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Integration of ART-Kohonen neural network and case-based reasoning for intelligent fault diagnosis

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Abstract

This paper presents a new approach for integrating case-based reasoning (CBR) with an ART-Kohonen neural network (ART-KNN) to enhance fault diagnosis. When solving a new problem, the neural network is used to make hypotheses and to guide the CBR module in the search for a similar previous case that supports one of the hypotheses. The knowledge acquired by the network is interpreted and mapped into symbolic diagnosis descriptors, which are kept and used by the system to determine whether a final answer is credible, and to build explanations for the reasoning carried out. ART-KNN, synthesizing the theory of adaptive resonance theory and the learning strategy of Kohonen neural network, can solve the plasticity-stability dilemma of conventional neural networks. It can carry out ‘on-line’ training without forgetting previously trained patterns (stable training), and recode previously trained categories adaptive to changes in the environment and is self-organizing, which differs from most of networks that only can be carried out off-line. The proposed system has been used in the faults diagnosis of electric motor to verify the system performance. The result shows the proposed system performs better than self-organizing feature map (SOFM) based system with respect to classification rate.

Keywords: Case-based reasoning; Artificial neural network; Diagnosis; Electric motor

1. Introduction

Fault diagnosis of machines is gaining importance in industry because of the need to increase reliability and to decrease possible loss of production due to machine breakdown. Efficient incipient faults detection and accurate faults diagnosis have been become critical to machinery normal running. When some faults appear in production process, the efficient condition monitoring and maintenance can reduce the cost due to machinery failures and downtime. However, engineers who have expert knowledge and experience are rare in the real world. Even if experts are available, the technical information needed by the engineers is not always to hand, or received in the first instance. This is because the information is distributed centrally, but it is the responsibility of the distributor or subsidiary to relay it, and there are difficulties in remembering and applying this amount of knowledge for experts. In addition to the above issues, the correct diagnosis of a fault is fairly complicated. This is because:

- A symptom can be caused by different fault conditions.
- Some faults are not easy to recognize in the machine, due to the background noise.
- There are many components with machinery.
- There is a high level of interaction between these components.

While an artificial neural network (ANN) is used to make hypotheses and to guide the search for similar cases in the library, case-based reasoning (CBR) is used to select a most similar match for a given problem, supporting a particular hypothesis or deciding among hypotheses. The diagnosis descriptors are created and maintained according to the knowledge stored in the ANN, keeping an intelligible description of the knowledge represented in the network and defining a ranking scheme for the most important attributes observed in these cases. This ranking scheme is used for consultation purposes, for confirming or refuting a final result, and for building explanations (Reategui, Campbell, & Leao, 1997).

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CBR has been introduced in the early 1980s as a plausible reasoning approach supported by the idea that people reply on concrete previous experiences when solving new problems (Barletta, 1993; Aamodt & Plaza, 1994). CBR is a reasoning technique that reuses past cases to find a solution to the new problem. Typically, a CBR retains a fairly large number of previous cases in a case base. When a new problem occurs, it will be represented as a new case and compared to the cases in the case base. Thus, the cases similar to the new cases will be used to suggest to users a solution for the new problem. Usually, the solved new case will also be added into the case base. Many CBR systems have been reported for solving problems in various domains, such as diagnosis, planning, design, and image processing.

However, despite the relative success with which CBR techniques have been employed, they have brought with them some disadvantages. For example, previous cases may influence a CBR system in different directions without giving it many hints on which cases to consider as more important. This problem, associated with other difficulties in case-based indexing and retrieval, suggests that combining CBR with complementary forms of reasoning, such as rule-based, model-based or neural network, may be fruitful (Reategui et al., 1997; Reategui & Leao, 1993).

The goal in this work is to propose a new approach from integrating CBR with ANNs to solve diagnostic problems. By combining CBR with ANNs, we stand to benefit both from the logic-based and cognitive nature of symbolic systems and from the numeric, associative and self-adapting nature of ANNs.

