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Decision fusion system for fault diagnosis of elevator traction machine

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Abstract

Fault detection and diagnosis is critical for healthy operation of an elevator system. In order to realize a real-time and convenient diagnosis and satisfy the requirement of advanced maintenance of an elevator system, this paper proposes an intelligent fault diagnosis approach of induction motor for elevator traction machine using a developed decision fusion system. First, the basic knowledge of fusion techniques is briefly introduced which consists of classifier selection and decision fusion. Then a developed decision fusion system is presented. Next, four fusion algorithms–majority voting, Bayesian belief, multi-agent and modified Borda count–are employed for comparison in a real-world diagnosis experiment of a faulty elevator motor system. Based on the satisfactory results shown in the experiment, a big potential in real-world application is presented that is effective and cost saving only by analyzing stator current signals using proposed decision fusion system.

Keywords: Elevator traction machine; Induction motor; Fault diagnosis; Decision fusion system; Classifier Selection; Multi-classifier fusion; Stator current signal

1. Introduction

The advent of high-rise buildings in modern cities requires high-speed elevator systems to provide quick access within the buildings. The elevator is a typical example that serves people as a conventional transportation tool worldwide. About 210 billion times a year [1], people in the United States and Canada ride the estimated 660,000 elevators and 33,000 escalators that move 325 million elevator passengers and 245 million escalators passengers daily. Building owners and managers have their work cut out when it comes to ensuring that those rides are uneventful. Proper installation and ongoing maintenance and inspection are a must. Long-time continuous usage increases fault-occurrence probability, which requires trouble-shooting quickly [2]. According to the survey, the abnormal condition of a system is the main source for interrupting elevator service, especially faults in induction motors used for the traction machine (winding machine).

Although induction motors are reliable, the possibility of faults is unavoidable. These faults may be inherent to the machine itself or caused by severe operating conditions [3]. It is difficult to trace the root. Thus, to develop an intelligent fault diagnosis system for elevator doors is imperative [4]. Many intelligent diagnostic systems have been employed to assist condition monitoring tasks by correctly interpreting the fault data, such as expert systems, artificial neural networks (ANNs), support vector machines and fuzzy logic systems, and the results of these techniques are promising [5-7]. However, many researches have shown that an individual decision system can only acquire a limited classification capability that is only appropriate for special data and may not be enough for a particular application. The possibilities of using an intelligent decision system for fault detection applications are still relatively few in 'real' engineering applications and are not for elevator motors.

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Therefore, the application of a decision fusion system (DFS) has received considerable interest in recent years, and researchers have achieved considerable successes from this approach to solve complex pattern recognition tasks. DFS is also called multiple classifiers fusion (MCF), combination of classifiers, multiple experts and hybrid method. Due to the integration of different decisions from multiple classifiers, the technique can boost the recognition accuracy of elevator motor faults.

In this paper, a DFS is developed for the diagnosis of elevator motor faults, which contains feature calculation; multi-classifier: support vector machine (SVM), linear discriminant analysis (LDA), *k*-nearest neighbors (*k*-NN), random forests algorithm (RFA) and adaptive resonance theory-Kohonen neural network (ART-KNN); correlation-based classifier selection and decision fusion algorithms. First, raw data are collected from multiple sensors and values of features of the raw data are calculated that extract most of the important information. The generated feature sets are then grouped as the original input of the system to be sent into each classifier for recognition. Next, classifiers are selected in terms of correlation among the decision vectors in order to obtain the best fusion performance with the least classifiers. Finally, the optimal team obtained is applied in decision fusion. The rest of this paper is organized in sequence as: preliminary knowledge of decision fusion, decision fusion system used in elevator motor fault diagnosis, experiment results and discussion, and conclusion.

2. Preliminary knowledge

In this section, some basic knowledge of decision fusion used in this paper will be introduced. The contents are a method of classifier selection based on correlation value of decision vectors and four classifiers fusion algorithms: majority voting, Bayesian belief, multi-agent and modified Borda count.

2.1 Correlation based classifier selection

It is essential for multiple classifiers fusion to have a proper method for classifier selection because the combination of different classifiers can affect fusion accuracy. When we face many classifiers and sensor data sets, how to select them is often a problem before a final fusion strategy is employed. A proper classifier team should be robust and can generate the best fusion performance. It also should be optimal so that it can reduce the time for calculation and for saving the data in memory. Classifiers selection technique [8, 9] is an on-going active research area in recent years. Most of the selection methods are based on statistic theory such as Q statistic, generalized diversity and agreement [10-12]. Among them, the degree of correlation is an interesting sub-direction belonging to agreement of classifiers. Many researchers have found the dependency between classifiers can affect the fusion results. Goebel et al. [13] recommended an effective method for classifier selection based on calculating the correlation degree of n different classifiers which is shown in Eq. (1).

$$\rho_n = \frac{nN^f}{N - N^f - N^r + nN^f} \tag{1}$$

where, N^f means the number of samples which are misclassified by all classifiers, N^r means those samples which are classified correctly by all classifiers and N is the total number of experiment samples. Generally, smaller correlation degree ρ can lead to better performance of classifier fusion because the independent classifiers can give more effective information.

