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2012 J. Phys.: Conf. Ser. 364 012061

(http://iopscience.iop.org/1742-6596/364/1/012061)

Journal of Physics: Conference Series **364** (2012) 012061 doi:10.1088/1742-6596/364/1/012061

Case-based reasoning combined with statistics for diagnostics and prognosis

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Abstract.

Many approaches used for diagnostics today are based on a precise model. This excludes diagnostics of many complex types of machinery that cannot be modelled and simulated easily or without great effort. Our aim is to show that by including human experience it is possible to diagnose complex machinery when there is no or limited models or simulations available. This also enables diagnostics in a dynamic application where conditions change and new cases are often added. In fact every new solved case increases the diagnostic power of the system. We present a number of successful projects where we have used feature extraction together with case-based reasoning to diagnose faults in industrial robots, welding, cutting machinery and we also present our latest project for diagnosing transmissions by combining Case-Based Reasoning (CBR) with statistics. We view the fault diagnosis process as three consecutive steps. In the first step, sensor fault signals from machines and/or input from human operators are collected. Then, the second step consists of extracting relevant fault features. In the final diagnosis/prognosis step, status and faults are identified and classified. We view prognosis as a special case of diagnosis where the prognosis module predicts a stream of future features.

1. Introduction

Many approaches used for diagnostics today are based on a precise model. This is a powerful approach if it is possible to build a precise model or simulation of the object to diagnose. Unfortunately complexity, dynamics and costs to build precise models exclude diagnostics of many types of machinery in reality that cannot be modelled and simulated easily or without great effort. Our aim is to show that by also using human experience it is possible to diagnose complex machinery when there is no strong model or simulation available. This also enables diagnostics in a dynamic application where conditions change and new cases are often added. In fact every newly solved case increases the diagnostic power of the system.

Artificial intelligence is a cross disciplinary subfield of computer science concerned with understanding the nature of intelligence and the attempt to construct computer systems able to perform intelligent reasoning and action. Intelligence involves many aspects such as perception, problem solving, learning, planning, symbolic reasoning, creativity, and language understanding to mention a few. Rule based systems emerged during the eighties but their use is limited due to the knowledge acquisition bottleneck and the time and cost involved to create a large rule base, verify and validate them, and keep them up to date. An emerging method is CBR, reasoning out of the original cases. CBR has its root in cognitive science and has been applied to numerous application domains, among them fault diagnosis.

In this paper, we review previous research in CBR and the applications of CBR to fault diagnosis and prognosis. We also present three applications of CBR for fault diagnosis in detail where we have used feature extraction together with case-based reasoning to diagnose faults in industrial robots, welding, and cutting machinery. Finally, we present our latest project for diagnosing transmissions by combining case-based reasoning with statistical methods.

The paper is structured as follows. Section 2 gives an overview of CBR in general. In Section 3, we review previous work on CBR applied to diagnosis and prognosis. Section 4 contains detailed descriptions of three applications of CBR for fault diagnosis. Section 5 presents future work in combining CBR and statistics.

2. Case-based reasoning

The idea in CBR is to use experience to solve problems using a cognitive process similar to how humans reason [1, 2]. If we face a problem, we most often solve it by applying a solution from a similar situation from the past. A simple example of a CBR approach in the Internet era is how people, e.g. software developers, use search engines to solve problems. If they encounter a problem, they search the Internet for people having a similar problem. If a solution is provided, they adapt that solution to their own circumstances. Thus, CBR is about automating that process of defining problems and finding solutions.

One important principle in CBR is that inference is made directly from the set of observed cases (examples), and not from a model generalised from the cases. This basic idea of inference relates CBR very closely to machine learning, to which it is sometimes considered to be a subfield [3, 2]. However, CBR was also developed as a more flexible approach to knowledge modelling than rule based expert systems, which are in essence static and not very easily updated with new knowledge [4, 5]. Therefore, CBR is neither considered a machine learning technology nor a pure expert system, but a knowledge management methodology for problem solving [6, 2].

The CBR knowledge management cycle shown in figure 1 was first presented in [1]. First the problem is matched against the case library and similar cases retrieved. Similarity functions capture domain knowledge and similarity is based on how easily the solution can be adapted to the new problem. Adaptation is often a set of rules, e.g. in the medical area a child under 12 is recommended half the dose of medicine compared with an adult. The reuse step may not only adapt single cases, it may, depending on the domain need to merge cases, e.g. a patient may have two diseases at the same time. Revision is manual in many CBR systems and once the person is convinced that the proposed solution meets and solves the new problem then the solution is confirmed. Once confirmed and deployed, the new case and its results are stored in the case library.

