Case-Based Reasoning Supports Fault Diagnosis Using Sensor Information

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ABSTRACT
Fault diagnosis and prognosis of industrial equipment become increasingly important for improving the quality of manufacturing and reducing the cost for product testing. This paper advocates that computer-based diagnosis systems can be built based on sensor information and by using case-based reasoning methodology. The intelligent signal analysis methods are outlined in this context. We then explain how case-based reasoning can be applied to support diagnosis tasks and four application examples are given as illustration. Further, discussions are made on how CBR systems can be integrated with machine learning techniques to enhance its performance in practical scenarios.

Keywords
Fault Diagnostics, Case-based Reasoning, Sensors, Signal Processing, Feature Extraction, Crack Detection, Process Monitoring, Artificial Intelligence, Knowledge Discovery, Case Retrieval

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 equipment makes a crucial contribution to the enhancement of reliability in manufacturing and efficiency in product testing.

Sensor data provides rich and objective information for fault diagnosis in monitoring and maintenance. An experienced technician has skills to find symptoms for detecting an existing fault or predicting a failure in near future. However a junior technician may fail to do this due to the lack of knowledge and experiences. Artificial intelligence (AI) techniques offer valuable tools for building intelligent, computer-based systems for monitoring and diagnosis that are based on human knowledge and past experiences [12]. Such computer-based systems can offer decision support in practical applications by offering a second opinion.

Regarding pattern classifier for monitoring and diagnosis, a number of methods might 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 distinguish objects by defining linear boundaries between classes using a moderate number of attributes as function variables. For problems with nonlinear boundaries artificial neural networks would be a candidate approach because they are capable of realizing arbitrary nonlinear mappings between input and output units. Knowledge is represented implicitly in a neural network with a set of connection weights, which are not easily understandable by human users and not easily give an answer on the question “why” a certain answer is suggested. Comparatively case-based reasoning (CBR) [1] is more transparent by making decisions according to similar cases retrieved such that human users are given reference information to understand, verify, and occasionally also modify the suggested results. The explanatory issue is quite important in industrial applications where AI systems serve as decision support and every decision made has to be well justified before taking effect. This explains why this paper focuses on the use of CBR to classify time series signals for fault diagnosis in industrial scenarios.

The remaining of the paper is organized as follows. Section 2 gives an overview of the methods of signal analysis as a prior step for CBR. The CBR approach to fault diagnosis is introduced in section 3, which is followed by several application examples in section 4. In section 5 we discuss some ways to further improve CBR performance in diagnosing tasks. Finally section 6 gives concluding remarks.

2. ANALYSIS OF SENSOR SIGNALS PRIOR TO DIAGNOSIS
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 state systems and their profiles. We can then process and analyse the collected sensor recordings in order to find out hidden symptoms. Reasoning can be made based on detected symptoms to estimate 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 paradigm for signal-based diagnosis is illustrated in Fig. 1, which includes signal filtering, feature extraction, and pattern classifier as its important components.
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 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 [21][22]. 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 Error! Reference source not found. and particle filtering [15] are worthy of being used to acquire more accurate estimates of the states of the underlying machines or processes.

Feature extraction aims to identify characteristics of sensor signals as useful symptoms for further analysis. This stage is crucial in many practical domains in industry where the process in consideration is dynamic such that measured states generally change with the time. This means that it is not possible to depict sensor observations with static single values. Instead we need to identify a group of features to characterize a time series signal. The set of extracted features is desired to have a moderate number to facilitate efficient analysis and reasoning. On the other hand, features extracted also ought to be adequate to accommodate temporal information or transitional patterns of signals to be analysed.

Conventionally features extracted from signals fall into two categories, namely statistical features and frequency-based features. Statistical features are extracted from the profile of signal values with respect to calculated statistics as overall generalization. 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 use for signal representation is commonly ad-hoc and domain dependent. An example of using statistical features for case-based circuit diagnosis was illustrated in [27]. However one converts dynamic data streams into static values when making statistical features, which may lead to the loss of information about temporal relation between data.

