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EXPERT SYSTEM FOR INDUCTION MOTOR FAULT DETECTION BASED ON VIBRATION ANALYSIS

EKSPERTSKI SITEM ZA DETEKCIJU KVAROVA NA ASINHRONIM ELEKTROMOTORIMA ZASNOVAN NA ANALIZI VIBRACIJA

Željko KANOVIĆ, Boris JAKOVLJEVIĆ, Milan RAPAIĆ, Zoran JELIČIĆ
Faculty of Technical Sciences, 21000 Novi Sad, Trg Dositeja Obradovića 6, Serbia
e-mail: kanovic@uns.ac.rs

ABSTRACT

This paper presents an expert system for induction motor fault detection based on vibration analysis and support vector machines (SVM). Vibration signals of healthy and faulty induction motors are collected and characteristic features, as indicator of fault presence, are calculated, in both time and frequency domain. Two types of faults were considered, static eccentricity and bearing wear. Obtained feature sets were then used for training of support vector machines classifiers, a type of artificial intelligence classification technique which determines whether some of considered faults is present or not. An expert system for fault detection is designed combining a database of calculated features and trained SVM classifiers. This system was tested and validated on a number of healthy and faulty motors in the laboratory and in industrial facility for sunflower oil processing. Obtained results prove that this system can detect faults in early stages with high accuracy and reliability. Thus, it provides malfunction and failure prevention and improves overall performance and efficiency of industrial systems.
Key words: *fault detection, induction motor, vibration analysis, support vector machines.*

REZIME

Praćenje stanja i dijagnoza kvarova na mašinama imaju važnu ulogu u sistemu održavanja, jer smanjuju troškove i poboljšavaju produktivnost, efikasnost i iskorišćenje mašina. U ovom radu predstavljen je ekspertski sistem za detekciju kvarova na asinhronim elektromotorima baziran na analizi vibracija i potpornim vektorima (SVM). Analiza vibracija primenjena je zbog svoje visoke tačnosti i pouzdanosti. Snimljeni su signali vibracija više tipova ispravnih i neispravnih elektromotora, pomoću kojih su izračunata karakteristična obeležja, koja predstavljaju indikatore prisustva pojedinih kvarova. Razmatrana su dva tipa kvarova, statički ekscentricitet rotora i oštećenje ležajeva. Karakteristična obeležja su primenjena za obuku SVM klasifikatora, baziranih na veštačkoj inteligenciji, koji detektuju prisustvo kvara. Kombinovanjem obučenih SVM klasifikatora i baze podataka sa snimljenim signalima, napravljen je ekspertski sistem za detekciju kvarova, koji je ispitan u laboratorijskim uslovima i u postrojenju za preradu suncokretovog ulja. Dobijeni rezultati pokazuju da ovaj sistem sa visokom tačnošću i pouzdanošću može detektovati kvarove u ranim stadijumima, te da stoga omogućava prevenciju kvarova i otkaza i poboljšava performance i efikasnost industrijskog sistema.
Ključne reči: *detekcija kvarova, asinhroni elektromotor, analiza vibracija, klasifikatori sa potpornim vektorima.*

