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An Availability of Low Cost Sensors for Machine Fault Diagnosis

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Key Words : MEMS, Accelerometer, Current, Machine Fault Diagnosis

ABSTRACT

In recent years, MEMS sensors show huge attraction in machine condition monitoring, which have advantages in power, size, cost, mobility and flexibility. They can integrate with smart sensors and MEMS sensors are batch product. So the prices are cheap. And the suitability of it for condition monitoring is researched by experimental study.

This paper presents a comparative study and performance test of classification of MEMS sensors in target machine fault classification by 3 intelligent classifiers. We attempt to signal validation of MEMS sensor accuracy and reliability and performance comparisons of classifiers are conducted. MEMS accelerometer and MEMS current sensors are employed for experiment test. In addition, a simple feature extraction and cross validation methods were applied to make sure MEMS sensors availabilities. The result of application is good for using fault classification.

최근 MEMS 센서는 기계상태감시에 있어서 전력소모, 크기, 비용, 이동성, 응용 등에 있어서 각광을 받고 있다. 특히, MEMS 센서는 스마트센서와 통합가능하고, 대량생산이 가능하여 가격이 저렴하다는 장점이 있다. 이와 관련한 기계상태감시를 위한 많은 실험적 연구가 수행되고 있다.

이 논문은 MEMS 센서들을 3 가지 인공지능 분류기 성능평가를 위한 비교연구에 대해 설명하고 있다. 회전기계에 MEMS 가속도와 전류센서들을 부착하여 데이터를 취득했고, 특징추출과 파라미터 최적화를 위해 Cross validation 기법을 사용하였다. MEMS 센서를 이용한 결함 분류기 적용은 적합하다고 판단된다.

1. 서 론

Condition monitoring (CM) has been regarded a key of maintenance problem. It is tool which can realize the condition based maintenance (CBM). Over the past few decades, CM has been developed [(1)]

In recent years, sensor trends are changing quickly. Micro electro mechanical systems (MEMS) technologies and smart sensors are becoming the focus of the current sensor development. The greatest progress in innovation, however, will happen where MEMS technologies overlap with smart technologies [(2)].

MEMS was made in the 1980's to describe the new sophisticated mechanical systems on a chip, such as micro electric motors, resonators, gears, etc. Today, MEMS in practice is used to refer to any microscopic device with a mechanical function, which can be fabricated in a batch process. MEMS technology is the integration of mechanical elements, sensors, actuators, and electronics on a common silicon substrate through micro fabrication technology.

By the way, several fault diagnosis algorithms are developed for intelligent machine fault identification. Many kinds of traditional accelerometer and clamp type current sensor are employed for detecting dynamic fault conditions [(3)]. But it is a few researches combining with

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MEMS or smart sensors to intelligent fault diagnosis system [4].

In this paper, MEMS based sensor signals are analyzed in induction motors diagnosis. Three classifiers are used for comparison of machine fault diagnosis.

2. Sensors

2.1 MEMS accelerometer

MEMS accelerometer MEMS accelerometer contains a polysilicon surface-micromachined sensor and signal conditioning circuitry to implement open-loop acceleration measurement architecture. The output signals are analog voltages that are proportional to acceleration. It uses sensing changes in capacitance as shown in figure 1. In this figure, the deflection of the inertial mass changes the capacitance between the finger beams and the adjacent cantilever beams. The sensor structure is surrounded by supporting electronics, which converts the capacitance changes due to acceleration into a voltage [5].

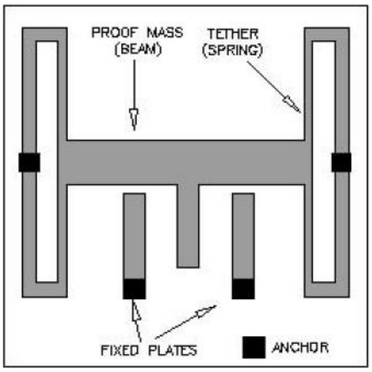


Figure 1 Capacitive MEMS accelerometer.

2.2 Hall Effect current sensor

Hall Effect current sensor is a single-axis, integrated magnetic field sensor based on the Hall Effect. The Hall Effect is the production of a voltage difference (the Hall voltage) across an electrical conductor, transverse to an electric current in the conductor and a magnetic field perpendicular to the current. Edwin Hall discovered this effect in 1879[6]. Hall Effect sensors measure current by converting the magnetic field generated by current flowing through a conductor into a voltage proportional to that field. The sensor output is linear to the magnetic field, and because the field is linear to the current in the conductor, the output voltage will provide a linear voltage that is directly proportional to the current.

