchronous averaging (TSA) and analyzed in the frequency domain with methods such as the Wavelet Transform (WT) or the FFT. A similar approach is to use a microphone instead of an accelerometer and record the noise from the gearbox. This method was used to detect faults in industrial robots [1] and further work on noise recordings is also presented in this paper.

The expected noise spectrum from a gearbox should contain the gear meshing frequencies and integer multiples of it. There is also common with harmonics and sidebands due to gear eccentricities and geometric errors. Figure 8.1 shows an FFT of the recorded noise of an industrial robot.

The recordings are first pre-processed in order to remove unwanted noise. In this case the recordings are filtered with a low pass filter that removes all noise above 200 Hz. The result contains the most important meshing frequencies, which localizes the amplitude increments during a rotation period. These amplitude increments arise from the transient force effects introduced by the cracked tooth in the driven gear wheel.

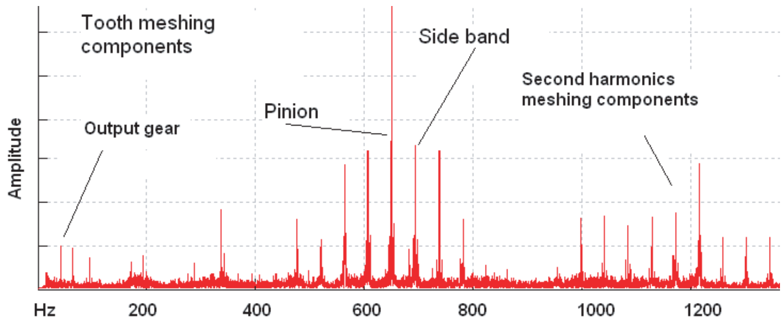

Figure 8.1: FFT spectrum of gear noise analysis.

8.3 Simulation of a Drive Model in Dymola / Modelica

A dynamical model enables a visualization of how a typical design of a multibody system performs with emphasis on our target. This was achieved with the Dymola tools and the Modelica Library [4, 6]. The components in the Modelica Mechanical Rotational package was developed for the fundamental units of a mechanical system e.g. inertia, gear, gear efficiency, friction in bearings, clutches, brakes, external torques, backlash, cut of torque of a flange and others. Every basic mechanical component from the Modelica Library has at least one interface to connect the element rigidly to other mechanical elements. The underlying feature of this library is the component-oriented modeling, which is based on the solution of mixed continuous/discrete systems of equations, or DAE's equations. Figure 8.2 presents a structural model of the gearbox drive train where T_{1-2} stands for input and output torque, f_{1-2} represents the rotational speed of the input and the output shaft and Z_{1-4} represents the number of teeth on each gear.

Figure 8.3 presents a composition diagram of a sample system build in the Dymola environment with icons from Modelica. It is a composite model, which specifies the topology of the system to be modeled in terms of components and connections between the components.

The following setup parameters and assumptions are applied to the model simulation: $I_1 = 0,6kgm^2$ is a motor inertia (pos.3 on diagram) that is driven by a sinewave motor torque T_1 (pos.1 and 2 on fig.3). The torque sinusoidal signal is provided by the values: torque amplitude $T_a = 12nm$ and simulation (case-study) frequency $fr = 0,4; 0,5Hz$ (rps). These frequencies are obtained from a real time rotation period of a robot arm. The rotation period of the robot arm is $\tau = 2-2,2sec$. Via a gearbox (pos.4) the rotational energy is transmitted to a load (inertia) I_2 (pos.5). For simulation purpose we used the following variable cases of the inertia of the load: $I_2 = 20; 40; 50kgm^2$.

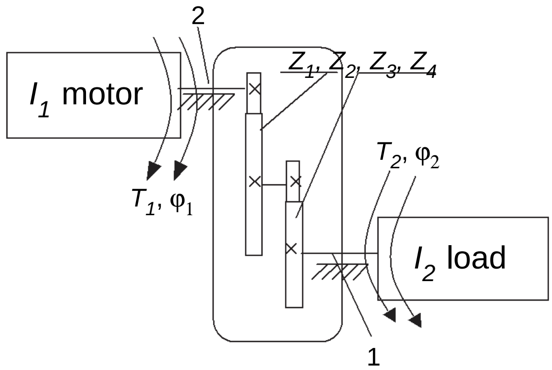

Figure 8.2: Dynamical model of the gearbox drive.

The library gearbox model is specified by the statement $Gear2\_i = 100$ (see Figure 8.3). It is a component assembly model of several components taking essential effects of gear vibration and noise into account. This leads to different faults between gears teeth. In particular, component *lossyGear* defines gear efficiency due to friction between teeth and bearing friction and component *elastoBacklash* defines gear elasticity, damping and backlash.

