Journal of Mechanical Science and Technology (KSME Int. J.), Vol. 20, No. 12, pp. 2013~2024, 2006 **2013**

Fault Detection of Reciprocating Compressor for Small-Type Refrigerators Using ART-Kohonen Networks and Wavelet Analysis

Bo-Suk Yang*, Soo-Jong Lee
School of Mechanical Engineering, Pukyong National University, San 100 Yongdang-dong, Nam-gu, Busan 608-739, Korea
Tian Han
School of Mechanical Engineering, University of Science and Technology Beijing, 30 Xueyuan Road, Haidian District, 100083, Beijing, China

This paper proposes a condition classification system using wavelet transform, feature evaluation and artificial neural networks to detect faulty products on the production line of reciprocating compressors for refrigerators. The stationary features of vibration signals are extracted from statistical cumulants of the discrete wavelet coefficients and root mean square values of band-pass frequencies. The neural networks are trained by the sample data, including healthy or faulty compressors. Based on training, the proposed system can be used on the automatic mass production line to classify product quality instead of people inspection. The validity of this system is demonstrated by the on-site test at LG Electronics, Inc. for reciprocating compressors. According to different products, this system after some modification may be useful to increase productivity in different types of production lines.

Key Words : Fault Classification, Feature Extraction, Wavelet Transform, Neural Network, Reciprocating Compressor

1. Introduction

Nowadays production lines of small-type compressors for refrigerators or air-conditioners are relative large and highly automated. Thus the quality examination of compressors becomes indispensable part in the manufacturing process. Since small-type compressors are mostly used in family electrical appliances, especially the refrigerators and air-conditioners. These units are normally located in the living room and the level of the noise from these units is an important assessment index of the product quality. For a compressor, the sources of noise are usually from the large side clearance and the top clearance between the piston and cylinder, air gap misalignment, looseness of the stator bolts, insufficient lubrication and incorrect assembly. So far, there is no efficient approach to detect all these faults in the production line. (Yang et al., 2005)

Conventional quality examination approaches can be briefly summarized in three sequential phases : in the first phase, the faulty products are detected using auditory approach senses by the field engineers for semi-product sampled. The judgment criterion is based on the personal experience. In the second phase it involves the checking of the final products. Inspectors still uses auditory approach to pick up the faulty compressors. Finally, the inspector samples 4 to 5 products per 1,000 units, and examines them using

* Corresponding Author,
E-mail : bsyang@pknu.ac.kr
TEL : +82-51-620-1604; **FAX** : +82-51-620-1405
School of Mechanical Engineering, Pukyong National University, San 100 Yongdang-dong, Nam-gu, Busan 608-739, Korea. (Manuscript **Received** July 2, 2005; **Revised** August 30, 2006)

special apparatus. The criterion of spot-test is obtained from the anechoic room. In order to get an accurate assessment of the real work conditions the products had to run for several hours until steady-state condition is reached. The shortcomings of the conventional approach can be summarized as follows :

(1) Personal assessment affects the examination results.

(2) That good ones can be mistaken and result in production loss.

(3) Faulty compressors can be missed during quality check and can affect manufacturer credibility.

(4) Sample examination is only partial and can not represent the quality of all products.

(5) In the manufacturing process, inspectors have to always give their full attention to the product quality and have no time for other tasks.

In order to solve the above stated problems, and to overcome the shortcomings of the conventional approach, it is necessary to have an intelligent system that can examine all products, which can be carried out through synthesizing : the wavelet transform, statistics approach, band-pass filtration and artificial neural networks (ANNs). Yang et al.(2005) proposed a novel scheme to detect faulty products at semi-product stage in an automatic mass product line of reciprocating compressors for small-type refrigerators. The results confirmed that proposed scheme give high classification accuracy and are the best techniques for classifying healthy and faulty conditions of compressors. But, it is necessary to develop a practical classification system to select faulty products at final product stage of reciprocating compressors.

The wavelet transform has become a valuable analysis tool due to its ability to elucidate simultaneously both spectral and temporal information within the signal. This overcomes the basic shortcoming of Fourier analysis, which contains only globally averaged information, hence leading to location specific features in the signal being lost. Order statistics approach is popular and is used in many fields of scientific research including medical science, geophysics, engineering, image analysis, fluid turbulence and financial analysis.

The recent development in ANNs provides a powerful tool for classifying machinery conditions (Yang et al., 2002 ; Tahk and Shin, 2002). In general, ANNs have the capability of learning heuristically from the past data about a machine's healthy/ faulty conditions. This information can be stored and employed for later use. The advantage of ANNs is that they could learn a machine's condition-indicating information without understanding the detailed dynamics inside the machine. ANNs is one of the clustering algorithms that attempt to organize unlabeled feature vectors into clusters such that points within a cluster are more similar to each other than to vectors belonging to different clusters (Yang et al., 2000). The representative ANNs for clustering are self-organizing feature maps (SOFM) and learning vector quantization (LVQ) which are introduced by Kohonen (1992, 1995, 1996). Kohonen's work has become particularly timely in recent years because of the widespread resurgence of interest in the theory and applications of ANN structures. However, SOFM and LVQ are 'off-line' ANNs that 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 condition 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 (Liobet, 1999). In the real world, although part of condition signals can be obtained, it is very difficult to compose the training dataset representing the features of all conditions. Nobody knows what will happen next time. These characteristics limit the applications of 'off-line' ANNs in condition monitoring and fault diagnosis field. The ANNs for monitoring 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. A human brain is able to learn many new events without necessarily forgetting events that occurred in the past. So we want an intelligent system capable of adapting 'on-line' to changes in the environment, the system should be able to deal with the so-called the stability-plasticity dilemma (Carpenter and Grossberg, 1987, 1988, 1991, 1992). That is the system should be designed to have some degree of plasticity to learn new events in a continuous manner, and should be stable enough to preserve its previous knowledge, and to prevent new events destroying the memories of prior training. As a solution to this problem, the adaptive resonance theory (ART) networks were developed (Gardner et al., 1996). Recently the ART-KNN network is developed that synthesizes the theory of adaptive resonance theory (ART) and the learning strategy of Kohonen neural network (KNN), and has been applied with some success to on-line condition monitoring and diagnosis (Yang et al., 2004). These algorithms require only one learning epoch for training and is therefore, fast and suitable for real-time applications.