According to the correlation measurement principle, a team of classifiers needs to be selected and the steps of classifier selection can be summarized as:

Step 1: Select an appropriate performance measure as the initial evaluation criterion, such as accuracy rate that is the ratio of number of samples classified correctly to the total samples;

Step 2: Find the best performance of classifier as the first classifier of the team;

Step 3: Calculate the correlation degree between the first classifier and the other classifiers respectively using Eq. (1);

Step 4: Select the classifier having the "low correlation" for fusion. A practical improvement in this paper is that when a similar low correlation degree appears for more than one classifier, the classifier that has higher recognition rate is chosen;

Step 5: Repeat step 3 to step 4 between selected classifiers and the classifiers yet to be selected until all the classifiers are determined.

Finally, the optimal sequence of classifiers can be found.

2.2 Decision fusion

According to the characteristic of output information of the classifiers, decision fusion methods can be divided into three styles [14]:

- The abstract style: a classifier C only generates a single class output with an input x;
- The rank style: a classifier C ranks all classes in a queue and chooses the top one;
- The measurement style: a classifier C evaluates each class using a probability value that the x subjects to the class.

Among the styles mentioned above, the required information for a classification increases in sequence and the abstract style contains the least information while the measurement style involves the most information. Accordingly, the decision fusion algorithms of the measurement style can produce the best results. However, the classifiers that can obtain the output of each class's probability are seldom available. As a result, the decision fusion algorithms belonging to an abstract style are commonly used.

In this section, we briefly introduce some methods of decision fusion used at abstract level: majority voting, Bayesian belief, multi-agent, and modified Borda count. A brief comment also will be given for each method.

Majority voting method (MVM): Voting may be the easiest method in decision fusion [15]. There are various voting strategies such as unanimity, majority and Borda count. Among them, majority voting is the most popular method. In this method, the class voted by most of classifiers will be regarded as the result of fusion decision. If no class wins more than half of the votes, the input is rejected. The method is simple and easy to realize. Nevertheless, it does not consider the characteristics of each classifier that are related to the performance of classifier fusion.

Bayesian belief method (BBM): To compare with voting method, BBM [16] offers a soft fusion strategy that is more dynamic. This method is based on the assumption of mutual independency of classifiers and considers the error of each classifier. For a multiple class recognition problem with classes 1 through M, the error for kth classifier can be represented by a two-dimensional confusion matrix as Eq. (2).

$$PT_k = \begin{bmatrix} n_{11} & n_{12} & \cdots & n_{1M} \\ n_{21} & n_{22} & \cdots & n_{2M} \\ \cdots & \cdots & & \cdots \\ n_{M1} & n_{M2} & \cdots & n_{MM} \end{bmatrix}, (k = 1,\ldots, K) \quad (2)$$

where the rows stand for classes: c_1, …, c_M which consist of input sample x, and the columns indicate the classes which consist of the input sample assigned by the classifier e_k . The element n_{ij} illustrates the input samples from class c_i while assigned to class c_j by classifier e_k. On the basis of the confusion matrix, a belief measure of recognition can be calculated for each classifier by the belief function Eq. (3):

$$Bel(x \in c_i / e_k(x)) = P(x \in c_i / e_k(x) = j_k) \quad (3)$$

where $i, j = 1, \ldots, M$ and Eq. (4)

$$P(x \in c_i / e_k(x) = j_k) = n_{ij}^{(k)} \Big/ \sum\nolimits_{i=1}^{M} n_{ij}^{(k)} \quad (4)$$

Combining the belief measures of all fusion classifiers will result in the final belief measure of the multiple classifier system and is shown as follows:

$$Bel(i) = P(x \in c_i) \frac{\prod_{k=1}^{K} P(x \in c_i / e_k(x) = j_k)}{\prod_{k=1}^{K} P(x \in c_i)} \quad (5)$$

For practical implementation, an approximation of Eq. (5) is often used as follows in Eq. (6);

$$Bel(i) = \eta \prod_{k=1}^{K} P(x \in c_i / e_k(x) = j_k) \quad (6)$$

η is a constant and has Eq. (7)

$$\frac{1}{\eta} = \sum_{i=1}^{M} \prod_{k=1}^{K} P(x \in c_i / e_k(x) = j_k) \quad (7)$$

Finally, x is classified into a class with the highest combined belief measure Bel (i). However, one of the significant limitations of BBM is that it requires mutual independencies among multiple classifiers which do not usually hold in real application [17].