Presently, the fault diagnosis is increasingly intelligent with wide applications of ANNs. However, conventional 'off-line' ANNs are unable to well adapt to unexpected changes in the environment. Furthermore, the data of the dataset used to train networks need be added, as new fault or case occurs. In this case, the 'off-line' network requires to be retrained using the complete dataset. This can result in a time consuming and costly process. In the real world, although part of fault signals or cases can be obtained, it is very difficult to compose the training dataset representing the features of all faults. Nobody knows what will happen next time. These characteristics limit the applications of 'off-line' ANNs in fault diagnosis field. The ANNs for fault diagnosis of machinery are required to learn gradually the knowledge in operating process, and to have the adaptive function expanding the knowledge continuously without the loss of the previous knowledge during learning new knowledge. The authors (Yang, Han, & An, 2003) proposed a fault diagnosis network (ART-Kohonen neural network, ART-KNN) which synthesizes the adaptive resonance theory (ART) (Carpenter & Grossberg, 1988) and the learning strategy of Kohonen neural network (KNN) (Kohonen, 1995). ART-KNN does not destroy the initial learning and can adapt the additional training data that is suitable for fault diagnosis of rotating machinery (Yang et al., 2003). The advantage of ANNs is that they could learn something without understanding the detailed knowledge of things, just depending on the training pattern (Liobet et al., 1999; An, 2002).

The main aim of this paper is to build one diagnosis system to solve rare engineers and other problems in the real diagnosis process. The proposed system can provide diagnosis results depending on measurement condition and signal, and also can update on-line, that new case of the diagnosis procedure and results obtained by experts are automatically added to the system. The hybrid system have been used the diagnosis of electric motors and confirmed the validity with a good level of accuracy.

2. ART-Kohonen neural network

ART-KNN combines the theory of ART (Carpenter & Grossberg, 1988) with Kohonen's learning strategy (Kohonen, 1995) to realize machinery fault diagnosis. The architecture of ART-KNN is shown in Fig. 1.

This network is similar to ART1's, excluding the adaptive filter. ART-KNN is also formed by two major subsystems: the attentional subsystem and the orienting subsystem. Two interconnected layers, discernment layer and comparison layer, which are fully connected both bottom-up and top-down, comprise the attentional subsystem. The application of a single input vector leads to patterns of neural activity in both layers. The activity in discernment nodes reinforces the activity in comparison nodes due to top-down connections. The interchange of bottom-up and top-down information leads to a resonance in neural activity. As a result, critical features in comparison are reinforced, and have the greatest activity. The orienting subsystem is responsible for generating a reset signal to discernment when the bottom-up input pattern and top-down template pattern mismatch at comparison, according to a similarity. In others words, once it has detected that the input pattern is novel, the orienting subsystem mush

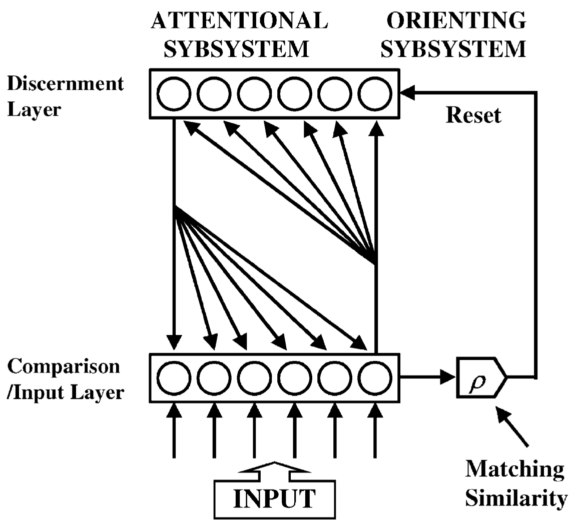


Fig. 1. Architecture of the ART-KNN network.

prevent the previously organized category neurons in discernment from learning this pattern (visa a reset signal). Otherwise, the category will become increasingly non-specific. When a mismatch is detected, the network adapts its structure by immediately storing the novelty in additional weights. The similarity criterion is set by the value of the similarity parameter. A high value of the similarity parameter means than only a slight mismatch will be tolerated before a reset signal is emitted. On the other hand, a small value means that large mismatches will be tolerated. After the resonance check, if a pattern match is detected according to the similarity parameter, the network changes the weights of the winning node.