For simulation purposes we tried to adjust the parameters of the simulated gearbox as close to the parameters of the actual gearbox as possible. The parameters set were:

- Transmission ratio
- Bearing friction

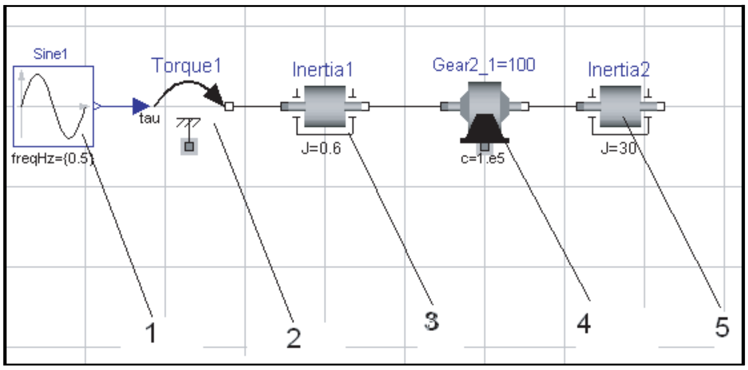

Figure 8.3: Composition diagram of the gearbox drive in Dymola/Modelica.

- Gear elasticity
- Total backlash

We simulated the model with three different payloads. Each simulation was run for 30 seconds. One simulation case is shown in Figure 8.4. Figure 8.4 presents a plot of the behavior of the internal torques on the driven shaft by the variable Inertia2 $flangea\_tau$. We then applied the CF formula on all obtained data. All calculation results are prepared in table 1.

8.4 Noise Experimental Setup

The gearbox of an industrial robot was used to perform the testing. The robot was mounted in a test cage and a microphone was attached to the gear housing of the axis.

The tested gearbox consists of a common drive train. The drive train has two helical gears driven by a pinion gear that is mounted on the shaft of an electrical motor. The output gear is directly mounted on the robot axis.

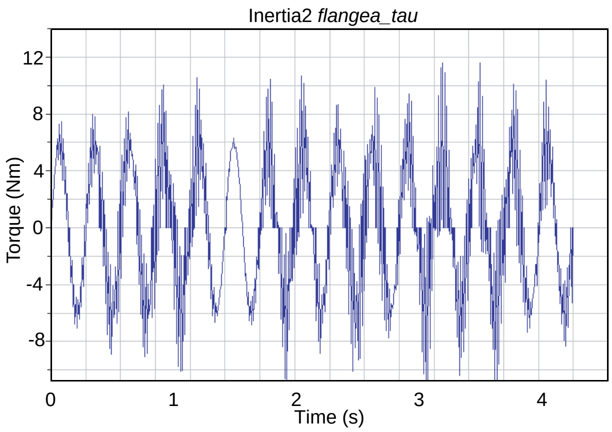

Figure 8.4: Torque on driven gearbox shaft. Time history. Fr=0,5 Hz; J2=30 kgm2.

The gear ratio of the gearbox is 100. It means that one revolution on the output gear corresponds to 100 revolutions on the pinion gear.

The tested gearbox is protected by a housing on which a microphone was attached. The location of the microphone was selected in order to get it as close to the gear drive train as possible. A magnet was used to attach the microphone. The microphone is of a common capacitor type and was connected to the sound card of a computer. The sampling frequency was 8 kHz.

8.5 Recording of Noise

The axis was run back and forward with a driver pinion speed of 270 rad/s during the recordings resulting and in an output (driven) shaft speed of about 2.7 rad/s. The recorded unfiltered sound is shown in Figure 8.5.

The figure shows three periods of rotations of the output axis. The rotational speed of the output axis is 2.7 rad/s. Two types of faults were observed and recorded with the procedure described above. The sources

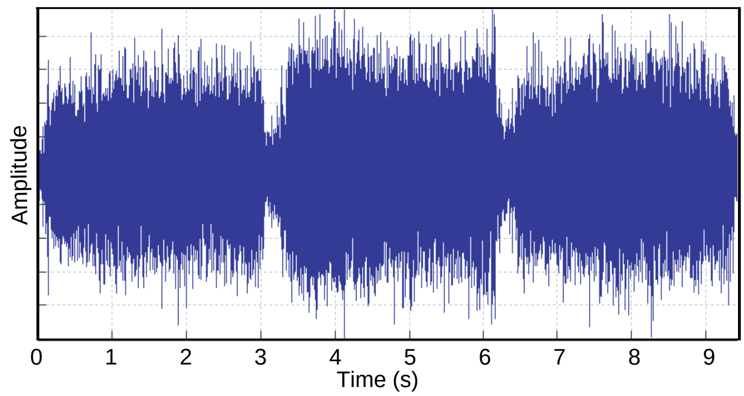

Figure 8.5: Unfiltered noise.

of the faults were:

1. A notch on the output gear
2. Play between the transfer gear and the output gear

The noise signal from the gearbox needs to be pre-processed in order to extract information about the condition of a specific gear wheel. As can be seen in fig. 1 the meshing frequency of the output gear is below 200 Hz and thus all frequencies above 200 Hz was removed by a low pass filter leaving only frequencies from 0-200 Hz in order to reveal the impulse peaks from the noisy sound recordings. A filtered recording of a fault caused by a notch on the driven gear is shown in Figure 8.6.