Multi-agent method (MAS): This algorithm absorbs the properties of a multi agent system into the algorithm of classifiers fusion [18]. It integrates Bayesian belief at the starting phase and majority voting at the final phase. A co-decision matrix is set up for information exchange between the classifier agents so that Bayesian belief matrix can be modified dynamically

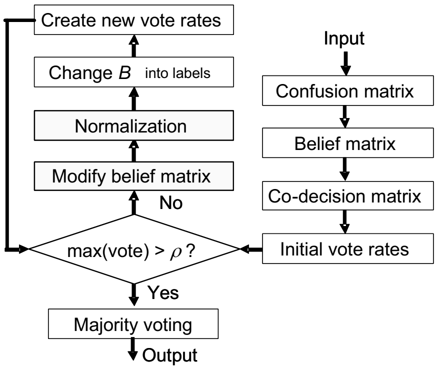


Fig. 1. Flowchart of multi-agent fusion algorithm.

until a predetermined criterion is satisfied. Finally, a combination decision is made. The flowchart of MAS is shown in Fig. 1.

First, the confusion matrix is created as a training parameter, which accumulates the errors of each classifier. Then an initial belief matrix can be calculated easily for each test sample based on the training parameter. In the initial belief matrix, the rows indicate kth classifier, where $k = 1, \ldots, K$, and columns stand for class $c_1, \ldots, c_M$. The elements in kth row show the probabilities of an input sample x belonging to different classes estimated by kth classifier using Eq. (5). The processes of calculating the confusion matrix and initial belief matrix are based on Bayesian belief method.

After calculation of the two matrixes, a five-dimensional co-decision matrix is required as the last training parameter. Each cell in the co-decision matrix stands for decision correlation between two classifiers, which is calculated through following Eq. (8):

$$d_{j_1,j_2,i,k_1,k_2} = P\left(E=i \middle| e_{k_1}=j_1, e_{k_2}=j_2\right) = \frac{\left|\left\{x \middle| E(x)=i, e_{k_1}(x)=j_1, e_{k_2}(x)=j_2, \forall x\in U_2\right\}\right|}{\sqrt{\left|\left\{x \middle| E(x)=i, e_{k_1}(x)=j_1, \forall x\in U_2\right\}\right|}\cdot\sqrt{\left|\left\{x \middle| E(x)=i, e_{k_2}(x)=j_2, \forall x\in U_2\right\}\right|}} \tag{8}$$

where $E = i$ is the expectation of input sample x, that is, the real class of x range from c_1 to c_M; j_1 and j_2, respectively, stands for the decision of classifiers k_1 and k_2 where $k_1 \neq k_2$ and U_2 are the training samples set of the fusion modal. Each element in the matrix shows the probability of classifier k_1 classifying x as j_1 class and classifier k_2 assigning x as j_2 class.

After the necessary statistical parameters are obtained, the confusion matrix and co-decision matrix, the initial vote rates for input sample x can be calculated. The column class corresponding to the maximum of kth row of belief matrix is regarded as kth classifier's decision. By doing this, the belief matrix can be transformed into a decision label vector. Then, the voting strategy can be employed and original vote rate of each class is calculated for input x.

Next, an accordance criterion is set to compare with the maximum vote rate. A higher accordance criterion is set to allow for less different decisions. If the maximum vote rate is less than the threshold, a repeating modification scheme is fired and the original belief degrees have to be modified dynamically using Eq. (9). The exchange of information of the two classifiers based on the co-decision matrix is added to the vote rates using following equation:

$$b^*_{ki} = b_{ki} + \frac{1}{K}\sum_{k_n=1,k_n\neq k}^{K} d_{j,j_n,i,k,k_n}\cdot\sqrt{b_{ki}\cdot b_{k_n,i}} \tag{9}$$

where the original belief matrix b is acquired by the confusion matrix based on Eq. (5); K is the number of total fusion classifiers; b_{ki} represents belief probability of classifier k to class i and d_{j,j_n,i,k,k_n} which is the exchange of information between kth classifier and k_nth classifier.