The learning strategy is introduced by the KNN (Kohonen, 1995). The Euclidean distances of all weights between input vector X and each neuron of the discernment layer are evaluated as the similarity given by Eq. (1), the smallest one becomes the winning neuron.

$$\|B_J - X\| < \|B_j - X\|, \qquad j, J = 1, 2, \ldots, n;\ j \neq J, \tag{1}$$

where B_j is the weight of jth neuron in the discernment layer, B_J is the weight of the winning neuron. After producing the winning neuron, input vector X returns to the comparison layer. The absolute similarity S is calculated by

$$S = \frac{\|B_J\| - \|B_J - X\|}{\|B_J\|} \tag{2}$$

If B_J and X in Eq. (2) are same, $\|B_J - X\|$ is equal to 0, and S is 1. The larger the Euclidean distance between B_J and X is, the smaller S is. A parameter ρ is introduced as the evaluation criterion of similarity. If $S > \rho$, it indicates that the Jth cluster is sufficiently similar to X. So X belongs to the Jth cluster. In order to make the weight more accurate to represent the corresponding cluster, the weight of Jth cluster is improved by the following equation:

$$B_J = (n \times B_{J0} + X)/(n + 1), \tag{3}$$

where B_J is the enhanced weight, B_{J0} is the origin weight, and n is the changed time.

On the contrary, as $S < \rho$, it means that X is much different with the Jth cluster. Thus there is no cluster that matches X in the original network. The network needs one more neuron to remember this new case by resetting in the discernment layer. The weight of new neuron is given by

$$B_{n+1} = X. \tag{4}$$

3. Case-based reasoning system

Basically, a CBR system is a model of human reasoning. The idea behind CBR is that people rely on concrete previous experiences when solving new problems (Joh, 1997). A CBR system solves new problems by adapting solutions that were used to solve old problems. CBR is to solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation (Yang, Lim, & Lee, 2000; Yang, Lee, & Lim, 1997). The case base holds a number of problems with their corresponding solutions. Once a new problem arises, the solution to it is obtained by retrieving similar cases from the case base and studying the similarity between them. A CBR system is a dynamic system in which new problems are added to the case base, redundant ones are eliminated, and others are created by combining existing ones (Fyfe & Corchado, 2001). Since the CBR model was first proposed, it has proved successful in a wide range of application areas (Kolodner, 1993; Kolodner & Mark, 1992; Kolodner, 1991; Pal, Dillon, & Yeung, 2000). There are two main phases in a CBR system:

Initial development: A number, usually large, of previous cases of faults and their known solutions are encoded into the systems. This is known as developing the case base.
Routine use: A current problem, with unknown origin and unknown solution, is presented to the system, initially as a textual description. The system then searches the case base in an attempt to find historically known cases, which match this current problem as closely as possible. In situations in which there are several matches of a similar degree of closeness, the system may ask one or more questions to try to disambiguate these previous cases, and to narrow down the solution to one (or a few) which match the current problem closely.

Conceptually CBR is commonly described by the CBR cycle shown in Fig. 2. This cycle is composed of four sequential phases which are recalled every time that a problem needs to be solved (Aamodt & Plaza, 1994; Kolodner, 1993; Watson, 1997). The first phase retrieves the most similar case or cases to the new problem from a set of case base. Then, in the second phase, the system tries to

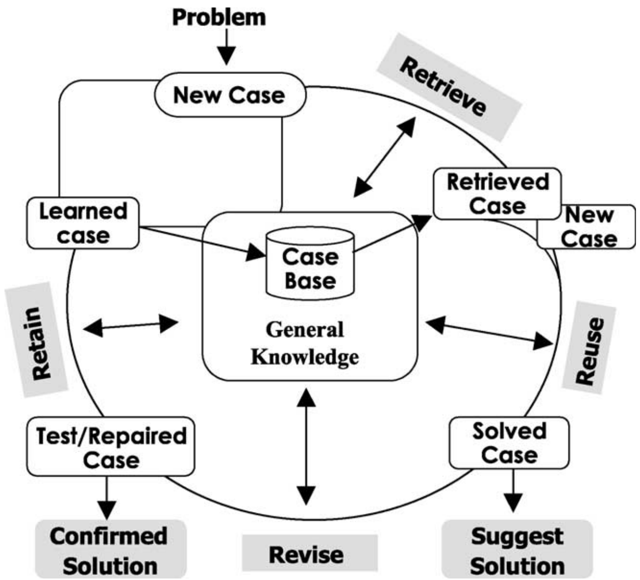


Fig. 2. The model of the CBR cycle (Aamodt & Plaza, 1994).

reuse the information and knowledge of the previously retrieved cases for solving the new problem. Next, the third phase revises the proposed solution if there is a difference between the new problem and the retrieved case. Finally, the fourth phase retains the new solution as part of a new case likely to be useful for future problem solving.