The sensitivity of Hall Effect current sensor calculates is as

$$V_{out} \approx \frac{0.056 \times I}{(d + 0.3mm)} \qquad (1)$$

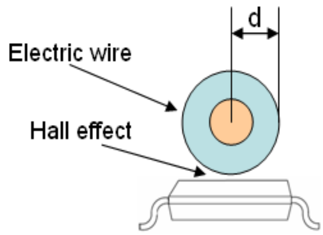


Figure 2 MEMS current sensor.

2.3 Implemental sensors

We employed two kinds of MEMS sensors in figure 3. Both of sensors are commercial product that is specified in Table 1. The PCB designs are made by us and the signals are analog outputs.

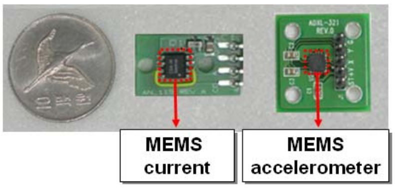


Figure 3 Low Cost sensors.

Table 1 Specification of MEMS sensors.

MEMS accelerometer	MEMS current
• Name : ADXL-321 • Company : Analog Device • Frequency rage : 0 ~ 2,500Hz • Sensitivity : 57mV/g • Shock rage : 10,000g • Power : 2.4 ~ 6VDC • Temperature : -20 ~ 70℃	• Name : CSA – 1V • Company : GMW • Bandwidth : DC ~ 100kHz • Sensitivity : 13 mV/A • Power : 0 ~ 6VDC • Temperature : - 40 ~ 125℃

3. Theories of fault diagnosis

3.1 Feature extraction

Kernel principal component algorithm (KPCA) is one approach of generalizing linear PCA into nonlinear case using the kernel method [7]. If a PCA is aimed at decoupling nonlinear correlations among a given set of data (with zero mean), xj ∊ ℜm, j = 1, …, N through diagonalyzing their covariance matrix, the covariance can be expressed in a linear? Feature space F insteads of the nonlinear input space, i.e. the idea of KPCA is to firstly map the original input vectors xj into a high-dimensional feature space Φ(xj) and then to calculate the linear PCA in Φ(xj). The linear PCA in Φ(xj) corresponds to a nonlinear PCA in xj. By mapping xj into Φ(xj) whose dimension is assumed to be larger than the number of training samples l, KPCA solves the eigenvalue problem.

$$\lambda_j \mathbf{u}_j = \tilde{\mathbf{C}} \mathbf{u}_j ,\ i = 1, \dots, N , \qquad (2)$$

where $\tilde{\mathbf{C}} = \frac{1}{N} \sum_{j=1}^{N} \mathbf{\Phi}(\mathbf{x}_j) \mathbf{\Phi}(\mathbf{x}_j)^T$ is the sample covariance matrix of Φ(xj). λ_j is one of the non-zero eigenvalues of $\tilde{\mathbf{C}}$. $\mathbf{u}_i$ is the corresponding eigenvector. Eigenvalues $\lambda \ge 0$ and $\mathbf{u} \in \mathbf{F} \setminus \{0\}$.

3.2 Cross-validation

Cross-validation method introduced by Stone[8] takes a more sophisticated approach to just one feature set. In k-fold cross-validation, the dataset is randomly partitioned into k disjoint blocks (the folds), of (approximately) equal size d (d ≈ N/k). The learning algorithm runs k times. In the ith time, the ith training set is formed by the initial dataset without the ith fold, while the test set is formed using the ith fold alone. Let $\hat{\theta}_i$ be the ratio of classified instances to the total number of tested instances in the ith run. The estimator $\hat{\theta}_k$ of the accuracy for the k-fold cross-validation method is calculated as

$$\hat{\theta}_k = \sum_{i=1}^{k} \hat{\theta}_i / k .$$

3.3 Feature extraction

Parameter optimization (Cross-validation) Support vector machines (SVM) is relatively a supervised learning method used for classification and regression based on statistical learning theory. This classifier is implemented by mapping the training data into a feature space and the aid of kernel function. It separates the data using a large margin hyperplane [9]. For two-class data set, we examine a hyperplane that separates the data points "neatly", with maximum distance to the closest data point from both classes – this distance is called the margin. The vectors that are closest to this hyperplane are called the support vectors. By applying a nonlinear kernel function that transforms data points into high-dimensional feature space, SVM can also treat nonlinear classification problem. Some common kernels include: polynomial, radial basis function (RBF), linear and sigmoid. According to the different classification problems, the different kernel functions can be selected to obtain the optimal classification results.