The objective of this study is to develop an accurate, simple, fast and reliable system to select faulty products at final product stage, which can perform well even with a limited amount of time and data. In this work, three intelligent classifiers were used to classify the condition of compressors: SOFM, LVQ and ART-KNN networks. The proposed system was successfully applied in the classification to detect faulty products at final product stage in an automatic mass product line of reciprocating compressors for small-type refrigerators used in family electrical appliances.

2. Theoretical Backgrounds

2.1 Feature extraction

Usually, the vibration signals are obtained in time domain. Although the data contain abundant feature information, the important part cannot show intuitively, and that much unnecessary information also is contained. Therefore, the feature extraction is essential for effectual estimation conditions of machinery. In this study, feature extraction approaches are FFT transform, discrete wavelet transform and statistical method.

2.1.1 Discrete wavelet transform

The wavelet transform is a technique for analyzing signals. It was developed as an alternative to the short time Fourier transform (STFT) to overcome problems related to its frequency and time resolution properties. More specifically, unlike the STFT that provides uniform time resolution for all frequencies the discrete wavelet transform (DWT) provides high time resolution and low frequency resolution for high frequencies and high frequency resolution and low time resolution for low frequencies. In that respect it is similar to the human ear, which exhibits similar time-frequency resolution characteristics. The DWT is a special case of the wavelet transform that provides a compact representation of a signal in time and frequency that can be computed efficiently. The DWT is defined by the following equation:

$$W(j,k)=\sum_j\sum_k x(k)^{-i/2}\psi(2^{-j}n-k) \quad (j,k=1,2,\cdots) \tag{1}$$

where $W(j,k)$ is wavelet transform, $\psi(t)$ is a time function with finite energy and fast decay called the mother wavelet, t is the time parameter, taken as a series of integer k, and j is the frequency parameter coefficient. The DWT analysis can be performed using a fast, pyramidal algorithm related to multi-rate filter-banks (Mallat, 1989).

As a multi-rate filter-bank the DWT can be viewed as a constant Q filter-bank with octave spacing between the centers of the filters. Each sub-band contains half the samples of the neighboring higher frequency sub-band. In the pyramidal algorithm the signal is analyzed at different frequency bands with different resolution by decomposing the signal into a coarse approximation and detail information. The coarse approximation is then further decomposed using the same wavelet decomposition step. This is achieved by successive high-pass and low-pass filtering of the time domain signal and is defined by the following equations:

$$y_{high}[k]=\sum_n x[n]g[2k-n] \tag{2}$$

$$y_{low}[k]=\sum_n x[n]h[2k-n] \tag{3}$$

where $y_{high}[k]$, $y_{low}[k]$ are the outputs of the high-pass g and low-pass h filters, respectively after sub-sampling by 2. Because of the down-sampling the number of resulting wavelet coefficients is exactly the same as the number of input points. A variety of different wavelet families have been proposed in the literature. In our implementation, the 10 coefficients wavelet family (db10) proposed by Daubechies (1988) is used.

2.1.2. Statistical feature information

The features described in this section are termed statistics because they are based only on the distribution of vibration samples with the time series treated as a random variable. Many of these features are based on moments or cumulants and therefore the method of estimating these and their relationship with the distribution of the random variable. In most of cases, the probability density function (pdf) can be decomposed into its constituent moments. If a change in condition causes a change in the probability density function of the signal then the moments may also change therefore monitoring these can provide diagnostic information.

For a given data set $x_i, i=1,\cdots,N$, the moments of the signal are defined as follows (Altmann and Mathew, 1999):

$$m_n=E\{x^n\}=\frac{1}{N}\sum_{i=1}^{N} x_i^n \tag{4}$$

where $E\{\cdot\}$ represents the expected value of the function, x_i is the time historical data, and N is the number of data points.