Each of the steps of the CBR cycle requires a model or method in order to perform its mission. The algorithms selected for the retrieval of cases should be able to search the case base and to select from it the most similar problems, together with their solutions, to the new problem. Cases should therefore represent, accurately, problems and their solutions. Once one or more cases are identified in the case base as being very similar to the new problem, they are selected for the solution of this particular problem. These cases are reused using a predefined method in order to generate a proposed solution. This solution is revised (if possible) and finally the new case is stored. Cases can also be deleted if they prove to be inaccurate; they can be merged together to create more generalized ones and they can be modified.

Through the CBR cycle, it can be seen that if the best-retrieved case is a perfect match, then the system has achieved its goal and finishes. However, it is more usual that the retrieved case matches the problem case only to a certain degree. In this situation, the closest case may provide a sub-optimal solution or the closest retrieved case may be revised using some pre-defined adaptation formulae or rules (Choy, Lee & Lo, 2003).

There are three methods of case indexing for case retrieval (Barletta, 1991): *k* nearest neighbor (*k*-NN), inductive learning (IL), and knowledge-guided. In the *k*-NN algorithm which is the most widely used technology in CBR, all features of a new case are matched to their corresponding feature of all previous cases stored in the case base, and the degree of matching for each pair is computing using a matching function. The IL-indexing method indexes previous cases based on the most important features affecting the outcomes as induced from the data itself (Buta, 1994). This method can make retrieval more effective and efficient than no indexing method, but it has some disadvantages such as the difficulty in optimizing the induction tree and the vulnerability to insufficient cases and poor case descriptions (Kolodner, 1993; Kim & Han, 2001). The knowledge-guided indexing method is similar to expert system and it uses rules which human users or experts determine the features used to index cases. Generally, these methods summarized as follows: (1) *k*-NN indexing is preferred when a retrieval goal is not well defined and only a few cases are available. (2) IL-indexing is preferred if the retrieval goal is not well defined and many cases are available. (3) Knowledge-guided indexing is preferred if the retrieval goal is well-defined (Barletta, 1991).

4. Intelligent diagnosis system

In this paper, the hybrid system is proposed through synthesizing the characteristics of ART-KNN and CBR. The structure of the system is illustrated in Fig. 3. The procedure of this system can be summarized as three main parts: case base, feature description and ART-KNN. Three different parts can be distinguished, each playing a different role in the reasoning process.

4.1. Standard case base

The case base is used to collect learned cases from case history as one uniform pattern. A case base consists of prototypical previous cases experienced in electric motors. These cases were acquired from troubleshooting reports which were experienced in industrial fields. We rearranged the standard case on the basis of every kind of technical troubleshooting reports concerned with case history, and constructed the case-base in the format of Hyper Text Mark-up Language (HTML) that can read through Web browser. Each case was arranged in the standard form: number of

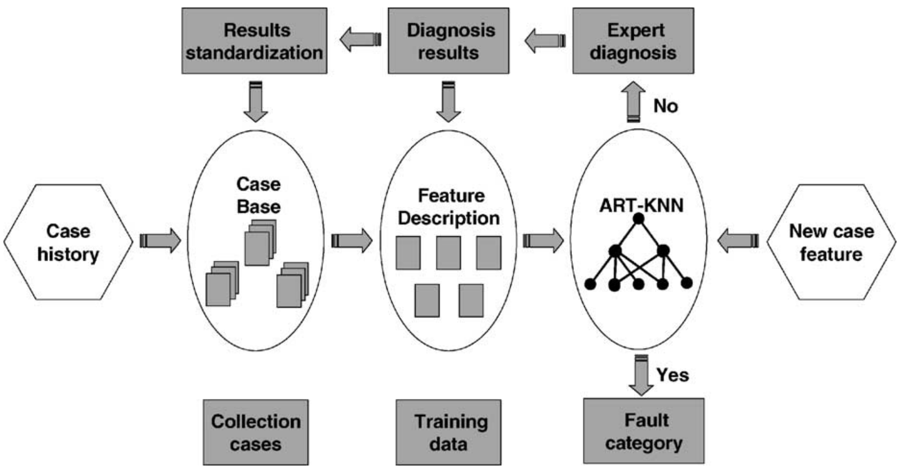


Fig. 3. General structure of hybrid system.

