Tran, Van Tung

Intelligent Fault Diagnosis System using BEMD based Thermal Image Enhancement And Support Vector Machines

Intelligent Fault Diagnosis System using BEMD based Thermal Image Enhancement And Support Vector Machines

Van Tung Tran*, Tan Tung Phan*, and Bo-Suk Yang**

* Faculty of Mechanical Engineering, Hochiminh City University of Technology, Hochiminh City, Vietnam
(Tel : +84-8-38637897; E-mail: tvtung@hcmut.edu.vn)

** Department of Mechanical and Automotive Engineering, Pukyong National University, Busan, Korea
(Tel : +82-51-629-6152; E-mail: bsyang@pknu.ac.kr)

Abstract: This study proposes an investigation of a novel thermal image enhancement based on bi-dimensional empirical mode decomposition (BEMD) and applies this method for rotating machinery fault diagnosis system. In this work, thermal images of machine conditions are firstly decomposed into intrinsic mode functions (IMFs) by utilizing BEMD. At each decomposition level, the IMF is expanded and fused with the residue by using gray-scale transformation and principal component analysis fusion technique, respectively. Finally, the enhanced image is rebuilt from the improved IMFs in reconstruction process. In order to diagnose the machine faults, histogram features are extracted from enhanced image. This results in high dimensionality of feature set which causes difficulties for data storage and decreases the accuracy in fault diagnosis. The high dimensionality is surmounted by employing the generalized discriminant analysis (GDA), which is one of the feature extraction methods. The features obtained from GDA are subsequently utilized for fault diagnosis system in which support vector machine is used as classifier. The results show that the proposed enhancement method is capable of improving the accuracy of classification and efficiently assisting in rotating machinery fault diagnosis

Keywords: Thermal image, Bi-dimensional empirical mode decomposition, Rotating machinery fault diagnosis, Generalized discriminant analysis

1. INTRODUCTION

Rotating machinery covers a wide range of mechanical equipment and is of importance to industrial applications. Therefore, the faults of rotating machinery may drastically affect the product operations in industry and even the safety of machine operators. To minimize the machine breakdown as well as to increase the machine reliability, machine conditions are necessary for monitoring and early detecting the symptoms or incipient faults. By this way, the life of machine could be prolonged and the catastrophic consequences could be avoided due to machine failures. Consequently, machine fault diagnosis and machine condition monitoring for rotating machinery have been the subjects of considerable researches in recent years.

However, the evolution of science and technology has been gradually enabling the rotating machinery in modern industry to be more automatic and precise. This leads to difficulties in detecting potential faults of rotating machinery. Therefore, it is necessary to increase fault diagnosis capability and implement suitable signals which intensify the fault detection. In general, acoustics and vibration are signals which are commonly used due to their easy-to-measure characteristics and analysis. Numerous approaches referred in [1-8] as some outstanding works have been used these signals for machine fault detection and fault diagnosis. Recently, infrared thermal image has been considered as a new signal to be applied for fault diagnosis due to the fact that the object's conditions in operating process can be indicated through its temperature. Consequently, researches on machine fault diagnosis area using thermal image signal have been cogitated in which some primary approaches were carried out in [9-10].

Similarly to the process of using other signals for condition monitoring and fault diagnosis, thermal image processing is firstly required to modify the original images obtained from machine to improve their quality, extract the useful information, and change their structure. Image enhancement, which is a function of image processing, aims to augment some information in an image as a specific requirement, weaken or remove some unwanted information, so that it changes the original image into a more suitable form for human observations or computer analysis. Traditionally, image enhancement technologies can be divided into two categories [11]: image enhancement on spatial domain and image enhancement on frequency domain. Several methods consisted of histogram equalization, adaptive contrast enhancement, smoothing, sharpening, color processing, etc. have been utilized in these categories.

The first commonly used method for image enhancement is histogram equalization (HE). As a consequence, HE flattens the density distribution of the resultant image and enhances the contrast of the image, since it has an effect of stretching dynamic range [12]. However, HE changes the brightness of the image significantly and makes the image become saturated with very bright or dark intensity values [13]. The second method is unsharp masking (USM). The classic linear USM is implemented by passing a low-contrast image through a linear two-dimensional high-pass filter and then adding a fraction of its output to the origin. This method enlarges the image noise, particularly in uniform areas of even slightly noisy images and causes overshoot artifacts in high-contrast regions. HE and USM are only the compromise between de-noising and enhancing image details. Furthermore, they are also less sensitive to noise presented in the input. Another commonly used method is wavelet transformation. The main advantage of this method is that no artificial information is introduced into the enhanced image. This allows some flexibility to be required in different applications. Nevertheless, this method has a main drawback which the basis function has to be defined a priori and this choice may influence the final results.