The first four cumulants, mean C_1, standard deviation C_2, skewness C_3 and kurtosis C_4, can be computed from the first four moments using the following relationships:

$$\begin{aligned} &C_1=m_1,\ C_2=m_2-m_1^2,\ C_3=m_3-3m_2m_1+2m_1^3, \\ &C_4=m_4-3m_2^2-4m_3m_1+12m_2m_1^2-6m_1^4 \end{aligned} \tag{5}$$

Moments of order higher than five are not considered in the present work to keep the input vector within a reasonable size without sacrificing the accuracy of classification. For a perfect normal (Gaussian) distribution, skewness C_3 and kurtosis C_4 are equal to zero. For most (but not quite all) nongaussian random variables, skewness and kurtosis are not zero. A negative value is due to skewness towards lower values while a positive value indicates non-symmetry towards higher values. For small data sets, one often gets values that differ from zero. The kurtosis or flatness C_4 can be either positive or negative, and is very close to unity for a normal distribution. Random variables that have a negative kurtosis are called subgaussian, and those with positive kurtosis are called supergaussian. Supergaussian variables have typically a spiky pdf with heavy tails, i.e. the pdf is relatively large at zero and large values of the variable, while being small for intermediate values. On the other hand, subgaussian variables have typically flat pdf, which is rather constant near zero, and very small for larger values of the variable. These statistical parameters may be used to perform a quick check of the changes in the statistical behavior of a signal (Nandi and Dickie, 1994; Dickie, 1995).

2.2 Artificial neural networks

In this work, three intelligent classifiers were used to classify the condition of compressors: SOFM, LVQ and ART-KNN networks. The SOFM, an unsupervised learning, was proposed in 1982 while Kohonen proposed the LVQ as a supervised learning approach. For detailed tutorials on the subject the reader can refer to references (for examples, Kohonen (1992, 1995, 1996) and references cited therein. ART-KNN combines the theory of ART (Carpenter and Grossberg, 1987, 1988, 1991) with Kohonen's learning strategy (Kohonen, 1995) to realize on-line clustering. In following sections we just outline the basis of the methods.

2.2.1 SOFM algorithm

The SOFM is a neural network model that implements a characteristic non-linear projection from the high dimensional space of sensory or other input signals onto a low-dimensional array of neurons. The SOFM is an unsupervised learning algorithm which produces a map pattern features on its output layer (Kohonen, 1995). Input patterns with similar features are mapped onto neighbouring output nodes. The network consists of an input layer with N neurons and an output layer with M neurons. The image of the signal space tends to manifest the clusters of input information and their relationship on the feature map. With every node j, a parametric reference vector $\mathbf{w}_j \in R^n$ is associated. In an abstract scheme it may be imagined that at time k the input $\mathbf{x}(k)$, by means of some parallel computing mechanisms, is compared with all the $\mathbf{w}_j(k)$, and the location of best match in some metric is defined as the location of the response. However, in many practical applications, the Euclidean distances $\|\mathbf{x}(k)-\mathbf{w}_j(k)\|$ can be made to define the best-matching node (neuron) i, signified by the index $i(\mathbf{x})$:

$$\begin{aligned} i(\mathbf{x}) &= \arg\min \|\mathbf{x}(k)-\mathbf{w}_j(k)\| \\ &= \arg\min \{\|\mathbf{e}_j(k)\|\}, \\ &\quad (j=1,2,\cdots,N\,;\ k=1,2,\cdots,M) \end{aligned} \tag{6}$$

where, $\mathbf{x}(k)=\{x_1,x_2,\cdots,x_M\}^{\mathrm{T}}$ means input vectors and $\mathbf{w}_j(k)=[w_{j1},w_{j2},\cdots,w_{jM}]^{\mathrm{T}}$ $(j=1,2,\cdots,N)$ represent weight vectors of the j-th output vectors. $\mathbf{e}_j(k)$ is the error which means the same as $\|\mathbf{x}(k)-\mathbf{w}_{,i(\mathbf{x})}(k)\|=\min\{\|\mathbf{e}_j(k)\|\}$.

In the beginning the reference vectors $\mathbf{w}_j(0)$ are random. The self-organization is achieved using the following learning process,

$$\mathbf{w}_j(k+1)=\mathbf{w}_j(k)+\eta(k)\,h_{j,i(\mathbf{x})}(k)\,\mathbf{e}_j(k) \tag{7}$$

where $k=0,1,2,\cdots,M$ is an integer, the discrete-time coordinate. $\eta(k)$ is the learning rate factor which is usually decreased with increasing iterations $(0<\eta(k)<1)$. In Eq. (7) the neighbourhood function $h_{j,i(\mathbf{x})}$ plays an important role, and $h_{j,i(\mathbf{x})}(k)\rightarrow 0$ when $k\rightarrow\infty$. The Gaussian distribution function is usually selected for the neighbourhood function as follows :

$$h_{j,i(\mathbf{x})}(k)=\exp\{-d_j^2/2\sigma^2(k)\} \tag{8}$$

where d_j is the grid distance between the best-matching neuron i and the j-th neighbourhood neurons. $\sigma(k)$ is the effective width of the neighbourhood defined as a monotonically decreasing function of the time,

$$\sigma(k)=\sigma_0\exp(-k/\sigma_t) \tag{9}$$

σ_t being constant value.