Table 1
Uniform pattern of case collection in the case base

Case M-23	Electric fault by eccentricity of electric motor rotor
Object machine	Induction motor for driving centrifugal compressor, 700HP, 3600 rpm
Occurring symptom	Higher axial vibration than normal, growling continuous noise
Data analysis	• High 1X, 3X components of axial direction • Some small sidebands components but nothing significant
Estimated cause	• Motor was running off its magnetic center • No grease in coupling
Corrective action and results	• Removed from service. • Maintenance personnel check alignment and realign as necessary • Correction of magnetic center by realigning • Lubrication in coupling
Reference	Guy K.R. (1993). Case histories: power industry, Vibration Institute, p. 38

Table 2
Feature descriptions of case characteristics

Feature domain	Descriptor
Vibration and measurement positions	• Bearing radial direction • Bearing axial direction • Motor foundation • Motor casing
Operation condition	• Vibration changes with load • Vibration changes with flow rate • Instantly disappear when power off
Rotating frequency (f_r) components	• Running frequency component (f_r) • Harmonics components ($2f_r$, $3f_r$, …) • Sub-harmonics components ($1/2f_r$, $1/3f_r$) • Sidebands components around f_r • Sharp increases of harmonics
Line frequency (f_L) components	• Beat • Sidebands around f_L, $2f_L$ • $2f_L$ component
Characteristic bearing frequencies	• Outer race defect frequency • Inner race defect frequency • Ball defect frequency
Others	• Periodic noise • Abnormal noise

case, object machine, occurrence symptoms, data analysis, estimated cause, corrective action and results, and reference as shown in Table 1. The previous cases also include a set of attribute value pairs and their degree of importance which were acquired from a domain expert. These are necessary for matching. Relevant symptoms, fault causes, analysis results and their interrelationships applicable to a previous case were determined by the expert by reference to the troubleshooting reports.

4.2. Feature description

The feature description consists of six categories, 20 variables shown in Table 2. It means that features of diagnosis procedure are extracted from the case base. The descriptors described in the feature domains rank the most important findings for each diagnosis. The descriptors referenced by these features are characterized by their frequency and specificity in relation to the diagnosis. The previous cases also include descriptors and their degree of importance (i.e. weight) which were acquired from a domain expert. Usually, the descriptor weights can only be determined after the case has been solved (Gupta & Montazemi, 1997a). Hence, the descriptors of a new case are equally weighted. In previous cases, the local descriptor weights are used as follows. After the domain expert identifies the descriptors in a previous case, they are sorted in to symptoms. The domain expert was provided with a five-point Likert-type scale that assigns a degree of importance to individual descriptors qualitatively (Gupta & Montazemi, 1997a; Cognitive Systems, 1992). The scale ranges from the least important descriptor 0 to the most important descriptor 2. When corresponding phenomenon occurs, it has some values; otherwise, it is 0 (Fig. 4).

4.3. The combinatorial neural network

The final part, ART-KNN, is carried out the classification for new case depending on the known knowledge. If the new case cannot be solved, the expert involves the fault diagnosis. Then the conclusion, which is got from the expert, is retained, and the new case is added into case

0.8	0	0.35	0	0.30	0	L
0	0	0.1	1.0	0	0	A
0.3	0	1.6	0	0	0	M
0	0	0.4	0	0	0	L
0.5	0.7	0	1.0	0	0	A
0	0.7	0.8	0.25	0	0	A
0	0	0	1.0	0	0	S
0.5	0.7	0	1.0	0	0	A
0.3	0	0	1.75	0	0	R
0	0	0.8	0.4	0	0	A
0	0.7	0	1.0	0	0	R
0.5	0	0.8	0.25	0	0	A
0	0	0.8	0	0	0	R
0	0.7	1.05	1.0	0	0	A
0.5	0.7	0	1.5	0	0	R
0	0	0.35	0	0	0	R
0.5	0	0	1.0	0	0	S
0	0	0.35	1.75	0	0	R
0.8	0	0	0	0	0.1	BI
0.5	0.7	0	1.5	0		R
0.8	0	0	0	0	0.5	BO
0.3	0	0.1	1.5	0	0	R
0.8	0	0	0	0	0.7	BB
0	0	0	1.5	1.2	0	R

Fig. 4. Case base for electric motor.

base. Moreover, the network is revised correspondingly for reuse in future. The neural model is used here in three main tasks:

- To learn which are the findings and combinations of findings that are commonly observed for each diagnosis considered.
- To make hypotheses for the diagnosis of new cases.
- To guide the CBR module in the search for similar cases that can support one of the hypotheses designated in the previous step.

