

A Survey of Case-Based Diagnostic Systems for Machines

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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.

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 2 gives an overview of five CBR diagnostic systems for machines. Section 3 discusses and compares features of the systems. Section 4 gives a brief conclusion of the systems.

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.

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:

$$\frac{[\sum w_c]^2}{[\sum w_s][\sum w_n]} \quad (1)$$

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 was 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%.

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 1. Case Structure. The Measurement Part.

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

Table 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 3.

Table 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 C_1 because of its similarity in the measurements. The deviation is far from normal so the case will be introduced 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%.

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 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 where 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:

$$d_g(R, W) = \frac{1}{k} \sum_{i=1}^k d_i(R_i, W_i) \quad (2)$$

The system notifies the user if a new case is considered interesting. The new case is considered interesting in 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.

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 5. displays a part of the case structure.

Table 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.

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 which 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%.

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 over-filled 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.

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.

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