The algorithm is repeated using successive data samples, and as the algorithm proceeds, the different neurons start representing specific clusters of the input space. It can be shown that the algorithm can be interpreted as a gradient approach to minimize the energy function $E_j(k)$ in each neuron j :

$$E_j(k)=\sum h_{j,i(\mathbf{x})}(\kappa)\,(\mathbf{e}_j(\kappa)^{\mathrm{T}}\mathbf{e}_j(\kappa)), \quad \kappa=0,1,\cdots,k \tag{10}$$

2.2.2 LVQ algorithm

From now, we review briefly LVQ3 algorithm previously published by Kohonen. For a review of another versions of LVQ algorithm, see Kohonen (1992). This is the phase of classification which enhances characteristics of classification boundaries via supervised learning using input vectors (or codebook vectors) $\mathbf{x}(k)$. The input layer of an LVQ network is connected directly to the output layer. Each node in the output layer has a weight vector (or prototype) attached to it. Assume that a number of codebook vectors $\mathbf{m}_i(k)$ (free parameter vectors) are placed into the input space to approximate various domains of the input vector by their quantized values. Some parts of the entire codebook vectors can be used for reducing calculating speed and memory allocation. It is assumed that output vectors of LVQ is $\mathbf{m}_i(k)$. If $\mathbf{m}_i(k)$ is the most similar vector to $\mathbf{x}(k)$, $\mathbf{m}_c$ is determined by k-nearest neighbour rule. Let

$$\mathbf{m}_c(k)=\arg\min\|\mathbf{x}(k)-\mathbf{m}_i(k)\|, \quad (i=1,2,\cdots,N) \tag{11}$$

define the nearest $\mathbf{m}_i(k)$ to $\mathbf{x}(k)$, denoted by $\mathbf{m}_c(k)$. Values for the $\mathbf{m}_i(k)$ that approximately minimize the misclassification errors in the above nearest-neighbour classification can be found as asymptotic values in the following learning process. Let $\mathbf{x}(k)$ be a sample of input and let the $\mathbf{m}_i(k)$ represents sequences of the $\mathbf{m}_i(k)$ in the discrete-time domain.

Starting with properly defined initial values, the following equations define the basic LVQ process. If $\mathbf{x}(k)$ and $\mathbf{m}_c(k)$ belong to the same class,

$$\mathbf{m}_c(k+1)=\mathbf{m}_c(k)+\alpha(k)(\mathbf{x}(k)-\mathbf{m}_c(k)) \quad (12)$$

If $\mathbf{x}(k)$ and $\mathbf{m}_c(k)$ belong to the different class,

$$\mathbf{m}_c(k+1)=\mathbf{m}_c(k)-\alpha(k)(\mathbf{x}(k)-\mathbf{m}_c(k)) \quad (13)$$

Otherwise, for $i \neq c$,

$$\mathbf{m}_c(k+1)=\mathbf{m}_i(k) \quad (14)$$

Here $0<\alpha(\mathrm{k})<1$, and $\alpha(k)$ may be constant or monotonically decrease with time. It is recommended that the initial value of $\alpha(k)$ not to be taken more than 0.1 in accordance with the basic LVQ algorithm.

The data can be learned in a self-organized fashion by only choosing the learning rate and the number of output neurons compared with other neural network methodologies. Also, the feature map capability has an advantage. It can visualize the classification result.

2.2.3 ART-Kohonen neural network

ART-KNN (Yang et al., 2004) combines the theory of ART with Kohonen's learning strategy to realize machinery condition monitoring. 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

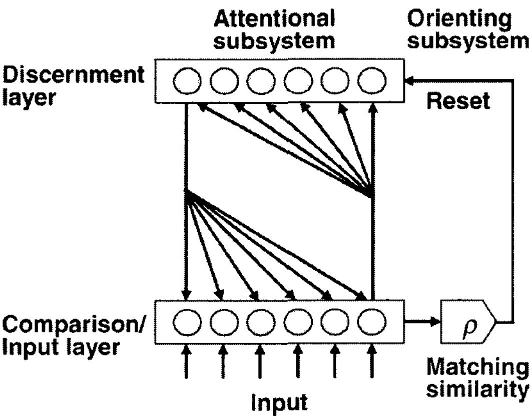


Fig. 1 Architecture of the ART-KNN network

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 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 Euclidean distances of all weights between input vector $\mathbf{X}$ and each neuron of the discernment layer are evaluated as the similarity given by Eq. (15), the smallest one becomes the winning neuron.

$$\|B_J-\mathbf{X}\|<\|B_j-\mathbf{X}\|,\ j,J=1,2,\cdots,n\ ;\ j\neq J \quad (15)$$

where B_j is the weight of j-th neuron in the discernment layer, B_J is the weight of the winning neuron. After producing the winning neuron, input vector $\mathbf{X}$ returns to the comparison layer. The absolute similarity S is calculated by

$$S=\frac{\|B_J\|-\|B_J-\mathbf{X}\|}{\|B_J\|} \quad (16)$$

If B_J and $\mathbf{X}$ in Eq. (16) are same, $\|B_J-\mathbf{X}\|$ is equal to 0, and S is 1. The larger the Euclidean distance between B_J and $\mathbf{X}$ is, the smaller S is. A parameter ρ is introduced as the evaluation criterion of similarity. If $S>\rho$, it indicates that the J-th cluster is sufficiently similar to $\mathbf{X}$. So $\mathbf{X}$ belongs to the J-th cluster. In order to make the weight more accurate to represent the corresponding cluster, the weight of J-th cluster is improved by the following equation :

$$B_J=\frac{nB_{J0}+\mathbf{X}}{n+1} \tag{17}$$

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

On the contrary, as $S<\rho$, it means that $\mathbf{X}$ is much different with the J-th cluster. Thus there is no cluster that matches $\mathbf{X}$ 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

$$B_{n+1}=\mathbf{X} \tag{18}$$

3. Condition Classification of Reciprocating Compressors

The configuration of reciprocating compressor for refrigerators is shown as Fig. 2. It consists of electric motor, cylinder, piston, cover, valve and support segments. As the outset of the whole procedure, vibration signals of unqualified and qualified product are measured. The characteristics of the signals are found by analyzing them accordingly. Then features are extracted and the conditions are classified using above-mentioned methods.