After the original belief is modified by Eq. (9), a normalization process is required to bring the summation of each row probabilities of new belief matrix equals to one. We call the element b^*_{ki} in the new belief matrix as the optimized belief probability of classifier k to class i. Then the new belief matrix b^* can be transformed into a decision vector, so the new vote rates can be acquired. If the maximum vote rate is still less than the predetermined criterion, the repeating modification process will continue until the maximum vote rate reaches the threshold. Finally, an improved majority voting method is utilized for the output of fusion decision, which only chooses the class gaining the most votes as the fusion decision and does not need more than half of votes as the original voting strategy.

Nevertheless, the information exchange of two classifiers cannot always improve the fusion accuracy; when several classifiers give wrong decisions, the exchanged result may lean to the worse edge and decrease the fusion performance.

Modified Borda count (MBC): The conventional Borda count (BC) is defined as a mapping from a set of individual rankings to a combined ranking leading to the most relevant decision. For a particular class c_k Borda count B (c_k) is defined as a sum of the number of classes ranked below class c_k by each classifier. The magnitude of the BC reflects the level of agreement that the input pattern belongs to the considered class. To a certain degree, the BC can be treated as a generalization of the majority-voting rule. This method is based on the assumption of additive independence among the contributing classifiers. It is easy to implement and does not require any training. Weak point of this technique is that it treats all classifiers equally and does not take into account the confidence values produced by various classifiers. Verma et al. [19] proposed an MBC that contains three improvements as follows:

First, assign and use a *rank* in the calculation of a BC, instead of calculating the numbers of classes below the class to be recognized. The rank for a particular sample can be calculated by using the following Eq. (10).

$$Rank = 1 - (position\ of\ a\ class\ in\ top\ N\ classes / N) \tag{10}$$

Second and very important, use the *confidence values* produced by different classifiers. Each classifier computes a confidence value for each class. A higher confidence value means that the class is closer to the true class. Finally, use a *weight variable* for every classifier and try to find the optimum value. Here, we can simply assign weights based on the training accuracy rate of each classifier. The MBC can be calculated as Eq. (11):

$$\begin{aligned} MBC = (rank \times weight \times cf)^{classifier\ 1} + \ldots + \\ (rank \times weight \times cf)^{classifier\ N} \end{aligned} \tag{11}$$

Compared to the traditional BC method, the MBC considers the ability of each classifier and can generate better performance.

3. Decision fusion system used in elevator motor fault diagnosis

In this paper, we developed a decision fusion system for elevator motor fault diagnosis, which is based on a self-designed fusion diagnosis toolbox by MATLAB language (version 7.0). This system contains four process levels: feature extraction, multi-classifier decision, classifier selection and decision fusion. Each module of the system includes some algorithms independently, which can be extended or chosen flexibly with different application case. The structure of proposed system is shown in Fig. 2. First, features are extracted from input signals and then, five classifiers are employed to get a group of decisions. Finally, the decisions are combined by using the classifiers fusion algorithm after a correlation-based pre-selection process. As a comparison of decision fusion performances, four fusion algorithms–MVM, BBM, MAS and MBC–are employed.

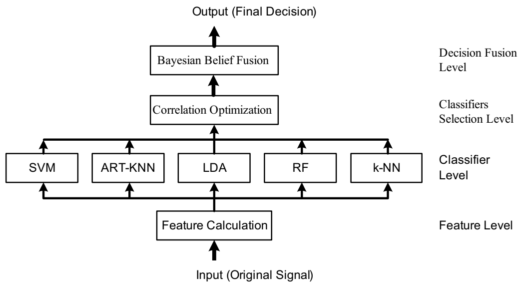


Fig. 2. Framework of self-designed fusion diagnosis system.

3.1 Experiment apparatus

An elevator is driven by a motor connected to the sheave at the top of the elevator shaft. Each cable passes over an idler sheave and is attached to a counterweight (Fig. 3). The purpose of the counterweight is to offset the weight of the elevator and reduce the torque on the motor when the elevator is stationary or moving at constant velocity. In order to accelerate the car upward, the motor must supply additional torque to the sheave. This increases the tensions in the cables above the car and decreases the tensions in the cables above the counterweight. The net result is that the motor must provide enough additional torque to accelerate the entire inertia of the system, including the elevator car, counterweight, cables, and drive sheave [20].

In general, the induction motor is subjected to primary types of fault and related secondary faults. The sources of motor faults may be internal, external or environmental. Internal faults can be mainly categorized into mechanical and electrical. Bearing failure, which may also cause rotor eccentricity misalignment, is the common mechanical fault. Other mechanical faults are bent shaft (dynamic eccentricity) and rotor unbalance. Electrical faults contain stator faults, rotor

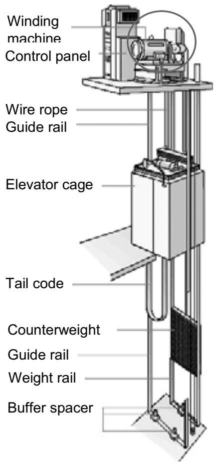


Fig. 3. Structure of elevator traction machine.