How each step is implemented varies from application area to application area, and in each step, different methods from other research areas, in particular machine learning and knowledge representation and reasoning, can be applied. For instance, similarity and adaptation may be implemented with a large variety of techniques such as conceptual models, neural nets, fuzzy rules, Bayesian nets, mathematical algorithms etc. Using CBR will reduce repetition of mistakes if similar unsuccessful cases are presented for the user as warning examples. Explaining why two cases are similar is also important and transfers knowledge to the user. Cases may in some application domains contain large volumes of sensor data.

3. Fault diagnosis

Fault diagnosis is about identifying the type of fault, its severity, location and time of detection before it causes damage [7, 8]. Figure 2 shows a generic fault diagnosis process, where we view the fault diagnosis process as three consecutive steps. In the first step, sensor fault signals from

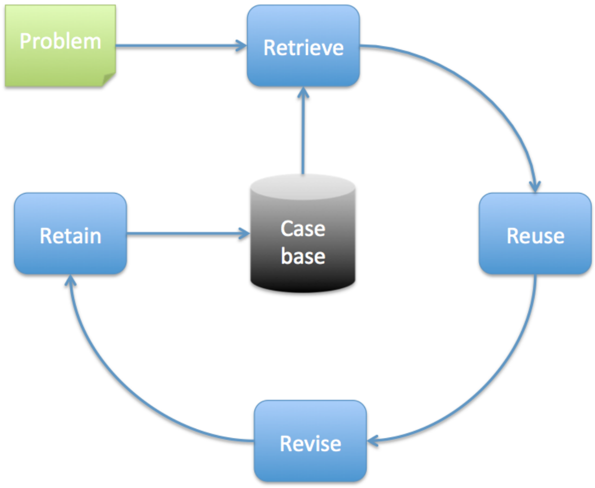

Figure 1: The CBR cycle, adapted from [1].

machines and/or input from human operators are collected. Then, the second step consists of extracting relevant fault features. In the final diagnosis/prognosis step, faults are identified and classified. In case of also doing fault prognosis, there is a parallel step that uses the current features to predict the future stream of features, which is then used as input to the diagnosis.

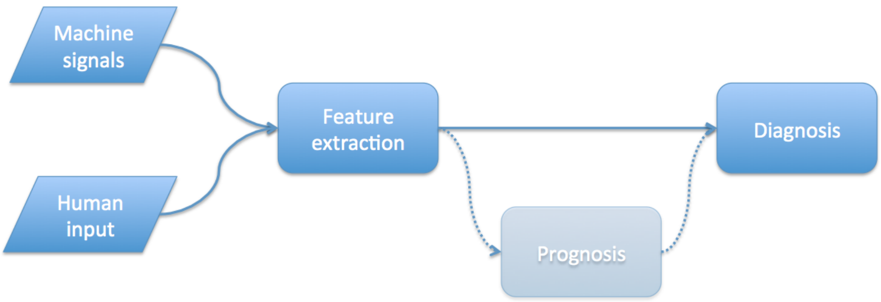

Figure 2: The generic fault diagnosis process.

There are mainly two approaches to fault diagnosis and prognosis, model-based and data-driven. In the former case, a detailed model of the physical system is built that can given fault data, identify the faults or predict them. In the latter case, the system learns to recognize and predict faults from examining the stream of fault data. The drawback of the former is that the approach requires a lot of work and a lot of detailed knowledge while the latter will not be able to identify faults that never have occurred (it may only identify a deviant behaviour not similar to any past cases). Thus, many times it can be a good idea to combine both approaches. CBR can be used in both the diagnosis step as well as in the prognosis as we can see in the next sections.