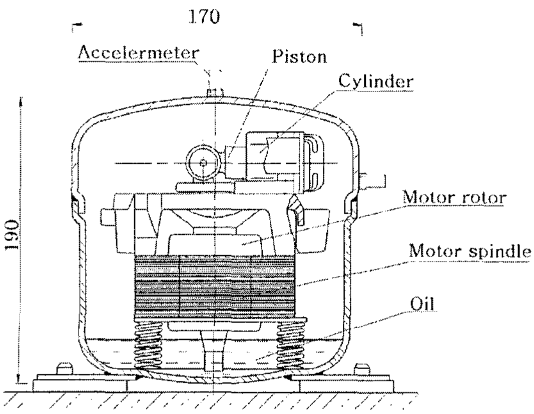


Fig. 2 Schematic of reciprocating compressor

In Fig. 3, it shows integrated on-line classification system. The system contains three modules : database, data training and condition classification (Lim et al., 2001). The function of database module is to save discrete signal data after A/D conversion, compressor specifications, measurement time and other direct or indirect information on the compressors. Data training module acquires the data from database, and then extracts the features using the wavelet transform for condition classification. Daubiches wavelet db10 is selected as an analyzed wavelet. After transformation, all scales are treated using statistical method. The feature values can be obtained, average value, standard deviation, skewness and kurtosis. Sequentially, it provides input vectors of SOFM and LVQ neural networks for training. The procedure of training means the optimum weights of neurons. After training, the networks can distinguish the normal/faulty conditions of compressors.

Classification module is to identify the compressor conditions on-line. The concrete processing sequence is getting the data from sensors, feature extraction and condition classification. This system was validated in the product line for semi-manufactured goods and confirmed that the classification rate reached 100% (Yang et al., 2005). The maximum frequency of used signal is 10 kHz and the number of sampled data is 4,096. The training data derived from 5 unqualified compressors and qualified ones, respectively. For further validation its availability, the system is applied to finished product.

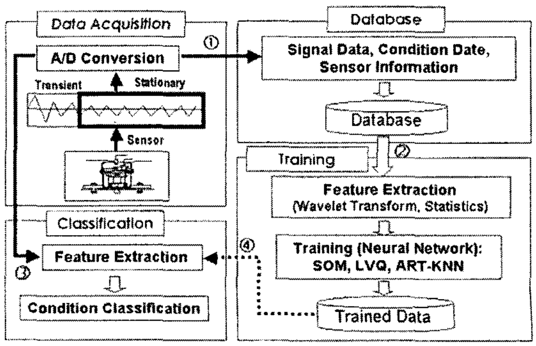


Fig. 3 Integrated classification system for classification

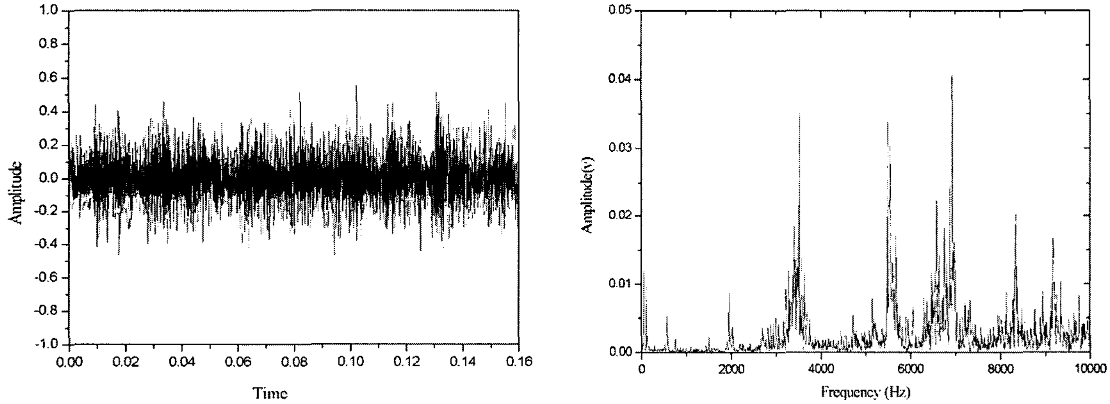
3.1 Data acquisition

Final decision of normal/faulty condition is performed in the anechoic chamber on cycling condition and the criterion of condition is 43dB, which is experienced value from compressor maker. However it is impractical since the environment noise is too high, can reach 60dB above the criterion. Therefore vibration signals, which have a close relationship with sound (noise) and easiness of data acquisition, were used for investigating the condition classification.

The compressors are set to operate for 5s at 110V (regular voltage) to acquire the vibration signals. The vibration signal was acquired by two accelerometers (horizontal and vertical directions) mounted on the top of the cover. Each product was measured 12 times continuously. This gives a total of 2,880 training data. The maximum data acquisition frequency band used for signal recording is 10 kHz and the number of sampled data is 4,096. At last the noise signals of these compressors were measured in the soundproof room and the conditions were confirmed.