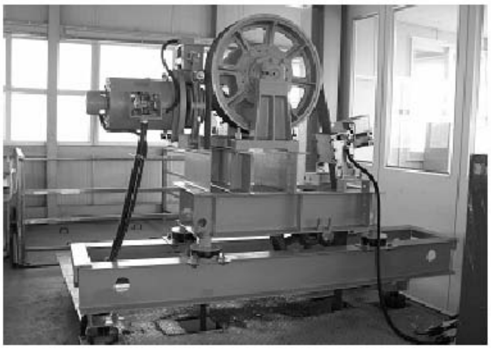


Fig. 4. Experimental apparatus.

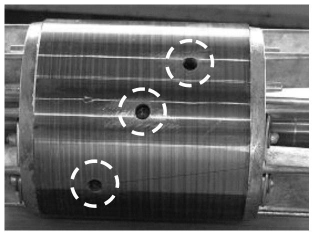
bar faults. Rotor bar faults mainly consist of rotor bars broken and end rings broken. As the weakest component of motors, bearing faults cover almost all of the motor faults.

In order to demonstrate the effectiveness of the proposed system in real-world operating conditions, an experiment was carried out using an induction motor system of an elevator as shown in Fig. 4.

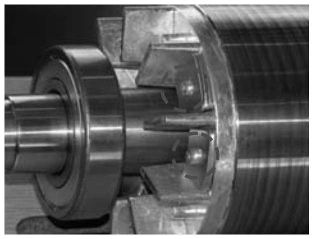
The test objects were ten 15 kW, 50 Hz and 4-pole induction motors for elevators. Their basic specifications are shown in Table 1. This motor was set to operate at full-load conditions. One of the motors was normal (healthy), which was used as a benchmark for comparing with faulty motors. The others were faulty motors with rotor unbalance, stator eccentricity, rotor eccentricity, broken rotor bar, bearing housing looseness, bearing inner race looseness, ball fault, bearing outer race fault and inner race fault, as shown in Fig. 5. The conditions of faulty induction motors are described in Table 2.

Table 1. Basic specification of the motor tested.

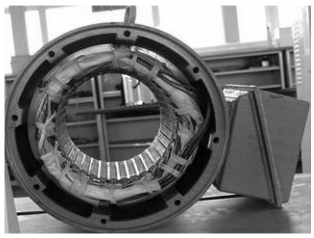
Type	Induction motor
Voltage	340 V
Current	34.2 A
Rotating speed	1450 rpm
Line frequency	50 Hz
Bearing (DE)	#6310
Bearing (NDE)	#6308
Weight	1402 N
Power	15 kW
Number of stator slot	36



(a) Broken rotor bar



(b) Rotor unbalance



(c) Stator eccentricity

(d) Bearing outer race fault

Fig. 5. Faults in the induction motors.

Table 2. Description of fault types of the motor tested.

Faults types	Fault details
Rotor unbalance	In-phase, 60 g·mm/kg
Stator eccentricity	30% (+0.23 mm)
Rotor eccentricity	Out-of-phase, 80 g·mm/kg
Broken rotor bar	1 spot
Bearing housing looseness	Between outer race and housing
Inner race looseness	Between shaft and inner race
Ball fault	Diameter 2 mm, depth 1.5 mm
Outer race fault	Diameter 2 mm, depth 2 mm
Inner race fault	Diameter 2 mm, depth 2 mm

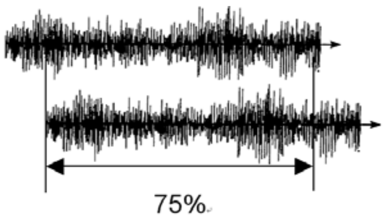


Fig. 6. Overlap process of steady signal.

3.2 Description of experiment data

Three accelerometers and one AC current probe were used to measure the vibration signals of horizontal, vertical, axial directions and stator current signal to evaluate the fault diagnosis system. The maximum frequency of sampling signals was 3 kHz and the number of sampled data was 16384. Sampling time was 2.133 seconds and a Hanning window was chosen for filtering. Each condition was measured two times.