INTRODUCTION

Induction motors play an important role as prime movers in manufacturing, process industry and transportation due to their reliability and simplicity in construction. Although induction motors are reliable, the possibility of unexpected faults is unavoidable. The issue of robustness and reliability is very important to guarantee the good operational condition. Therefore, condition monitoring of induction motors has received considerable attention in recent years. Early fault diagnosis and condition monitoring can reduce the consequential damage, breakdown maintenance and reduce the spare parts of inventories (*Matić et al., 2010*). Moreover it can prolong the machine life and increase the performance and the availability of the machine. Many researchers have proposed techniques and systems for doing the diagnosis process. Various techniques have been used, such as motor current signature analysis (*Kulić et al., 2010*), electromagnetic torque measurement (*Thollon et al., 1993*), acoustic analysis (*Lee et al., 1994*) and partial discharge (S*tone et al., 1996*). However, the most popular techniques are vibration analysis and stator current analysis due to their easy measurability, high accuracy and reliability. Support vector machines (SVMs) have been extensively employed to solve classification problems. In machine condition monitoring and fault diagnosis, some researchers have used SVMs as a tool for classification of different kind of faults, such as ball bearing faults (*Jack and Nandi, 2002*), gear faults (*Samanta, 2004*), condition classification of small reciprocating compressor (*Yang et al., 2005a*), cavitation detection of butterfly valve (*Yang et al., 2005b*) and so on. To perform good classification using SVMs, the preparation of data inputs for classifier needs special treatment to guarantee the good performance. Recently, the use of feature extraction and feature selection for data preparation to avoid the redundancy before inserting into classifier has received considerable attention (*Cao et al., 2003*). There are numerous papers and studies that describe laboratory experiments and applied techniques conducted in purpose of different kinds of induction motor faults detection. However, application of these techniques and their results in real industrial systems is not so common. In this paper, an expert system for induction motor fault detection is presented, which represents an attempt to implement very well known fault detection techniques in real industrial system. This system consists of several modules, which perform all necessary tasks in fault detection and classification process (vibration signal acquisition, data processing, SVM fault detection and visualization and archiving of obtained results). Two kinds of faults are considered, bearing wear and static eccentricity. The system is developed and tested using real data from laboratory and sunflower oil processing industry. It can be used as stand-alone tool for condition monitoring of induction motors. Use of this system in industrial facilities could assist in early fault detection and prevent malfunctions and failures of production systems, improving their overall performance and efficiency. The paper is organized as follows. In section 2 fault detection process using vibration analysis and support vector machines is described, presenting shortly all included phases and applied techniques. Section 3 illustrates the structure of expert system and its embedded modules. In section 4, results of system testing performed in laboratory and oil industry facility are presented. Section 5 concludes the paper.

MATERIAL AND METHOD

Vibration analysis and support vector machines in fault detection

Vibration signals are frequently used for fault diagnosis of mechanical systems since they carry information on the dynamic state of the mechanical elements themselves. Fault diagnosis is conducted typically in the following phases (as shown in Figure 1):

- vibration data acquisition
- feature extraction and
- fault detection

Vibration data acquisition

Vibration signals are initially obtained as a series of digital values representing acceleration in the time domain. These signals are then analyzed using many different techniques proposed in the literature, in time and/or frequency domain. In this study, both time and frequency domain features of acquired signals were used for fault detection.

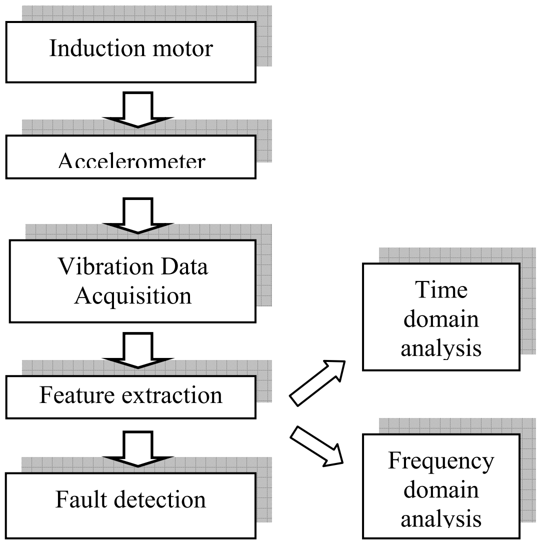

Fig. 1. Diagram of fault detection process using vibration signal analysis

In time domain, we chose to observe statistical features, such as mean, root mean square, skewness, kurtosis, C factor, L factor, S factor and I factor, often used in literature (*Stepanić et al., 2009*). In frequency domain, we chose to observe power spectrum, whose amplitude is the square of the amplitude of the spectrum, which is an effective method to diagnose machinery faults (Yang et al., 2003). Eight characteristic features were used. They represent the sum of amplitudes of power spectrum in the region around characteristic frequencies. The summation is performed in the band $f_C \pm 3Hz$, where f_C is characteristic frequency. First three features represent sum around twice supply frequency ($f_S = 50Hz$) and its sidebands ($2f_S \pm f_r$, where f_r is rotor frequency), which are the indicators of static eccentricity in induction motor (*Kanović et al., 2011*). The following five features are related to condition of bearings. They represent the sum of amplitudes of power spectrum around bearing characteristic frequencies, which are:

outer race fault frequency:

$$f_{rpfo} = f_r \times \frac{N}{2}\left(1 - \frac{d}{D}\cos\phi\right) \tag{1}$$

inner race fault frequency:

$$f_{bpfi} = f_r \times \frac{N}{2}\left(1 + \frac{d}{D}\cos\phi\right) \tag{2}$$

rotation frequency of the rolling element:

$$f_{bsf} = f_r \times \frac{D}{2d}\left[1 - \left(\frac{d}{D}\right)^2 \cos^2\phi\right] \tag{3}$$

rolling element fault frequency:

$$f_{bff} = 2 \times f_{bsf} \tag{4}$$

cage fault frequency:

$$f_{ftf} = f_r \times \frac{1}{2}\left(1 - \frac{d}{D}\cos\phi\right) \tag{5}$$

where N is the number of rolling elements in the bearing, ϕ is the contact angle of the rolling element, d is the rolling element diameter and D is the diameter of the bearing shell (*Stepanić et al., 2009*).