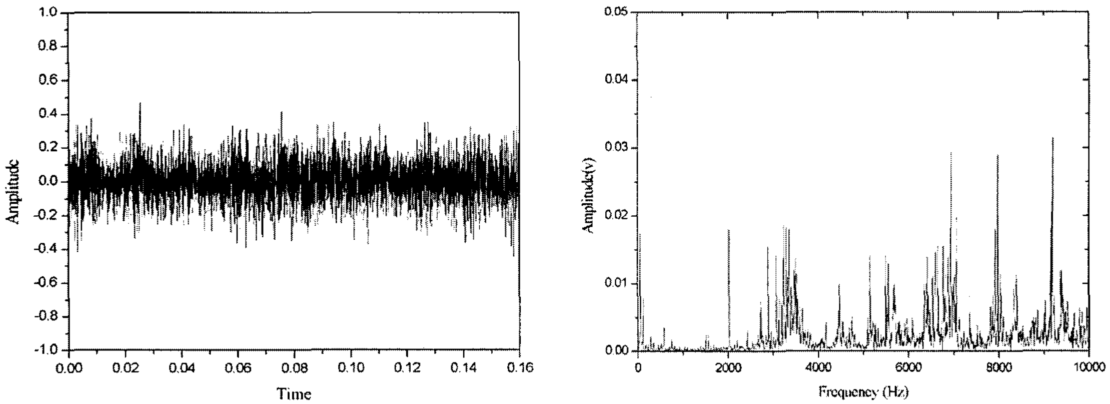
3.2 Feature extraction

An example of the time waveform and frequency spectrum of healthy (normal) and faulty (abnormal) compressors is shown in Figs. 4 and 5. The distinguished features of all pieces of compressors are appeared in the frequency bands, 3-4 kHz, 5-6 kHz, 6.3-7.3 kHz and 9-10 kHz. However, it is difficult to differentiate apparently the vibration energy change between healthy and faulty conditions. From the time series waveform, no



(a) Time waveform (b) Frequency spectrum

Fig. 4 Typical time waveform and frequency spectrum for healthy condition



(a) Time waveform (b) Frequency spectrum

Fig. 5 Typical time waveform and frequency spectrum for faulty condition conspicuous difference exists between two conditions. There is a need to come up with a feature extraction method to classify them. The vibration signals were preprocessed to obtain the characteristic features of the high-frequency components dominated by the fault. Two schemes were studied for comparison: simple preprocessing techniques such as band-pass filtration and wavelet transform. The signals were subjected to band-pass filtration to remove the low-frequency interference components. Four band-pass frequencies of filters were chosen as BP1 (3-4 kHz), BP2 (5-6 kHz), BP3 (6.3-7.3 kHz), and BP4 (9-10 kHz). A time-domain feature, root mean square (RMS) value, were obtained from each of these filtered high-frequency signals and used in the ANN-based classification procedure.

The acquired vibration signals were processed through DWT using Daubechies wavelet order 10 (db10) at level 4 to obtain the coefficients (d_1-d_4) (Daubechies, 1992) as shown in Table 1. Frequency ranges for these coefficients were in the descending order, i.e. d_1 had highest frequency content (5-10 kHz), and d_4 had lowest frequency content (0.625~1.25 kHz). Table 2 illustrates statistical parameters for original vibration signal and its sub-bands (d_1-d_4) in healthy and faulty conditions. Fig. 6 shows the detail sub-bands bands (d_1-d_4) and approximations (a_4) of vibration signal for healthy and faulty conditions, respectively. Time domain features, mean, standard deviation, skewness and kurtosis, were obtained from each of these wavelet transformed signals and used in the ANN-based classification procedure.

3.3 Condition classification

Three classifiers used are ART-KNN, SOFM and LVQ. Same data are used to compare with these networks. The input feature parameters are to use 12 values that are calculated from the RMS values of four band-pass frequencies and the statistical method (mean, standard deviation, skewness and kurtosis) in each level of wavelet coefficients. After the training process the systems were tested on 504 normal compressors and 120 abnormal ones. The general trend of classification success rate of ART-KNN as shown in Fig. 7 is increasing with the criterion parameter ρ. However, it is not continuous. Each cluster is composed of many neurons with the same property, and the cluster region becomes the summation of total neuron region representing its region (Yang et al., 2004). The number of neurons is directly proportional to ρ. The classification results of each classifier are shown in Table 3. The ART-KNN was the most classification rate with a best testing performance of all 100% for healthy and faulty conditions. The average test success of SOFM was 94.7% for wavelet transformed data whereas it was 91.0% for band pass filtration. The average