Frequency-based features characterize sensor signals by groups of quantities related to a diversity of frequencies. As numerous signal transforms are available to yield frequency spectra, we seem to have more solid basis for extracting features based on frequency than for deriving features based on statistics. The two most common signal transform methods are Fourier Transform and Wavelet Analysis Error! Reference source not found. However traditional feature extraction methods may have some drawbacks such as large number of features as well as the risk of losing temporal relationship existing in the original signals.

Symbolic approximation was proposed in [13] as a more compact and meaningful way to characterize the dynamic property of complex, longitudinal series of measurements. The solution is to convert the sampling-point based representation of the time series into an interval-based representation. An interval consists of a set of consecutive sampling points and thus encompasses multiple sampling periods in the time dimension. Then data within an interval have to be generalized and aggregated into one symbolic value; the symbolization is conducted via discretization of the range for possible values of the signal. By doing this, the primary time series is transformed into a symbolic series associated with intervals. Symbolic approximation of primary numerical time series signals would bring the following benefits:

- Symbolic series are shorter in length and more intensive in information content, while much of the important temporal information is still retained.
- Symbolic series facilitate higher computational efficiency and require less computational resource and memory space.
- Symbolic data are more robust and less sensitive to measurement noises.
- Symbolic data are easier for human understanding and inspection.

Temporal abstraction [30] from Artificial Intelligence provides a good technique to implement symbolic approximation, i.e., to transform time-stamped numerical signals into interval-based symbolic representations. It works by aggregating adjacent events exhibiting a common behaviour over time into a generalized concept. The ontology for basic temporal abstraction includes state abstraction and trend abstraction. The former focuses on the measured values themselves to extract intervals associated to qualitative concepts such as low, normal, and high, while the latter considers differences between two neighbouring records to detect specific patterns like increase, decrease, and stationarity in the series.

3. CASE-BASED REASONING FOR DIAGNOSIS

Case-based reasoning (CBR) offers an effective means to implement pattern classifier. 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 [24]. The main strength of CBR 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 perform CBR to make classification of faults using known cases in the case library as shown in Fig. 2. It starts with similarity matching to compare the query problem against cases stored in the case base and a set of similar cases are thereby retrieved. Then, in the next stage, the solutions (classes) of retrieved similar cases are combined in terms of their similarity values in order to estimate the fault class of the new problem.
Generally the working cycle for a CBR system consists of the following four steps: retrieve, reuse, revise and retain, as shown in Fig. 3. The first step is to retrieve a set of similar cases given a new problem. It is followed by the reuse step, which is tasked to reuse the information from the retrieved cases to suggest a new solution to the query problem. Usually the retrieved cases are not identical to the query problem; we need to perform adaptation or fusion of the retrieved solutions to fit the new situation. The third step is revise, in which the suggested solution will be verified for its correctness. Unsuitable solutions will be revised and re-verified in this step. Finally, in the retain step, a confirmed solution will be treated as a learned new case and stored into the case library for future usage.

4. INDUSTRIAL APPLICATION EXAMPLES USING CBR
In this section we briefly highlight several projects applying CBR techniques for process monitoring, diagnosis and quality control, which are being performed or have been completed by the Intelligent Systems Group at Mälardalen University, Sweden.

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 [19]. The aim is to determine the signature that is generated by an emerging crack during the welding process.

Some results from the case-based crack detection project are the following:
• Ultra sound sensor(s) were selected as suitable recording equipment
• A set of initial recordings from different phases of welding processes was collected and then the data from 2 normal welds 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. The result is that 100% of cracked welds were correctly classified and only one normal weld was incorrectly classified as cracked.

4.2 Process monitoring and diagnosis of milling machines
The milling machine project focused on nonintrusive monitoring of a milling process. The sensor data used were sound measurements recorded during the milling process. Adequate features were identified from the sound signals and they were used as inputs to represent cases in the case-based diagnostic system.