Based on both time and frequency domain features, after proper dimensional reduction, which is in this study conducted using principal component analysis, artificial intelligence classifier can be applied to detect faults in operation of monitored object.

Feature extraction

Obtained feature set has totally seventeen features for every recorded signal. Using all of them for fault classification might be inefficient, since this feature set contains redundancy. Its dimensionality is thus reduced using principal component analysis.

Principal component analysis (PCA) involves a mathematical procedure that transforms a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

PCA is mathematically defined as an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (called the first principal component), the second greatest variance on the second coordinate, and so on. PCA is theoretically the optimum transform for given data in least square terms.Given a set of centered input vectors $\mathbf{x}_t$ (t = 1,. . . , l and $\sum_{t=1}^{l} \mathbf{x}_t = 0$), each of which is of m dimension $\mathbf{x}_t = (x_t(1), x_t(2), \ldots, x_t(m))^{\mathrm{T}}$, usually $m<l$, PCA linearly transforms each vector $\mathbf{x}_t$ into a new one $\mathbf{s}_t$ by

$$\mathbf{s}_t = \mathbf{U}^{\mathrm{T}}\mathbf{x}_t \tag{6}$$

where $\mathbf{U}$ is the $m \times m$ orthogonal matrix whose ith column, $\mathbf{u}_i$ is the eigenvector of the sample covariance matrix

$$\mathbf{C} = \frac{1}{l}\sum_{t=1}^{l} \mathbf{x}_t \mathbf{x}_t^{\mathrm{T}} \tag{7}$$

The new components $\mathbf{s}_t$ are called principal components. By using only the first several eigenvectors sorted in descending order of the eigenvalues, the number of principal components in $\mathbf{s}_t$ can be reduced, so PCA has the dimensional reduction characteristic (*Jollife, 1986*).

Support Vector Machines in fault detection

SVMs are a kind of learning machine based on statistical learning theory. The basic idea of applying SVM to pattern classification can be stated as follows: first, map the input vectors into one features space, possible in higher space, either linearly or nonlinearly, which is relevant with the kernel function. Then, within the feature space from the first step, seek an optimized linear division, that is, construct a hyperplane which separates two classes. It can be extended to multi-class problems. SVM training always seeks a global optimized solution and avoids overfitting, so it has ability to deal with a large number of feature. A complete description about SVMs is available in (*Vapnik, 1995*).

In the linear separable case, there exists a separating hyperplane whose function is

$$\mathbf{w}\cdot\mathbf{x}+b=0 \tag{8}$$

which implies

$$y_i(\mathbf{w}\cdot\mathbf{x}+b=0)\geq 1, \quad i=1,\ldots,N. \tag{9}$$

By minimizing $\|\mathbf{w}\|$ subject to this constraints, the SVM approach tries to find a unique separating hyperplane. Here $\|\mathbf{w}\|$ is the Euclidean norm of **w**, and the distance between the hyperplane and the nearest data points of each class is $2/\|\mathbf{w}\|$. By introducing Lagrange multipliers α_i, the training procedure amounts to solving a convex quadratic problem (QP). The solution is a unique globally optimized result, which has the following properties

$$w=\sum_{i}^{N}\alpha_i y_i \mathbf{x}_i\ . \tag{9}$$

Only if corresponding $\alpha_i > 0$, these $\mathbf{x}_i$ are called support vectors.

When SVMs are trained, the decision function can be written as

$$f(\mathbf{x})=sign\left(\sum_{i=1}^{N}\alpha_i y_i(\mathbf{x}\cdot\mathbf{x}_i)+b\right)\cdot \tag{10}$$

The obtained sign of decision function result determines the class label of considered sample.