3.1. Case-based fault diagnosis

Case-based reasoning has been considered an option for fault diagnosis since the beginning of the CBR field. An early paper on evaluating the cognitive aspects of CBR for engineering diagnosis was presented in [9], and an early CBR system for technical diagnosis in engineering was MOLTKE [10, 11] and its extension PATDEX [12]. Another is CELIA, which is a CBR system for automobile troubleshooting [13]. In the INRECA project, a set of tools for developing, validating, and maintaining decision support systems using a combination of inductive decision tree learning and CBR and more were developed [14]. A sample application in INRECA is fault diagnosis on robots that integrates causal trees, decision trees and CBR [15]. In [16], the authors present a CBR system combined with an expert system for classifying images from ultrasonic rail-inspections in order to detect defects. The images are first classified by a set of expert rules. Then, if classification failed, the CBR system makes a classification, but if it also fails, the classification is left to the experts. Cases were created from a historical set of images with expert classifications. The paper also contains a qualitative comparison between the CBR approach and using expert rules or statistical classification, deeming CBR to be a more flexible approach. A hybrid CBR diagnostic system combining model-based diagnosis and CBR was presented in [17]. CBR was used to help the user find alternative solutions as a complement to the model-based suggestions, and to let the system learn from experience. The system was applied in two scenarios: diagnosis of a robot and of a nuclear ventilation system. ICARUS is a CBR-based system for off-board fault diagnosis of locomotives [18]. The system was built to use fault messages from the locomotive as input. Historical fault log and repair data, as well as expert knowledge were used to create cases and validate the functionality of the system. In [19], a hybrid CBR system with an ART-Kohonen neural network (ART-KNN) for diagnosing an electric engine is described. The ART-KNN is used for guiding the CBR system in finding similar cases, to find the best diagnosis. CBR diagnosis has also been applied in self-healing autonomic computing [20]. In the paper, CBR is used for automatically repairing faults in a service delivery context where cases are failure execution episodes mapped to corresponding solutions. A CBR approach for diagnosing faulty robot gearboxes was developed in the Ph.D. thesis by Olsson (et al.) [21, 22, 23]. The thesis is a compilation of papers where the author applies frequency and time analysis using Discrete Wavelet Transform as well as Discrete and Fast Fourier Transform in order to extract signal features. Then, the signal is classified using a CBR approach according to cases of known faulty and fully functioning gearboxes. More recently, in [24], an advanced CBR system for automobile service troubleshooting is described. It uses associate-rule mining, CBR and text mining to extract cases and propose solutions given fault symptoms. A customer support diagnosis system was developed in [25]. The authors created cases from existing machine diagnosis reports collected during the previous 5 years. Finally, [26] presents a comprehensive overview of applying CBR diagnosis in a condition based maintenance system. The authors look at the system as a whole and how CBR fits into the full picture. One of the conclusions is that the CBR system has some similarities to the OSA-CBM standard and another that the system can successfully reuse the experience of the maintenance personnel for fault diagnostics.

3.2. Case-based fault prognosis

There is less work in case-based prognosis compared to diagnosis. An early attempt to address the problem of doing fault prognosis and diagnosis on jet engines is presented in [27]. The authors developed a hybrid CBR system in combination with a model-based system. In [28] the authors present a CBR system for aircraft fleet maintenance. The system uses failure and warning messages that are generated by the aircraft equipment, which can be textual descriptions. Given the textual descriptions, the system proposes initial diagnosis and explanations. Another approach applied to predicting the remaining useful life of aircraft engines based on fuzzy instance-based learning was proposed in [29]. A set of nearest neighbours defined by a fuzzy based similarity metric are retrieved and then a prediction is made from a fuzzy aggregation of the neighbours remaining useful life. Genetic algorithms are used for keeping the similarity model updated given new training cases.

4. Three applications of case-based fault diagnosis

In this section, we review three successful projects where we applied CBR for fault diagnostics. The first project is about detecting cracks in a welding process using sensors and CBR. In the second project, we applied CBR to non-intrusive monitoring and diagnosis of milling machines. The third project is about decision support for adjustment of production equipment producing parts drifting towards unacceptable dimensions.

4.1. Crack detection in welding process

In the project about crack detection, recordings of several welding processes were done mainly focusing on the cool down time in the near seconds after a finished welding process [30]. The aim is to determine the signature that is generated by an emerging crack during the welding process. Figure 3 shows a metal test piece where the acoustic emission sensor is mounted at the top left.