Cases were created from recorded signals that contain typical patterns of cutting conditions and cutting stages of the milling machine. We then utilized these cases in a CBR procedure to estimate the status of the machine given new sensor measurements. The condition of the milling process can be classified into a category that is associated with a fault.

4.3 Geometric production adjustments
The on-going project is in collaboration with Volvo Car (in Sweden) with the objective of finding proper adjustment actions to produce precise geometric shape of car bodies in terms of specifications. A case-based tool has been developed for supporting the adjustments of a production line to prevent producing parts of the body drifting towards unacceptable dimensions (called defect parts) [25]. Measurements, adjustments and their outcome of defective parts are connected inside a case. A case library of such cases has been created and made available for real-time decision support. The reasoning with cases in the case library provides a mapping from measurements to suitable actions to correct the production back towards the desired state.
4.4 Robot fault diagnosis
A CBR approach for diagnosing faulty robot gearboxes was developed in [14] and [26]. The received sensor signals are processed by Wavelet Analysis and Fourier Transform 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 module that uses case-based reasoning to recommend a fault class for the probe case. The recommendation is based on previously classified cases in the case library and a new suggestion is made by combining the outcomes of similar cases. This approach has been applied to industrial robots in ABB Robotics (Sweden) and the results of experiments have shown that case-based diagnosis has attractive properties in the reuse of past experiences while not imposing high demand on the size of the case library.

5. FURTHER ENHANCING CBR PERFORMANCE
Although CBR is a powerful methodology to facilitate problem solving by resorting to previous similar experiences, the functionality of a CBR system may not always be optimal in practical applications. This is owing to the following two reasons. First, the cases available can be limited and hence they cannot cover the whole problem space. Secondly, CBR is usually performed in areas with poor domain theory and therefore there is no precise knowledge for guiding the utilization of individual cases in a case-based inference procedure. In the remaining of this section we shall discuss how these two possible limitations of CBR could be compensated by integration with model-based reasoning and knowledge discovery.

5.1 Integration with Model-Based Reasoning
CBR and model based reasoning are two alternative AI methods to solve problems. Model-based reasoning relies on a knowledge model constructed in advance to tackle new situations. However, it is frequently the circumstance that neither the cases at hand nor the available knowledge model can achieve a complete coverage of the problem space. Yet both can complement each other to solve problems in broader scope. Hence it is a natural practice to build a hybrid system with integration of both case-based and model-based reasoning in a cooperative manner to be able to identify more faults and problems.

In the INRECA project [3][4], the knowledge model of causal and decision trees were combined with CBR for applications in robot fault diagnosis. A CBR system combined with expert system was presented in [18] to detect defects in images from ultrasonic rail-inspections. The images were first classified by a set of expert rules. If the classification failed, then the CBR system was used to solve the classification task. The system in [11] hybridized CBR with model-based reasoning in two scenarios: diagnosis for robots and diagnosis of a nuclear ventilation system. The method of CBR was used in the system to help users finding alternative solutions as a complement to the model-based suggestions as well as to enable the system to learn from experience.

5.2 Discovery of CBR Knowledge
In order to conduct CBR optimally, intensive knowledge is required to guide the way of dealing with cases. For instance, retrieve knowledge is needed as criteria to judge which cases are similar and useful for solving a new problem. For case indexing, we need the knowledge and information for what attributes to adopt to concisely characterize the nature of a case. All such knowledge for CBR is domain related. In the following we shall discuss how to acquire the knowledge for case representation and case retrieval respectively via data mining and knowledge discovery.

5.2.1 Discovery of knowledge for case representation
We prefer a concise case index to keep a low input dimension for the case-based classifier. However, traditional methods of feature extraction usually produce a large number of features from the original signals. Some features may be irrelevant, redundant, or contaminated by heavy noise. With feature selection we intend to derive the knowledge about which features are important based on the given data set. Only important features are selected as inputs for building the case index. Selection of important features leads to improved CBR performance, lower input dimensionality, as well as reduced computational costs.