Table 1 Frequency sub-bands of the vibration signal

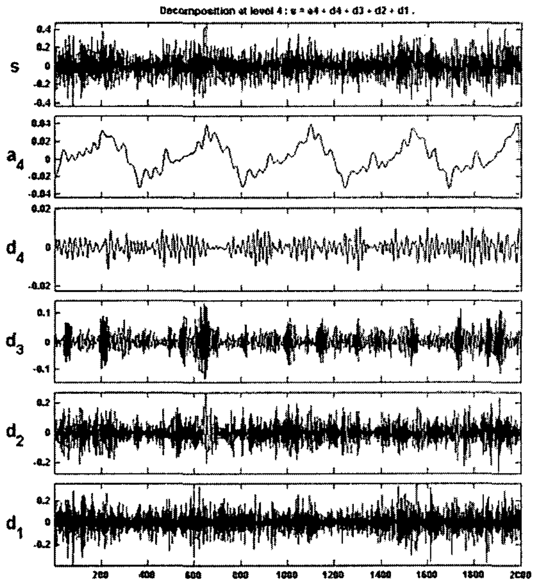
Details	Sub-bands (Hz)	Approximations	Sub-bands (Hz)
d_1	5000-10000	a_1	0-5000
d_2	2500-5000	a_2	0-2500
d_3	1250-2500	a_3	0-1250
d_4	625-1250	a_4	0-625
d_5	312.5-625	a_5	0-312.5
d_6	156.25-312.5	a_6	0-156.25
d_7	78.125-156.25	a_7	0-78.125
d_8	39.0625-78.125	a_8	0-39.0625
d_9	19.5313-39.0625	a_9	0-19.5313
d_{10}	9.7656-19.5313	a_{10}	0-9.7656

Table 2 Statistical parameters for original and sub-bands (d_1-d_4) in healthy and faulty conditions

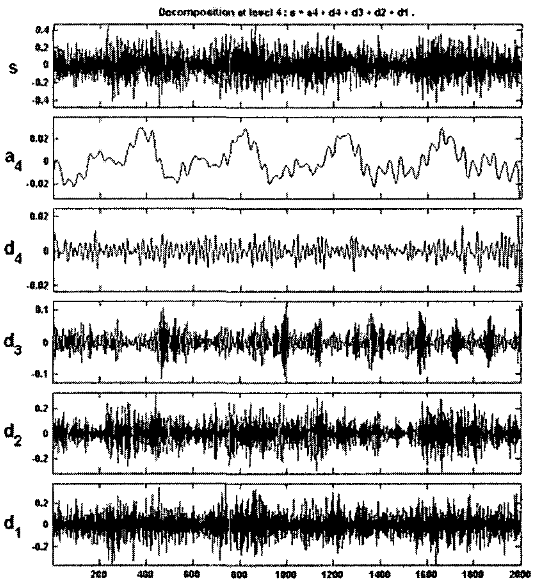
Level	Mean value C_1		Standard deviation C_2		Skewness C_3		Kurtosis C_4	
	Healthy	Faulty	Healthy	Faulty	Healthy	Faulty	Healthy	Faulty
d_1	7.533e-6	4.695e-7	0.110	0.097	0.034	0.007	3.475	3.335
d_2	−1.288e-5	−1.113e-6	0.085	0.061	0.012	0.013	3.823	3.610
d_3	−2.203e-5	1.722e-6	0.032	0.034	−0.006	0.005	4.402	3.945
d_4	−6.550e-7	−1.397e-5	0.004	0.004	−0.100	−0.059	3.639	2.991
Original	1.485e-3	1.454e-3	0.143	0.121	0.110	0.021	3.070	3.055

Table 3 Classification results according to classifiers

Classifier	Condition	Total data	No. of classification	No. of mis-classification	Classification rate (%)
ART-KNN (wavelet)	Healthy	504	504	0	100
	Faulty	120	120	0	100
LVQ (wavelet)	Healthy	504	469	35	93.1
	Faulty	120	80	40	66.7
LVQ (band pass)	Healthy	504	410	94	81.4
	Faulty	120	74	46	61.7
SOFM (wavelet)	Healthy	504	484	20	96.0
	Faulty	120	107	13	89.2
SOFM (band pass)	Healthy	504	481	23	95.6
	Faulty	120	87	33	72.5



(a) Healthy condition



(b) Faulty condition

Fig. 6 Detail sub-bands (d_1-d_4) and approximations (a_4) of vibration signal

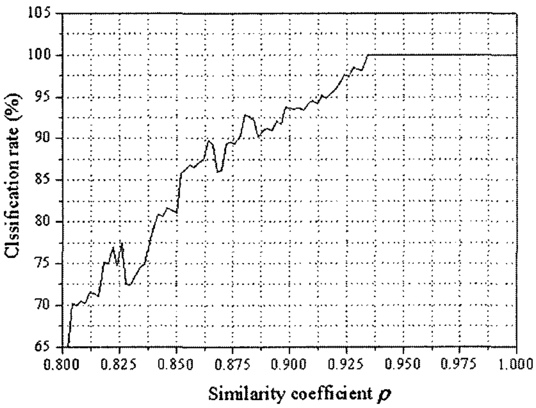


Fig. 7 Classification rate of ART-KNN network

classification rate of LVQ was unsatisfactory in most cases and achieves 88.0% with wavelet transform and 77.6% with band pass filtration, respectively.

The result indicates that ART-KNN is the most suitable to classifier compressor quality on production line. This final result can attribute to neural network category. SOFM and LVQ are off-line networks, and ART-KNN is on-line network. The off-line neural networks show good performance for steady classification problem. In this paper, the source that results in faulty compress is uncertain since there are many components in compressors. Thus, training data including all fault possibility is impossible. When the trained systems are used to test unknown faulty compressor, the classification will decrease. ART-KNN can overcome this shortcoming since it can adapt new conditions well based on its characteristics.