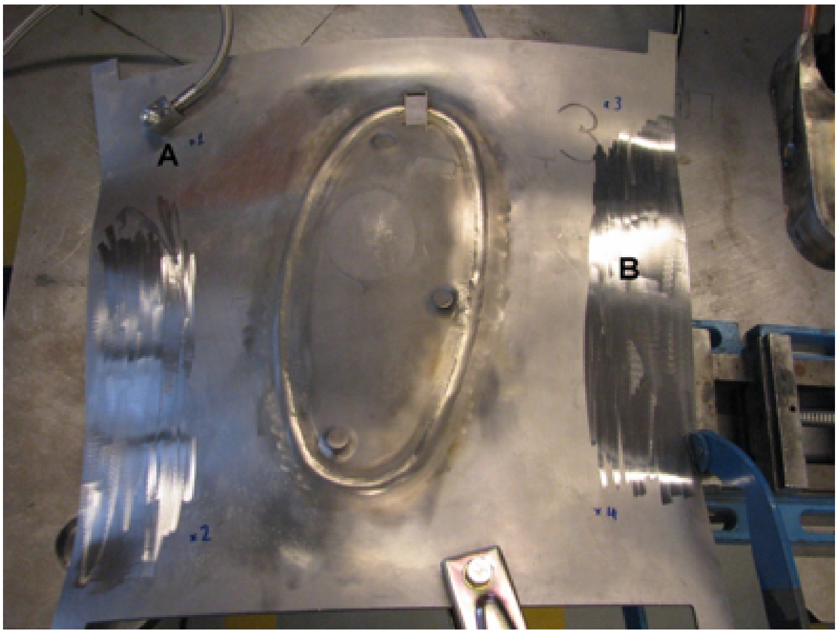

Figure 3: Metal test piece with the acoustic emission sensor mounted at the top left.

Some results from the case-based crack detection project are the following:

- Ultra sound sensor(s) were selected as a suitable recording equipment
- A set of initial recordings from different phases of welding processes was collected and then data from 2 normal and 10 welds with cracks were analysed.
- Suitable features to classify the condition of welding processes were selected
- Methods and algorithms for classification of welding processes were developed
  - 100% of cracked welds correctly classified
  - 1 normal weld incorrectly classified as cracked (false positive)

In figure 4, we show an example of extracted time-FTT of frequency bands 200-1000 kHz of a weld with cracks, depicting main and first order overtone spectrum of recorded cracks.

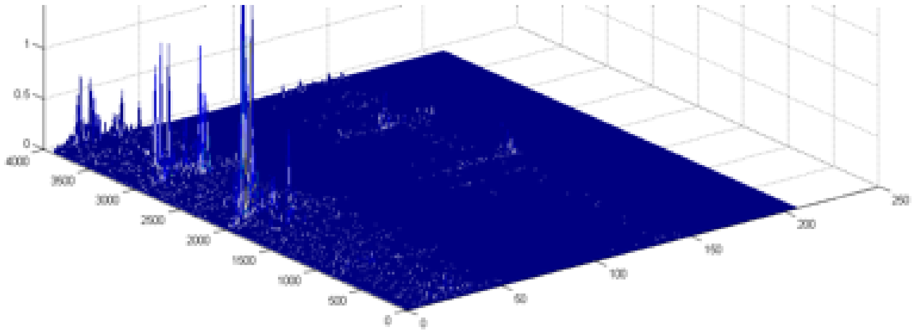

Figure 4: Example of extracted time-FTT of frequency bands 200-1000 kHz of a weld with cracks.

4.2. Process monitoring and diagnosis of milling machines

In the milling machine project, we made a case study of sensorless, nonintrusive monitoring of a milling process. We recorded sound measurements from the milling process, and identified adequate measurement features that were fed into a diagnostic algorithm. Figure 5 shows an unprocessed sample signal after the cutting tool was changed.

In the recorded signals, we have identified patterns that will enable condition monitoring to determine the cutting conditions and cutting stages of the milling machine. We used these patterns to determine the cutting conditions and cutting stages of the milling machine. A condition can be classified into the category that describes the fault.

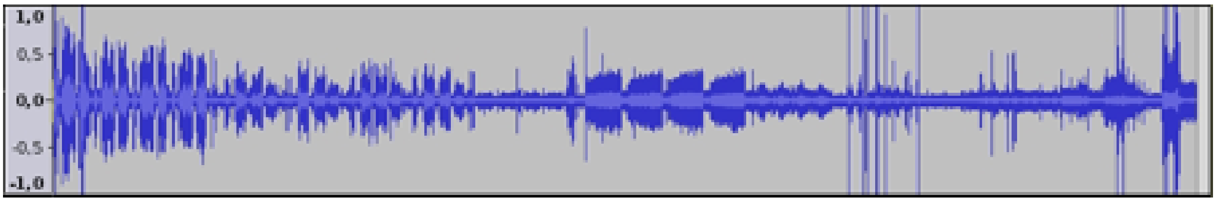

Figure 5: Unprocessed signal after cutting tool was changed.