The permitted measuring time for each fault is 15 seconds containing three running conditions: speed-up, steady and slow-down. Another real limitation is that many times of measurement per fault is nearly impossible, or else the elevator will break down severely in the real system experiment. As a result, each fault was measured twice, then steady signals were picked out for analysis. Considering the limit raw data that is not enough for fusion analysis and the periodicity of steady signal, an overlap method was employed to solve the problem. This method picks out each sample using an overlap rate predetermined from collected steady signals in sequence as in Fig. 6. The periodicity of a steady signal insures the rationale for using this method. The overlap rate was set as 0.75 in this experiment. Using the overlap method, we extended the steady signal of one time measurement into 10 times. So finally we acquired 20 samples per fault and total samples were 200. Among them, 100 samples were divided for training classifiers, 50 samples for training fusion algorithms and the remaining 50 samples for test.

Table 3. Description of values of features of signals.

Signals	Position	Values of features of signals		
		Time domain	Frequency domain	Auto regression
Vibration	Vertical Horizontal Axial	• Mean • RMS • Shape factor • Skewness • Kurtosis • Crest factor • Entropy error • Entropy estimation • Histogram lower • Histogram upper	• Root mean square frequency • Frequency center • Root variance frequency	• AR coefficients ($a_1 \sim a_8$)
Current	Phase A			

3.3 Description of features calculated

After data acquisition, a process of feature calculation was exerted. Although the time series data contain abundant feature information, the important part cannot be seen intuitively and much unnecessary information also is contained. Therefore, feature extraction is essential for effectual estimation of machine conditions. Statistical parameters, calculated in the time domain, frequency domain and auto-regression, are generally used to define average properties of acquired data [21]. Twenty-one values of features are acquired from each sensor consisting of the time domain (10 features), frequency domain (3 features) and regression estimation (8 features) shown in Table 3.

3.4 Description of classifier used

Next, five classifiers were utilized to classify the calculated features of vibration and current. The utilized classifiers are described as follows:

Support vector machine (SVM): SVM is a machine learning algorithm based on statistical learning theory. Compared with other classifiers, this technique can lead to good recognition rate with a few training samples. Kernel function is an important parameter for SVM classifier which contains linear, polynomial, Gaussian RBF and sigmoid parameters [22].

Linear discriminant analysis (LDA): As a non-

Table 4. Parameters of individual classifier.

Classifier	Parameters values
SVM	Linear kernel function, Euclidean distance type, one against all model
k-NN	$k = 3$
RFA	No. of variables randomly sample = 10, No. of trees = 1000, seeds = 123
ART-KNN	Distance-based optimization, initial similarity = 0.6, iterative step = 0.004, iterative No. = 20

parameter algorithm, LDA is popular for features drop-dimension and also can be used for classification. It projects features from parametric space onto feature space through a linear transformation matrix. This classifier can be efficiently computed in the linear case even with large data sets.

k-nearest neighbors (*k-NN): k*-NN is an easy and effective classifier [23]. The aim is to find the nearest neighbors of an unidentified test pattern within a hyper-sphere of pre-defined radius in order to determine its true class. It can detect a single or multiple number of nearest neighbors.

Random forests algorithm (RFA): is a classifier consisting of a collection of tree-structured classifiers $\{h(x, \Theta_k), k = 1, 2, \ldots\}$ where the Θ_k are independent identically distributed random vectors and each tree casts a unit vote for the most popular class at input x [24].

Adaptive resonance theory-Kohonen neural network (ART-KNN): ART-KNN [25] is a neural network that synthesizes the theory of ART and the learning strategy of the Kohonen neural network (KNN). It is able to carry out 'on-line' learning without forgetting previously learned knowledge (stable training), can adapt known categories to changes in the environment, and is self-organizing.

The relevant parameters setup for the four classifiers can be found in Table 4.

4. Results and discussion

This section describes the results of an experiment of elevator motor fault diagnosis using the proposed decision fusion system, based on which, a comparison and discussion are provided for each part of the decision fusion system.

4.1 Individual classification

Based on the calculated features in section 3.2, a process of classification was exerted for the five classifiers (SVM, LDA, *k*-NN, RFA, ART-KNN). The comparison of accuracy rates for test samples is shown in Fig. 7 and related values of which are shown in Table 5. In addition, a detailed comparison of the accuracy rates for each fault is shown in Table 6.

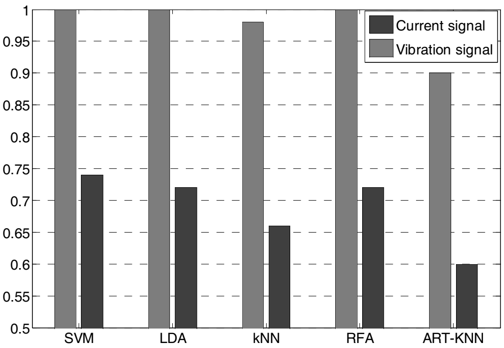


Fig. 7. Performance comparison of individual classifier.