Random forests algorithm (RF) introduced by Breiman[10] is a general term for ensemble methods using tree-type classifiers. RF builds a large amount of decision trees out of sub-dataset from a unique original training set by using bagging which is a meta-algorithm to improve classification and regression models according to stability and classification accuracy. Bagging reduces variance and helps to avoid over-fitting synchronously. This procedure extracts cases randomly from original training data sets and the bootstrap sets are used to construct each of the decision trees in the RF. Each tree classifier is named as component predictor. The RF makes decision by counting the votes of component predictors on each class and then selecting the winning class in terms of number of votes accumulated. So, the entire algorithm includes two important phases: the growth period of each tree and the voting period. The growth period is to train each decision tree classifier, and the sub-datasets are selected from whose training data set by using bagging random strategy. Then the test data is classified by majority voting. About one-third of the cases are left out of the bootstrap samples and not used in the construction of a particular tree. The samples left out of the kth tree are run through the kth tree to get a classification. In this way, a test set classification is obtained for each case in about one-third of the trees which can be used to assess the accuracy of the classifier.

Fuzzy k-Nearest Neighbor algorithm is to assign membership as a function of the object's distance from its K-nearest neighbours and the memberships in the possible classes. The k-nearest neighbor (k-NN) classifier is commonly used in pattern recognition. An input sample is assigned to the class that is represented by the majority of the k-nearest neighbors. However,

once an input sample is assigned to a class, there is no indication of its strength of membership in that class. It contains two steps: fuzzy labelling that computes the fuzzy vectors of the training samples, and fuzzy classification that computes the fuzzy vectors of the input samples [11].

4. Experiment for fault diagnosis

Five induction motors are used as the tested motors in this experiment with fault specifications listed in Table 2. These tested motors are set to operate at full-load conditions with one load-motor in figure 4. Among the five tested motors, one is normal (healthy) which is used as a benchmark motor. The remaining motors are fault ones involved bowed rotor, mass unbalance, faulty bearing and broken rotor bar respectively as shown in Table 2. Data acquisition system was employed wireless smart sensor system in figure 5. Data sampling rate is 8192Hz. Data number is 8192.

Table 2 Fault conditions of test motor.

Faults types	Fault description
Bowed shaft	Deflection 0.2 mm at mid-span
Mass unbalance	20 g at 1 end ring
Bearing fault	Bearing outrace fault
Broken rotor bar	4 ea broken

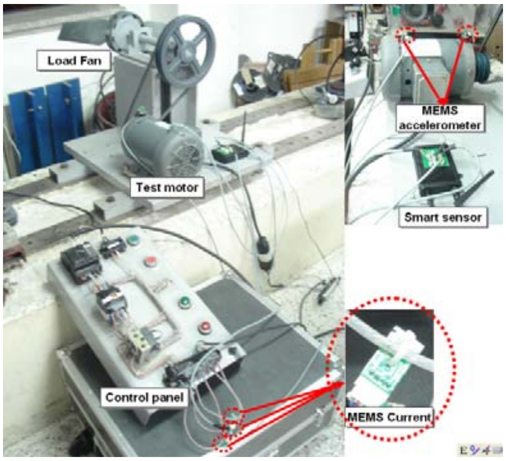


Figure 4 Experiment of smart sensor.

The fault diagnosis system flowchart is shown in figure 5. Server module receives data from wireless smart sensors. It then saves ASCII format file. 21 features are calculated from each channel [12]. Then a process of feature extraction is required because many features occur in calculation time delay and accuracy decrease. Extracted features are divided into training, validation, testing data sets. Training procedure contains cross validation. This method performs the optimization of parameters of classifiers. Finally, diagnosis results are reported.