The learning process composes three main tasks:

- Training the neural network.
- Incorporating new cases in the case library.
- Building the diagnosis descriptors.

The NN is trained according to the respective learning algorithms referenced in the previous section. The cases used to train the network are stored in the library in a sequential manner. The last learning step is the construction of a descriptor for each of the diagnosis considered.

Training and classification procedures of ART-KNN are as follows (Yang et al., 2003):

Step 1: Input of case base data into the network. Twenty input variables in six categories are selected as defined in Table 2. As the characteristics of ART-KNN are training and classification together, the ART-KNN is empty before application. Thus, as the first case 'L' in Fig. 4 enters the network, there is no neuron to compare with it. One neuron is added to remember this case (step 5).

Step 2: Calculating the Euclidean distances d between the first case data X and neurons of each pattern stored Z.

$$d = \|X - Z\| = \left[\sum_{t=1}^{n} (z_i - x_i) \right]^{1/2} \tag{5}$$

Step 3: The neuron that is nearest to the case data is considered as winning neuron. Then the similarity of winning neuron P_j and input vector of case data X is evaluated by using Eq. (6).

$$S = (\|P_j\| - \|P_j - X\|)/\|P_j\| \tag{6}$$

If P_j and X in Eq. (6) are same, $\|P_j - X\|$ is equal to zero, and S is 1. The larger the Euclidean distance between P_j and X is, the smaller S is. A parameter ρ is introduced as the evaluation criterion of similarity. If $S > \rho$, it indicates that the jth cluster is sufficiently similar to X. So X belongs to the jth cluster.

Step 4: If the similarity value is equal or larger than the matching value, the input case belongs to the winning neuron. Then the weight of the neuron is improved due to the input case.

Step 5: On the contrary, if the similarity value is lest than the matching value, one additional neuron is necessary to represent the new case, and used for classification in future.

When the second case 'A' inputs the network, the Euclidean distance is calculated again. Go without saying, the only one neuron is winner. Then the similarity of both is evaluated. And the comparison is implemented between similarity value and matching value (step 4 and 5). The third case "M" enters the network. The distances and similarity are calculated. If the matching value is properly set, one neuron should be added since it is new case for the network. The rest may be deduced by analogy.

5. Experiment and test results

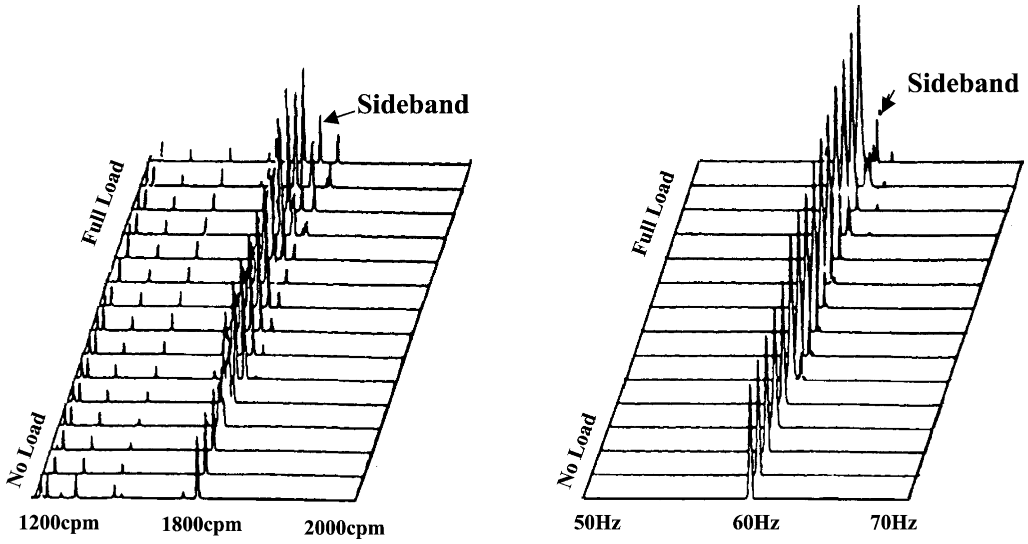
5.1. Experiment data

In this paper, electrical motors were taken for instance. Induction motors are the majority of the industry prime movers and are the most popular for their reliability and simplicity of construction. Although motors are reliable, they are subjected to some faults (Singh & Sas, 2003).