For a linear non-separable case, SVMs perform a nonlinear mapping of the input vector **x** from the input space $\Re^d$ into a higher dimensional Hilbert space, where the mapping is determined by kernel function (Gaussian RBF, polynomial,...). According to the different classification problems, the different kernel function can be selected to obtain the optimal classification results.

Expert System Structure

Expert system for induction motor fault detection presented in this paper implements all previously stated phases of detection process. Accordingly, it consists of following modules:

Vibration signal acquisition module, which collects signals from two accelerometers and transforms it in textual data file. The module is implemented in LabView software, compatible with hardware used for signal acquisition. This module also calculates signal spectrum and maps obtained data in textual file.

Data processing module; this module is implemented in Matlab. It imports textual data files outputted by previous module and performs characteristic features calculation, described in section 2. This module also applies PCA to reduce dimensionality of obtained feature set, decreasing number of features from sixteen in original set to six in reduced feature set, which is empirically proven to be satisfactory for successful fault detection process.

SVM fault detection module, also implemented in Matlab, which performs classification of input feature set and detects the presence of the fault. SVMs are trained on training data set, formed using feature sets of vibration signals of different induction motors. Using these trained SVMs, obtained feature set of the current motor is classified as faulty or healthy, concerning both observed faults. The result of the classification is then forwarded to next module.

Module for graphical representation, which illustrates classification results, creates diagrams for visual fault detection and performs data archiving.

The expert system is implemented in Microsoft Windows Visual Basic 6, with support of Microsoft Access for data archiving, and runs on Microsoft Windows operating system. This way, the executable file is rather small, since it uses only basic elements of Windows operating system, and thus has minor demands concerning operating memory. On the other hand, this implementation approach provides good interconnection with other software packages and is therefore suitable for application purposes.

The expert system can run in two different modes, manual and automatic. Manual mode implies that the application is used occasionally, on demand, for example in maintenance period or if there is any reason to suspect that some motor is faulty. Fault detection process is then performed once, providing information on motor condition. When running in automatic mode, application is executed continuously, monitoring condition of the motor during the entire production process. In both modes, obtained results are archived in data base, containing information on event's date and time, operation mode (manual / automatic), presence of the fault(s), diagrams of recorded signal and calculated signal spectrum. Also, the analysis can be carried out online, when all fault detection stages are conducted in continuous sequence, or offline, when detection stages are separated (e. g. data collection is conducted, text file with signal data is saved and the analysis is performed afterwards).

UML Use Case diagram of expert system is depicted in Figure 2, showing all provided cases of use.

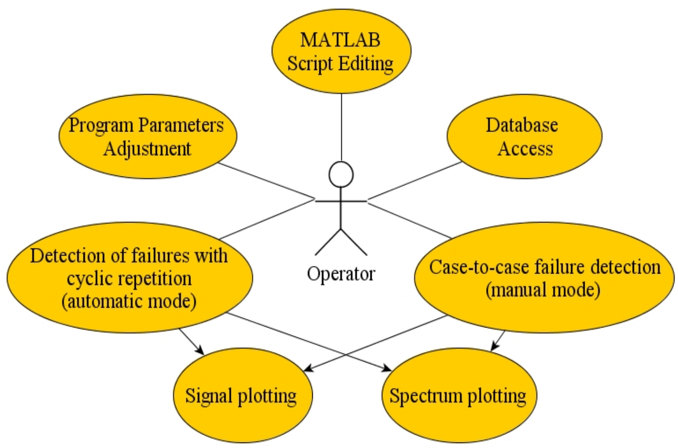

Fig. 2. UML Use Case diagram of expert system

One can see that operator can access and edit Matlab scripts for signal processing, feature calculation and SVM classification. Data stored in database are also available for review, control and monitoring. The operator can also adjust parameters concerning program execution and characteristic motor data, such as power, nominal speed, and bearing geometry data, which are needed for feature calculation. All these activities are processed using operator interface, depicted in Figure 3. It also shows sequences and phases of detection process, classification results and diagrams of vibration signals on both channels (vertical and horizontal accelerometers) and their spectrums.

RESULTS AND DISCUSSION

The system was tested and validated on real data, in the laboratory and in the sunflower oil production facility. Totally 200 vibration signals from induction motors were collected, using different speed and load. These signals are used for SVM classifier training. The structure of obtained signal set is presented in Table 1. Static eccentricity is denoted as Fault_1 and bearing wear as Fault_2.