The peaks at time 3.9 and 6.3 seconds in Figure 8.6 is the result of a small notch on the output gear. The notch is only visible in one direction of rotation and thus leaves the two surrounding periods uninfluenced. The notch is repeated every full rotation of the gear with the same frequency as the rotation speed of the gear.

In Figure 8.7 there are peaks visible in the end and the beginning of each rotation of the gear. These peaks are the results of play between the transfer gear and the output gear. At the end of each rotation the force between the transfer gear and the output gear is radically increased

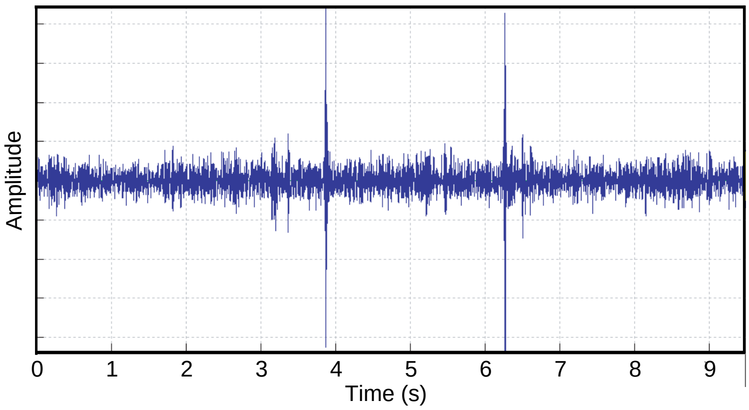

Figure 8.6: Filtered sound with notch fault.

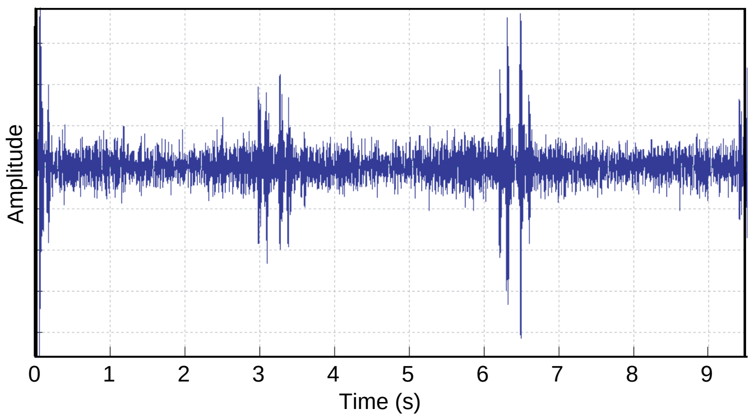

Figure 8.7: Filtered noise with play fault.

causing a backlash with a resulting impulse noise.

8.6 Crest Factor and Results Comparison

In order to make a comparison between the previously explained simulation results and the obtained sound recordings CF was introduced and calculated for each recorded fault and for each simulated fault. CF is based on the Root Mean Square (RMS) value of a signal. RMS is a simple measurement of the fluctuating effect of the signal. RMS is defined to be the square root of the average of the sum of squares:

$$RMS = \sqrt{\frac{1}{N}\left[\sum_{i=1}^{N}(S_i)^2\right]} \tag{8.1}$$

CF is calculated by dividing the peak value of a signal with the RMS of the signal (see 8.2). CF is based on the simple assumption that a signal with a few high amplitude peaks would produce a greater CF than a smooth signal. CF is a normalized parameter suitable for comparison between different measurements results.

$$CF = \frac{S_{max}}{RMS} \tag{8.2}$$

The results of the calculations of CF for the filtered recording of the gear notch fault and the gear play fault are shown in Figure 8.8 and in Figure 8.9 respectively.

The CF produces prominent peaks at each notch. The energy of the peaks is about seven times the average value of the CF.

The CF produces prominent peaks at each change of rotation of the axis. The energy of the most prominent peaks is more than four times the average value of the CF. Results from calculations of the CF parameter can be seen in table 8.1.