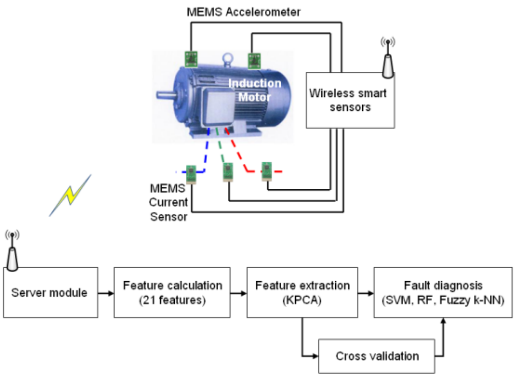
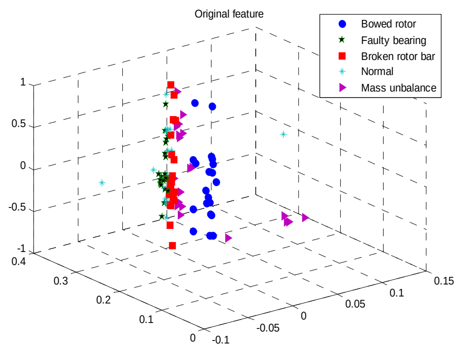


Figure 5 Fault diagnosis system using MEMS sensors.

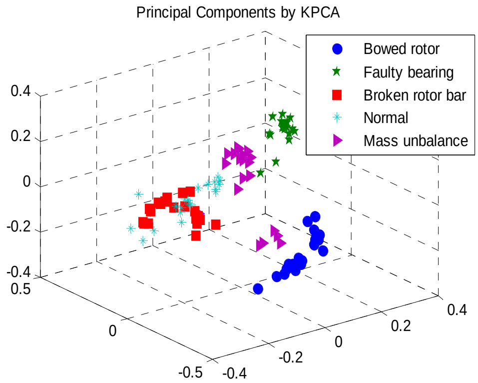
6. Result of fault diagnosis

After feature calculation, much unnecessary information also is contained. Therefore, the feature extraction is essential for effectual estimation of conditions of machine. Feature extraction procedure is easy to make clusters from original features. After feature extraction, clustering is good. But mass unbalance cluster was scattered than others in Fig. 6 (b). And next, 10-fold cross-validation was conducted. Cross-validation methods are induced to optimize the classifier parameters. It can be seen that the differences are slight. Generally speaking, the bias of results tends to slight improvements, which is the result of better average performance. Classification methods have parameters that can perform high accuracy.

Classification results of all MEMS sensors are shown in Table 3, and results of 2 type MEMS sensors are shown in Table 4. SVM classifier is the best for fault diagnosis. However, Fuzzy k-NN has 20% error in test procedure. MEMS accelerometer sensor is better than MEMS current sensor.



(a) Original feature



(b) KPCA

Figure 6 Result comparison of feature extraction.

Table 3 Classifier result fo all MEMS sensors.

	Validation type	Accuracy rate of each classifier (%)		
		SVM	RF	*Fuzzy k-NN*
Classifier Result	Train	100	100	100
	Test	100	86	80

Table 4 Classifier result of each MEMS sensors.

Sensor type	Validation type	Accuracy rate of each classifier (%)		
		SVM	RF	*Fuzzy k-NN*
MEMS accelerometer	Train	100	100	100
	Test	100	100	80
MEMS current	Train	94	100	100
	Test	62	56	42

7. Conclusion

This article presents comparative results of MEMS sensors for validations. MEMS accelerometer and MEMS current sensors signals are tested and smart sensors are employed for wireless data acquisition. Periodic and impulse tests were applied for the sensor's performance test. Basing on the results, comments can be summarized below:

• MEMS accelerometer sensor performances are good classification. Only MEMS current sensors are difficult to classify. The reason is that line frequency is dominant in current signals. And small amplitude fault signal contain in current signals. It means feature cluster is very narrow in each fault condition. This result is similar with conventional current sensors. Conventional accelerometer is easy to represent fault condition than conventional current sensor.

• SVM and RF classifier is best for fault diagnosis. However, Fuzzy k-NN is not proper .

In terms of the results in fault detection problem of machine fault diagnosis, smart sensor system has feasibility to substitute the conventional system.

In the future, the MEMS sensors integrating with online system will be developed. It will have advantage of low cost equipment including sensors. Therefore, cost-effective maintenance is expected to be realized.

후 기

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