Table 5. Accuracy rates of individual classifier.

Classifier		SVM	LDA	*k*-NN	RFA	ART-KNN
Accuracy rate (%)	Vibration signal	100	100	98	100	90
	Current signal	74	72	66	72	60

Table 6. Accuracy rates of classification of each fault for current data.

Faulty type	Classifier				
	SVM	LDA	*k*-NN	RFA	ART-KNN
Broken rotor bar	40	60	40	80	60
Ball fault	80	40	60	40	20
Inner race fault	100	100	100	100	20
Outer race fault	20	20	0	0	0
Bearing housing looseness	0	60	40	40	80
Inner race looseness	100	80	100	100	80
Rotor unbalance	100	60	80	100	100
Rotor eccentricity	100	100	100	80	100
Stator eccentricity	100	100	40	80	40
Normal condition	100	100	100	100	100

Classification performance using vibration data is better than current data obviously. Among them, three classifications can achieve 100% accuracy rates for vibration data. However, the highest accuracy rate for current data is less than 75% from SVM. Due to the high classification accuracy rates using vibration data that contains three accelerometer channels, the fusion experiment would be intended to focus on the current

Table 7. Results of optimal sequence of classifier fusion for current data.

Numbers of classifiers selected	Serial number of classifiers					Correlation degree
1	1					1.0
2	1	5				0.9592
3	1	5	2			0.9409
4	1	5	2	4		0.9231
5	1	5	2	4	3	0.9174

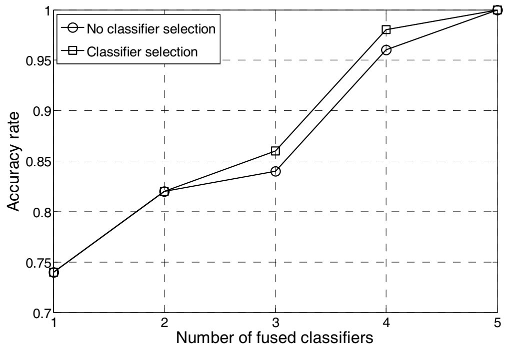


Fig. 8. Effect of classifiers selection using Bayesian fusion.

data containing only one channel for classifier fusion.

4.2 Selection of classifiers

After we acquired individual classification decisions, a process of classifier selection was exerted using the method based on correlation measure introduced in section 2.1. The calculated correlation degrees and optimized sequences of classifiers are shown in Table. 7.

To test the effect of classifier selection using the correlation measure method, a comparisation was done between the processes of selection with no-selection, then BBM was used for decision fusion. The fusion results are shown in Fig. 8. On the whole, the trend of accuracy rate of the selection process is higher than that of the no selection process. Therefore, selection of classifiers is proposed as a potential optimization process before the final decision fusion.

4.3 Decision fusion

According to the selected sequence in section 4.2, the decision vectors of multi-classifiers were fused in the step of classifier fusion. No. 1 to No. 5 means the sequence of classifiers to be fused and the corresponding location of No. i (i = 1, …, 5) shows the fusion accuracy using the decision vectors from No. 1 to No. i. For example, the fusion accuracy of 86 % using BBM in Table 8 is the result of fusing the decisions of classifier SVM, classifier ART-KNN and classifier LDA. Table 8 shows that the best accuracy of fusion could remarkably reach to 100 % using BBM.

Table 8. Fusion performances of multiple classifiers with different algorithms for current data.

	Fusion method	Classifier				
		SVM	LDA	*k*-NN	RFA	ART-KNN
Serial numbers of classifiers		1	2	3	4	5
Fusion sequence of classifiers		No. 1	No. 3	No. 5	No. 4	No. 2
Fusion accuracy rate (%)	MVM	74	78	76	76	74
	BBM	74	86	100	98	82
	MAS	74	82	96	94	78
	MBC	74	86	92	90	82

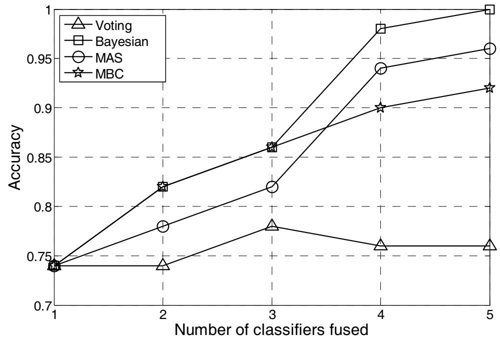


Fig. 9. Fusion performances of four algorithms for current data.