The database contained 64 cases for seven different motor defects, which are representative of problems that had occurred in the field in the past were selected for our test. The distribution of the cases for each diagnosis is the following: 14 cases with bearing faults, 20 cases with rotor damages, 5 cases with stator faults, 9 cases with air-gap related, 6 cases with misalignment, 3 cases with mechanical unbalance and 7 cases with components looseness (Baxter, 1987). The diagnosis and repair solution used in these cases was known from troubleshooting reports. The cases for theses defects have been corrected with the supervision of an expert. The validation of proposed system was demonstrated to subjects by reference to a previous troubleshooting event. Fig. 4 shows an example of electric motor case base composed for experiments. In experiment, 60 cases from database were selected to train the system. Four testing-sets were used to evaluate the system's performance in this experiment.

5.2. Test results and discussion

As a new problem for testing, a case of rotor fault was used from reference (Baxter, 1987). A 250 HP AC motor in a plant was detected high level of vibration and noise with beating frequency. Also, the vibration amplitude of running speed frequency, its second and third harmonics have occurred very high. On the basis of observed symptoms, advisor hypothesized an occurrence of 'rotor bar damage' and recommended relevant tests that could gather evidence toward confirmation of this fault. A zooming analysis of vibration and current signals was performed to improve the resolution ability around three harmonics and line frequency (60 Hz). Several sets of



(a) Vibration spectrum (b) Current spectrum

Fig. 5. Frequency spectrum of new problem (Baxter, 1987).

sidebands were observed at around 60 Hz as shown in Fig. 5. Sidebands are usually the result of either amplitude and frequency modulations or pulse modulation. The level of sidebands increased along with an increase in load. The width of sidebands are identified the product of number of pole and slip speed.

Table 3 presents the characteristics and input data of new problem summarized. This case enters the network after the feature extraction. In order to understand the relationships of criterion parameter ρ, number of neuron and classification success rate, Figs. 6 and 7 are used to explain it. The equation of classification success rate (CSR) is defined by

$$\mathrm{CSR} = C/(T - N) \times 100\% \quad (7)$$

where C is the number of accurate classification, T is the number of total data, and N is the number of generated neuron. $(T - N)$ means the number of used data for test, which equal to the input data number minus the training data number.

The general trend of CSR as shown in Fig. 7 is increasing with ρ. However, it is not continues. Each cluster is composed many neurons with same property, and the cluster region becomes the summation of total neuron region representing its region. The number of neuron is direct proportional to ρ. Because each neuron region becomes small and the number of neuron increases with increasing ρ, the region of the cluster changes bigger or smaller, which is decided by the space distribution of neurons with same property. Then, if the distance of adjoining clusters is close to each other, the CSR will be increased or decreased locally. The larger similarity coefficient is, the higher accuracy rate is. The number of neuron is deduced by analogy. In this paper, the similarity coefficient was set to 0.91. Accordingly the success rate is 96%, and the neuron number is 28.

With above description, the system retrieved two previous cases, M-19 and M-74. These results are shown in Table 4 together with results of similarity obtained by modified cosine matching function (MCMF) (Gupta & Montazemi, 1997a,b). The similarity of the new problem with the previous cases M-19 and M-74 determined by

Table 3
Features, input data and classification result of new problem

Features of new problem	Vibration increase due to load • Beat vibration • Excessive vibration of operating frequency • Increasing harmonics • Sidebands around line frequency
Input data	0 0.1 0.4 1.25 0
Classification result	Rotor bar damage

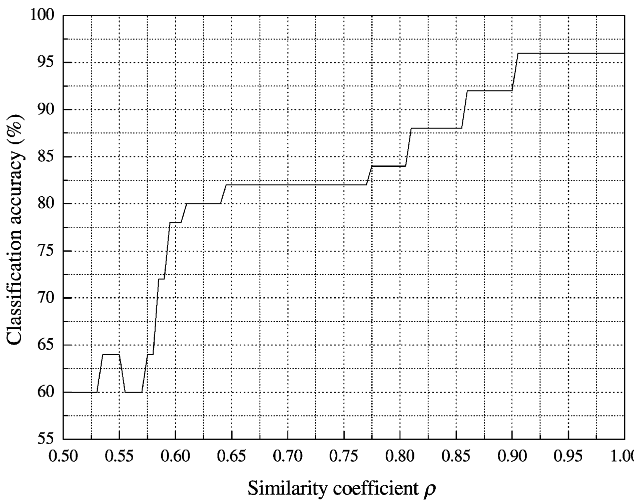


Fig. 6. Classification accuracy versus similarity coefficient.