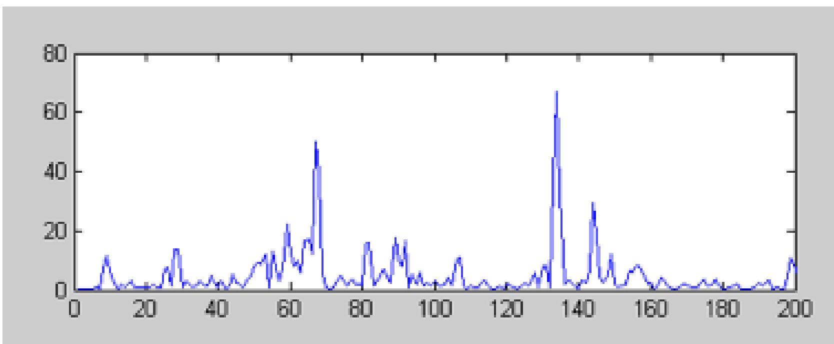

Figure 6: Processed signal from before the cutting tool was changed. A FFT window of size 100 milliseconds, frequency interval 1-200 Hz.

Figure 6 shows the frequency analysis with a FFT window size of 100 milliseconds and frequency interval 1-200 Hz. Amplitude of frequencies is increasing gradually when the cutting steel has to be changed. By the extraction of such information, we can build a library of boundary cases from these features. Figure 7 shows a sample of an extracted feature where there is a significant peak at 10 Hz before the cutting tool was changed.

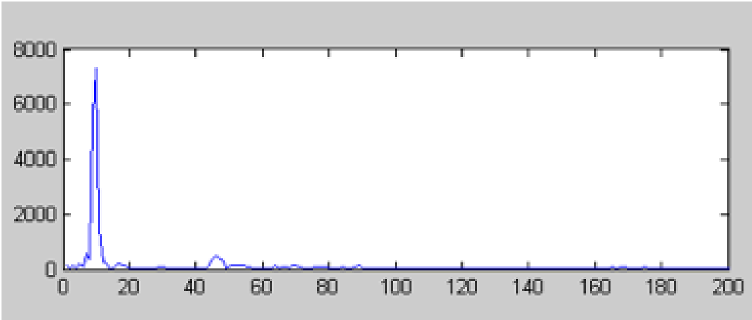

Figure 7: Significant peak at 10 Hz, extracted from the signal in figure 6

4.3. Geometric production measurements

In the project about production measurements, we have developed a case-based tool for supporting the adjustments of a production line producing parts drifting towards unacceptable dimensions (called defect parts) [31]. Measurements, adjustments and their outcome of defective parts are connected and saved as cases. A case maps measurement features from off-target parts (problems) to action taken previously to adjust production line (solution) to bring production back to target. A case library of such cases is assembled and made available to provide real-time decision support in any situation to technicians.

5. Future work: sound test of transmissions

In a doctoral thesis project, we will develop a statistical approach to CBR for fault diagnosis and prognosis of construction vehicle transmissions.

In the production line of vehicle transmissions, each transmission is tested in various ways to ensure that it functions correctly before being assembled in a vehicle. In one of the tests, the sound of the transmission is recorded and if it is outside some manually configured limits, it is considered faulty. We will develop a more flexible CBR-based approach that can learn from experience. Thereby, given feedback from the testers, it will also learn subjective impressions of faulty sounds. Consequently, next time the system encounters a sound similar to a previously encountered faulty sound, it will also be considered faulty, and a fault solution can be recommended.

CBR is a very intuitive, user-friendly, yet powerful approach to diagnosis. As a young and largely applied research field, its theoretical foundation is not fully developed. Statistics, on the other hand, is a very theoretically well-founded research field, but can be difficult to approach without a lot of prior knowledge. We will therefore investigate kernel-based non-parametric statistical methods as a means to keep the intuitiveness and user-friendliness of CBR while still adhering to the theoretical foundation and power of statistical methods. We will use the statistical methods for the retrieval and the reuse parts of the CBR cycle in figure 1. The similarity between a new problem, as well as the diagnosis of it, will be expressed as probability distributions over the set of known cases and known faults, respectively. In addition, we will be able to express how unlikely a new problem is compared to the previous cases, and thus, we will identify unknown cases that then can be manually diagnosed.

6. Conclusions

We have in the paper introduced CBR and presented three successful applications and one application currently being investigated. CBR is a method worth exploring especially when the domain knowledge is weak. This is often the case in engineering tasks since reality is often so complex that building a model and performing simulations is not possible or computationally too expensive. It may require a considerable amount of work to build such models and simulations may take much processor capacity beyond what is possible to calculate in a reasonable timeframe.

Acknowledgments

This work has been partially funded by the Swedish Knowledge Foundation (KK-stiftelsen) and the Swedish Foundation for Strategic Research (SSF, ProViking).

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