Comparing the performance of the four fusion algorithms shown in Fig. 9, we found that BBM is the best and MAS is the next, then MBC method, and MBM gave the worst fusion performance. In addition, the fusion accuracy rates of each fault for different numbers of classifiers using the four fusion algorithms are shown in Table 9. The results show that:

- The detection accuracy of bearing inner race looseness, rotor unbalance, rotor eccentricity, stator eccentricity and normal condition is always ideal 100 % with no reduction.
- The detection performance of broken rotor bar, ball fault, outer race fault and bearing housing looseness increased markedly, especially for outer race fault and bearing housing looseness.
- The detection of inner race fault cannot benefit from fusion strategy.

Table 9. Fusion accuracy rates of each fault for different numbers of classifiers using four fusion algorithms.

Faulty type	Fusion algorithm	Accuracy rates of classifier fused (%)				
		No. 1	No. 1- 2	No. 1- 3	No. 1- 4	No. 1- 5
Broken rotor bar	MVM	40	40	60	60	60
	BBM	80	60	60	100	100
	MAS	40	60	60	100	100
	MBC	80	60	60	80	80
Ball fault	MVM	80	80	60	60	60
	BBM	80	80	100	80	100
	MAS	80	80	80	80	80
	MBC	80	80	100	80	100
Inner race fault	MVM	100	100	100	100	100
	BBM	100	40	100	100	100
	MAS	100	40	100	100	100
	MBC	100	40	100	100	100
Outer race fault	MVM	20	20	0	0	0
	BBM	0	60	40	100	100
	MAS	20	20	20	60	80
	MBC	0	60	40	60	80
Bearing housing looseness	MVM	0	0	60	40	40
	BBM	0	80	60	100	100
	MAS	0	80	60	100	100
	MBC	0	80	60	80	60
Inner race looseness	MVM	100	100	100	100	100
	BBM	100	100	100	100	100
	MAS	100	100	100	100	100
	MBC	100	100	100	100	100
Rotor unbalance	MVM	100	100	100	100	100
	BBM	100	100	100	100	100
	MAS	100	100	100	100	100
	MBC	100	100	100	100	100
Rotor eccentricity	MVM	100	100	100	100	100
	BBM	100	100	100	100	100
	MAS	100	100	100	100	100
	MBC	100	100	100	100	100
Stator eccentricity	MVM	100	100	100	100	100
	BBM	100	100	100	100	100
	MAS	100	100	100	100	100
	MBC	100	100	100	100	100
Normal condition	MVM	100	100	100	100	100
	BBM	100	100	100	100	100
	MAS	100	100	100	100	100
	MBC	100	100	100	100	100

5. Conclusions

A decision fusion system has been presented in this paper that consists of the processes of feature calculation, classification, classifier selection and decision fusion. Excellent results were acquired in the fault diagnosis of an elevator motor using this system. Based on the satisfactory results shown in the experiment, an effective and cost-saving approach has been proposed that only requires analyzing current signals by using the decision fusion system. On the whole, classification accuracy rates considering the process of classifier selection are superior to the ones without the step. To compare the fusion performance, the Bayesian belief method is the best and the performance of the multi-agent method is a little worse than the Bayesian; both of them are assigned to the better level. Then is the modified Borda count method. The majority voting belongs to the worst level, because voting is a crisp fusion method which does not consider the character of individual classifiers. Decision fusion strategy can improve the accuracy rates remarkably. Fusion accuracy rate utilizing Bayesian achieved the ideal result, 100 %; while only 74 % from the best individual classifier, SVM, for current data in this paper.

For real-world application, the potential values of this experiment are obvious: the popular fault detection methods in rotating machinery using AI technique usually only analyze vibration signals, which can acquire good performance with full experience and an extensive literature introduction. However, the analysis based on vibration signals has some disadvantages:

- Accelerometers are usually so expensive that industrial maintenance is costly.
- Accelerometers are very sensitive to the environment and easily influenced by noise.
- Selecting appropriate accelerometers often makes maintenance engineers feel wearied.
- Selecting appropriate measure points to attach accelerometers onto diagnosed equipment is not easy sometimes, which can affect the diagnosis performance.

In comparison, current monitoring is cheaper and simpler than vibration monitoring. It is convenient for monitoring large numbers of motors remotely from one location and not affected by the operating environment. Though the effect of current signal diagnosis is not as good as vibration signal using individual classifier, decision fusion technology can improve the accuracy rate remarkably. As a result, current monitoring integrating decision fusion technology is an excellent approach that has low cost and easy monitoring while high recognition accuracy rates.

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