Table1. Overview of vibration signals of faulty and fault-free motors

Number of signals				Total number of signals
Fault-free	Fault_1 only	Fault_2 only	Fault_1 and Fault_2	
78	38	44	40	200

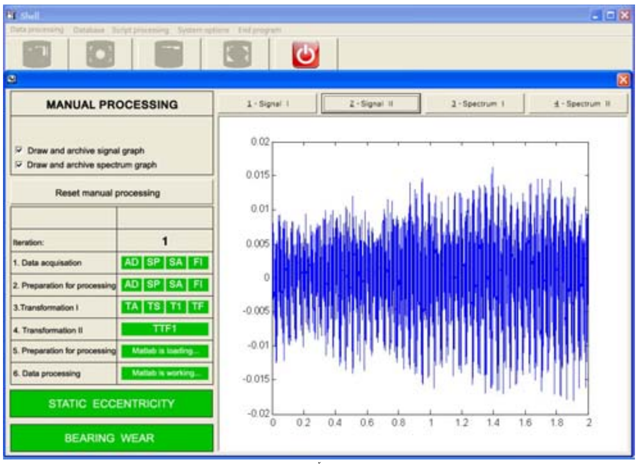

Fig. 3. Operator interface in manual mode

Two different types of motors were considered, five of each type. First type is 5.5kW motor with one pair of poles, nominal speed of 2925 rpm and nominal current of 10.4 A. These motors are driving the screw conveyors in the process plant. Two motors of this type were healthy, one motor had wear on both inner and outer race of the bearing, one motor had static eccentricity level of 30% and one motor had both faults present at the same time (inner and outer race wear and 50% static eccentricity). Second type is 15 kW motor driving the crushed oilseed conditioners, with one pair of poles, nominal speed of 2940 rpm and nominal current of 26.5 A. Two of these motors were healthy, two had static eccentricity level of 30% and 50% and one had defects on bearing ball, inner and outer race (Kanović, 2012). Multiple vibration measurements were conducted on each motor. Two high-sensitivity IEPE accelerometers (100 mV/g) were used for collecting signals of horizontal and vertical vibrations. Data acquisition card NI-9234 (4 Channel, ±5V, 52,2 kS/s, with 2mA IEPE accelerometer excitation) was used for signal collection. Figure 4 shows vibration measurement instrumentation layout.

Fig. 4. Instrumentation for vibration signal acquisition and fault detection

Signals were acquired for two seconds with sampling frequency of 25.6 kHz. The recorded signals were then used to calculate time and frequency domain features. Using obtained feature sets, two SVM classifiers were trained, one for each considered fault. Parameters of these trained classifiers were then imported in module for SVM classification providing a base for following fault detection.

It should be noted that characteristic features are common for different types of motors and that they are a function of construction parameters, such as nominal speed and bearing geometry. The trained SVM classifier can be applied to any similar motor, if proper parameters for feature calculation are known. However, to obtain universal applicability of this system, other types of motors should also be considered in SVM training to improve the classifier performance.

Testing is performed on induction motors of the same types as motors used for training phase. New vibration signals were collected and used as input signals. Testing is conducted in both manual and automatic mode. Test data set structure and obtained classification results are shown in Table 2.

Table 2. Fault classification testing results

		Static eccentricity classifier	Bearing wear classifier
Test data set	Faulty	22	18
	Fault-free	32	36
False fault classifications		1	1
Classification error [%]		**1.85**	**1.85**

These results demonstrate the efficiency of presented expert system for induction motor fault detection. For both present faults, there was only one false classification, which results in classification error less than 2 percent. These experimental results proved that presented expert system can be successfully applied in fault detection, providing accurate, efficient and reliable fault classifiers applicable in real industrial systems.

CONCLUSION

In this paper an expert system for induction motor fault detection is presented. Using programming software tools and packages combined with appropriate hardware and implementing well known fault detection and diagnosis procedures and techniques, this system is intended to be used as practical diagnostic tool for condition monitoring and fault, malfunction and failure prevention in industrial systems. The system is tested in real industrial environment and obtained results proved its accuracy and efficiency.

Further research could be conducted in several directions. First of them would be to extend the number of faults covered by the classification, such as broken rotor bar, dynamic eccentricity and so on. Also, the number of motor types used in SVM training should be extended, to cover wider range of motors. The other direction would be improvement of feature selection method, considering some other linear or nonlinear transformations or application of optimization procedures in feature selection. This would enable more efficient fault detection based on more comprehensive feature sets, which would improve maintenance procedure and decrease total cost in production processes.

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