Existing approaches to feature selection can be divided into two categories, called filter and wrapper respectively. Filter approaches [28], [10], try to assess feature goodness as an intrinsic property independent of the modelling algorithm. Usually they attempt to detect possible dependency between a pair of variables based on the given data. But individual features are evaluated in isolation of each other without considering the influence of others. In contrast, wrapper approaches [20], [23], [16] used a modelling algorithm to evaluate feature subsets in terms of the modelling accuracy. Hence they may yield higher classification accuracy than filtering approaches.

It is interesting to mention that feature selection and CBR can support each other. In [33] and [35] CBR was used as a criterion to evaluate the goodness of a feature subset. This proposed approach seems similar to wrapper but it reduces the complexity of wrapper by requiring no modelling procedure given a feature subset. Later, the paper [32] demonstrated that feature selection could be conducted to enhance CBR systems to reach high classification accuracy.

The other challenging issue for case representation lies with symbolic sequential data (after symbolic approximation of original signals), where the existing numerical approaches for signal processing are not applicable. This issue was tackled in [13] by focusing on transitions of states in time series. It is believed that in many real-word situations, key transitions of states are more important than symbolic values themselves in detecting possible faults. Such transitions of states are referred to as key sequences. It was suggested in [13] that the knowledge about key sequences being discovered based on a database of classified time series.

Once the key sequences are identified, they are utilized as reference to capture important contents in a time series of query. The symbolic series is checked thoroughly to detect any occurrences of key sequences in it. Then the information about whether a key sequence has occurred and with how many times is made use of in building a numerical case index. This case index is concise since it only considers appearances of key sequences while ignoring other trivial randomness. Various ways to construct such case indexes have been addressed in [13].

5.2.2 Discovery of knowledge for case retrieval
Similarity assessment plays an important role in the retrieval step of a CBR cycle. As the fundamental principle for CBR is that similar problems have similar solutions, we expect to rely on the
similarity model to retrieve the truly useful cases for solving a new problem. It was pointed out in [29] that a competent similarity model should function as a knowledge container by encoding domain knowledge.

So far the most common way of similarity modelling has been focused on feature weighting [31]. Features are assigned with different weights in accordance with their importance, and the global similarity metric is defined as a weighted sum of the local matching values in single attributes. Different approaches of interest have been proposed for identifying such weights automatically. Incremental learning attempts to modify feature weights according to feedback of retrieval results [6]. The probability of ranking principle was utilized in [8] for the assignment of weight values to features. Case-ranking information was utilized in [7] and [9] for weight adaptation towards similarity degrees of retrieved cases consistent with a desired order. Accuracy improvement represents another way for adapting the set of weights as discussed in [17] and [2]. Nevertheless, no matter how the values of weights are derived, the capability of these similarity-learning methods is inherently constrained by weighted combination of the local matching degrees. This limitation in the structure of similarity makes it hard to represent more general knowledge and criteria for case assessment and retrieval.

A new similarity model without feature weighting was proposed in [34] as an effort to seek more powerful representation of knowledge for case retrieval. The idea was to encode the information about feature importance into local compatibility measures such that feature weighting is no longer needed. Later, it was also analysed and demonstrated that the parameters of such compatibility measures can be learned from the case library in favour of coherent matching, i.e. to maximize the supportive evidence while minimize the amount of inconsistence derived from pairwise matching of cases from the case base.

6. CONCLUSIONS
Applying AI techniques for signal-based fault diagnosis presents an emerging trend in maintenance research. Interesting decision support systems can be built by using AI techniques to classify collected signal patterns. Case-based reasoning and supervised learning are two powerful AI techniques to classify sensor data in terms of faults and also improve system performance when experiences accumulate. The advantages of case-based reasoning include simplicity, easy understanding, good explanation, as well as the ability to survive with a small number of cases. On the other hand, supervised learning represents well-established and sound approaches to learning and generalization from a number of training examples. They can be trained to approximate training examples with satisfying accuracy. However, a weakness with supervised learning methods is that they require sufficient examples for training to avoid the risk of overfitting, hence they are not applicable in diagnosis tasks where the amount of gained experiences is rather limited.

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