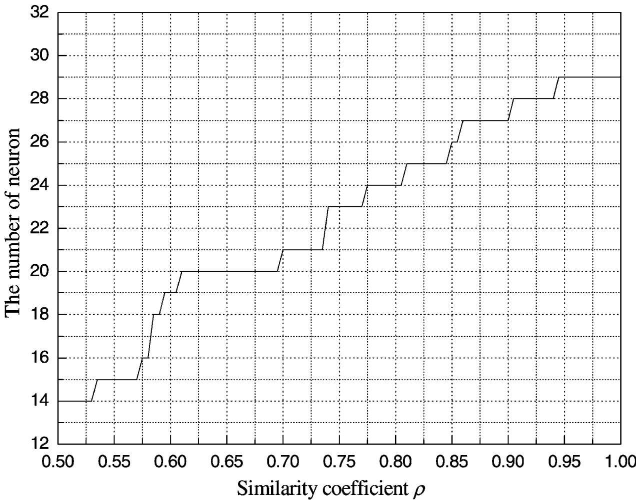


Fig. 7. Similarity coefficient versus the number of neuron.

MCMF are 0.586, 0.525, respectively. The similarity indicated that the previous case M-19 was more relevant than the previous case M-74 toward solving the new case. From Fig. 6, it can be noted that classification accuracy rate and the used neuron increase with the similarity. It goes without saying. Table 5 shows the performance of the ART-KNN-CBR system and SOFM-CBR system (Kim, Yang, & Kim, 2002). ART-KNN-CBR, diagnosing correctly 96.9% of the cases, performs considerably better than the SOFM-CBR achieved 87.5%. This is mainly because the ART-KNN-CBR system has a confirmation method that calculates and enforces a minimum level of credibility for final results. The threshold mechanism used by the SOFM-CBR is not as efficient when presented with cases that the neural network should not be able to diagnose. Especially, if cases presenting each cause are insufficient in training phase when input untrained cases misclassification occurs. There are two important factors that influenced the drop in the performance of the system. The first is the incompleteness of the description of previous cases in database. Secondly, and probably most importantly, there are shortage of cases of database. But, the indexing scheme based on the use of knowledge coming from the neural network enables a very big reduction in the number of cases compared (Reategui et al., 1997).

Table 4
Comparison of case retrieval results with similarity by MCMF (Gupta & Montazemi, 1997a)

	Previous case M-19	Previous case M-74
Similarity	0.586	0.525
Data analysis	• Vertical vibration • Beat vibration • Sidebands around line frequency • Sidebands around two times of line frequency • Abnormal beat noise	• Beat vibration • Sidebands around line frequency • Sidebands around two times of line frequency • Abnormal beat noise

Table 5
Performance of ART-KNN-CBR and SOFM-CBR (Kim et al., 2002)

Results	ART-KNN-CBR		SOFM-CBR	
Correct	62	96.88%	56	87.5%
Misclassified	2	3.12%	8	12.5%
Total	64	100%	64	100%

6. Conclusions

This paper has presented a hybrid system through synthesizing ART-KNN and CBR to deal with rare engineers and other encountered problems in the real diagnosis process. When solving a new problem, the neural network is used to make hypotheses and to guide the CBR module in the search for a similar previous case that supports one of the hypotheses. The knowledge acquired by the network is interpreted and mapped into symbolic diagnosis descriptors, which are kept and used by the system to determine whether a final answer is credible, and to build explanations for the reasoning carried out. ART-KNN, synthesizing the theory of ART and the learning strategy of KNN, can solve the plasticity-stability dilemma of conventional neural networks. It can carry out 'on-line' training without forgetting previously trained patterns (stable training), and recode previously trained categories adaptive to changes in the environment and is self-organizing, which differs from most of networks that only can be carried out off-line. The system was validated by faults cases for electric motor collected from the case history. The results show the success rate can reach 97%. It indicates that the system is feasible, and is promising for other fields.

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