The CF was calculated on two types of data:

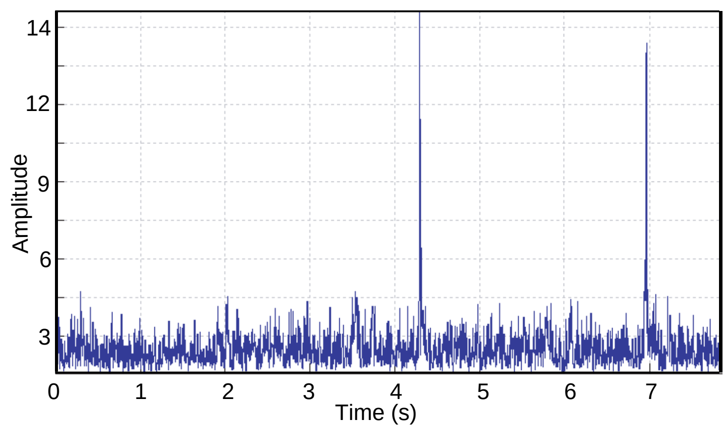

Figure 8.8: CF on notch fault.

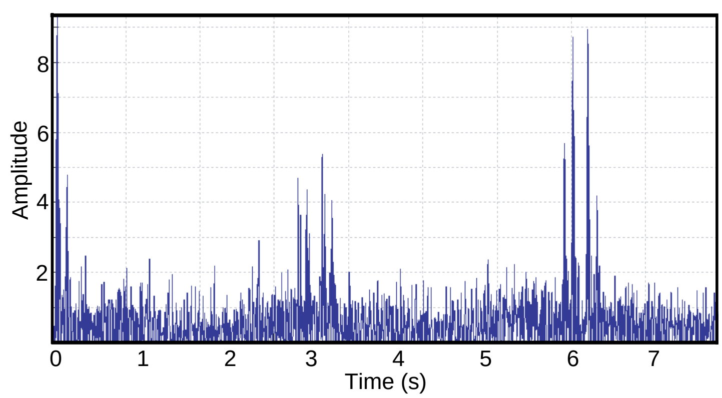

Figure 8.9: CF on play fault.

Table 8.1: CF parameter value from simulation and noise recordings.

Test type	Variable parameters	Mean CF	Peak CF
Torque Sim.	Applied payload 10kg	1.16	1.18
Simulation	Applied payload 125kg	1.14	1.15
Simulation	Applied payload 200kg	1.15	1.17
	Faults type		
Filtered Noise	Gearbox in normal cond.	2.51	3.43
Filtered Noise	Gearbox with play fault	2.94	9.35
Filtered Noise	Gearbox with notch fault	2.92	14.6

1. On low pass filtered noise signals. Recorded from the gearbox of an industrial robot
2. On the simulated torque from the input and output shaft of a dynamical model of the gearbox.

8.7 Conclusions

CF is able to make a normalized parameter from a low pass filtered noise spectrum that can be useful for fault monitoring of the gearbox. The CF increased with more than 200% on sound recordings in faulty case gearboxes compared to recordings of normal gearboxes.

The simulation results are available for engineering design. They can predict the tendency of faults development during the operating period while the design is subjected to varying parameters such as inertia, external torque and frequency/speed. Normal gearboxes with different payload setups were simulated in the component model. They resulted in a low and stable CF. Those results are closer to the calculations of CF from the recording of the normal gearbox than to the CF of the noise recordings of the faulty gearboxes. The CF obtained from the simulation and the experimental noise spectrum from the normal case gearbox is correlated.

Other useful results from this work consist in the following: for a comparative study of the dynamical behavior and vibration effects in gearboxes the statistical methods and factors are reasonable for faults detection.

Bibliography

[1] E. Olsson, P. Funk, and N. Xiong. Fault diagnosis in industry using sensor readings and case-based reasoning. *Journal of Intelligent & Fuzzy Systems*, 15:41–46, 2004.

[2] E. Beckenstein G. Bachman and L. Narici. *Fourier and wavelet analysis*. Springer, 2000.

[3] A. Aamodt and E. Plaza. Case-based reasoning: Foundational issues, methodological variations, and system approaches. *Artificial Intelligence Com*, 7:39–59, 1994.

[4] MODELICA HOMEPAGE. Modelica. http://www.Modelica.org.

[5] H. J. Decker. Crack detection for aerospace quality spur gears. *NASA/TM*, 2002.

[6] Dynasim AB. Dymola. http://www.dymasin.se.

[7] A. Barber. *Handbook of Noise and Vibration Control. 6th Edition.* Elsevier Advanced Technology, 1992.

[8] P. J. Dempsey. A comparison of vibration and oil debris gear damage detection methods applied to pitting damage. *Proceedings of COMADEM*, 2000.