4. Conclusions

This study presents a condition classification system for quality examination of small-type reciprocating compressors in an automatic mass production line. Three classifiers, namely, SOFM, LVQ and ART-KNN were used to compare with the classification performance. A synthesize of approaches, discrete wavelet transform, band-pass filtration and statistical method was used to extract features from vibration signals. The feasibility of the system was tested through test data and applied on a practical production line. The classification accuracy of ART-KNN was better than of SOFM and LVQ and was achieved 100% classification success in all test cases. Also the results indicate that wavelet transform can effectively improve system performance. In another words, wavelet transform can magnify the difference between normal and faulty compressors. The classification accuracy was 81.4-100% with features using wavelet transform and 61.7-89.2% with features using band-pass filtration. Currently it is applied to examine all products automatically on-line instead of quality examination using auditory approach by the field engineers. This system can be provided reliable condition classification which is accurate, fast, reliable and scientific examination. The system will also lead to increase productivity and reduce loss of components and downtime.

Acknowledgments

The data set was acquired from LG Electronics, Inc., Korea through an industrial cooperation research project. The authors thank Digital Appliance Research Laboratory, LG Electronics, Inc. for making the data set available and providing useful comments.

References

Altmann, J. and Mathew, J., 1999, "Automated DWPA Feature Extraction of Fault Information from Low Speed Rolling Element Bearing," *Proc. A-PVC '99*, pp. 637~641.

Carpenter, G. A. and Grossberg, S., 1987, "ART2 : Self-Organization of Stable Category Recognition Codes for Analog Input Patterns," *Applied Optics*, Vol. 26, No. 23, pp. 217~231.

Carpenter, G. A. and Grossberg, S., 1988, "The ART of Adaptive Pattern Recognition by a Self-Organizing Neural Network," *IEEE Trans. on Computer*, Vol. 21, No. 3, pp. 77~88.

Carpenter, G. A. and Grossberg, S., 1991, "ART3 : Hierarchical Search Using Chemical Transmitters in Self-Organizing Pattern Recognition Architectures," *Neural Networks*, Vol. 4, No. 3, pp. 129~152.

Carpenter, G. A. and Grossberg, S., 1992, "A Self-Organizing Neural Network," *IEEE Communications Magazine*, Vol. 30, No. 9, pp. 38~49.

Daubechies, I., 1988, "Orthonormal Bases of Compactly Supported Wavelets," *Communications on Pure and Applied Mathematics*, Vol. 41, pp. 909~996.

Daubechies, I., 1992, *Ten Lectures on Wavelets*, SIAM, Pennsylvania, USA.

Dickie, J. R., 1995, *An Investigation into Second- and Higher-Order Statistical Signal Processing Tools for Machine Condition Monitoring*, PhD thesis, University of Strathclyde.

Gardner, J. W., Hines, E. L. and Pang, C., 1996, "Detection of Vapours and Odours from a Multisensor Array Using Pattern Recognition : Self-Organizing Adaptive Resonance Techniques," *Measurement and Control*, Vol. 29, pp. 172~177.

Kohonen, T., 1992, *LVQ_PAK- The Learning Vector Quantization Program Package*, Department of Technical, Physics, Helsinki University of Technology.

Kohonen, T., 1995, *Self-Organizing Maps*, Springer-Verlag, Berlin.

Kohonen, T., 1996, "Engineering Application of the Self-Organizing Map," *Proc. IEEE*, Vol.

84, No. 10, pp. 1358~1384.

Lim, D. S., An, J. L., Yang, B. S. and Kim, D. J., 2001, "Intelligent Condition Classification System of Rotating Machinery Using Wavelet Transform, Feature Evaluation Index and LVQ," *Proc. 8th Int. Congress on Sound and Vibration*, pp. 2371~2378.

Liobet, E., 1999, "Fuzzy ARTMAP Based Electronic Nose Data Analysis," *Sensors and Actuators B*, Vol. 61, pp. 183~190.

Mallat, S. G., 1989, "A Theory for Multiresolution Signal Decomposition: the Wavelet Representation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 11, No. 7, pp. 674~693.

Nandi, A. K. and Dickie, J. R., 1994, "A New Approach to Condition Monitoring Using Higher-Order Statistics," *Proc. COMADEM-94*, pp. 197~203.

Tahk, K. M. and Shin, K. H., 2002, "A Study on the Fault Diagnosis of Roller-Shape Using Frequency Analysis of Tension Signals and Artificial Neural Networks Based Approach in a Web Transport System," *KSME International Journal*, Vol. 16, No. 12, pp. 1604~1612.

Yang, B. S., Lim, D. S., Seo, S. Y. and Kim, M. H., 2000, "Defect Diagnostics of Rotating Machinery Using SOFM and LVQ," *Proc. 7th Int. Congress on Sound and Vibration*, pp. 567~574.

Yang, B. S., Kim, K. and Rao, Raj B. K. N., 2002, "Condition Classification of Reciprocating Compressors Using RBF Neural Network," *International Journal of COMADEM*, Vol. 5, No. 4, pp. 12~20.

Yang, B. S., Han, T. and An, J. L., 2004, "ART-Kohonen Neural Network for Fault Diagnostics of Rotating Machinery," *Mechanical Systems and Signal Processing*, Vol. 18, No. 3, pp. 645~657.

Yang, B. S., Hwang, W. W., Kim, D. J. and Tan, A. C., 2005, "Condition Classification of Small Reciprocating Compressors for Refrigerators Using Artificial Neural Networks and Support Vector Machines," *Mechanical Systems and Signal Processing*, Vol. 19, No. 2, pp. 371~390.