To overcome the shortcomings of traditional methods, a novel enhancement method is proposed in this study. This method is based on empirical mode decomposition (EMD) primarily introduced by Huang et al. [14]. By using EMD, any complicated signal can be decomposed into a collection of intrinsic mode functions (IMFs) based on the local characteristic time scale of the signal. EMD is self-adaptive because the IMFs, working as the basis functions, are determined by the signal itself. Therefore, EMD is highly efficient in non-stationary data analysis. The bi-dimensional EMD (BEMD) is a two-dimensional generalization of the EMD which was firstly proposed by Linderhed [15] for image compression. In this work, to enhance the thermal images of machine conditions, BEMD is utilized to decompose the thermal image into the IMFs. At each decomposition level, the IMF is expanded and fused with the residue by using gray-scale transformation and principal component analysis fusion technique, respectively. The final enhanced image is obtained from the reconstruction process of BEMD.

In order to diagnose the machine condition based on thermal images, the next stage so called feature representation process is implemented to draw out useful information of image. According to Umbaugh [16], the image features consist of histogram, spectral, texture, and color. Among these, histogram features which are truly statistical features are a compact representation of image characteristics without requiring knowledge about them. Moreover, these features provide us with information about the characteristics of the intensity gray level distribution for the image. Hence, they are suitable for fully automatic characterization of images and are used in this study. Histogram features consist of mean, standard deviation, skew, energy, entropy, and kurtosis. Normally, these features are rarely usable due to the huge dimensionality which not only causes difficulties for data storage but also increases inaccuracy in fault diagnosis. Therefore, dimensionality reduction or feature extraction is an essential data preprocessing technique for classification tasks. In machine fault diagnosis, there have been numerous approaches for feature extraction such as independent component analysis, principal component analysis [17], and genetic algorithms [18]. In this study, the generalized discriminant analysis (GDA) based feature extraction is investigated with the aim of improving the classification performance.

Subsequent to feature extraction procedure, selecting the models for classification or diagnosis task is carried out for the next stage. These models have a wide range of approaches which are varied from model-based to pattern recognition-based. Amongst these approaches, machine learning and artificial intelligence techniques based machine fault diagnosis system is regularly used due to their accuracy and their flexibility. In this study, support vector machine (SVM) which is one of the remarkable machine learning techniques is used as classifier for classifying the different machine conditions such as normal, misalignment, mass unbalance, and bearing fault. The result shows that the proposed enhancement method in association with GDA and SVM is capable of improving the accuracy of classification and efficiently assisting in rotating machinery fault diagnosis.

2. BACKGROUND KNOWLEDGE

2.1. Histogram features

Histogram features are statistical ones which provide us information about the characteristics of the grey-level distribution for the image. Let's consider an image I, the first-order histogram probability P(g) can be defined as:

$$P(g) = \frac{N(g)}{M} \tag{1}$$

where M is the number of pixels in the image I, N(g) is the number of pixels at grey level g. The histogram features of image based on the first-order histogram probability are mean, standard deviation, skew, energy, entropy, and kurtosis. These features are expressed as followings

2.1.1. Mean: is the average value that gives some information about general brightness of image. Denote L as total number of grey levels for the available range from 0 to 255 for the image. The mean can be defined as:

$$\bar{g} = \sum_{g=0}^{L-1} gP(g) = \sum_r \sum_c \frac{I(r,c)}{M} \tag{2}$$

2.1.2. Standard deviation: is the square root of the variance. It provides us something about the contrast and also describes the spread in the data, so a high contrast image will have a high variance, vice versa. It is defined as follow:

$$\sigma_g = \sqrt{\sum_{g=0}^{L-1} (g-\bar{g})^2 P(g)} \tag{3}$$

2.1.3. Skew: measures the asymmetry about the mean in the gray-level distribution. It is defined as:

$$S = \frac{1}{\sigma_g^3} \sum_{g=0}^{L-1} (g-\bar{g})^3 P(g) \tag{4}$$

The skew could be also measured by using the mean, mode, and the standard deviation where the mode is defined as the peak or highest value. This method is more computationally efficient, especially when the mean and the standard deviation have already been calculated

$$S' = \frac{\bar{g} - \text{mode}}{\sigma_g} \tag{5}$$

2.1.4. Kurtosis: is the ratio of the fourth central moment and the square of the variance

$$K = \sum_{g=0}^{L-1} \frac{(g-\bar{g})^4}{\sigma^4} \tag{6}$$

2.1.5. Energy: is a measure that tells us something about how the gray levels are distributed:

$$ENERGY = \sum_{g=0}^{L-1} [P(g)]^2 \tag{7}$$

The energy measure has a maximum value of 1 for an image with a constant value, and it gets increasingly smaller as the pixel values are distributed across more gray-level values.

2.1.6. Entropy: is a measure that provides us how many bits we need to code the image data and is given by:

$$ENTROPY = -\sum_{g=0}^{L-1} P(g) \log_2 [P(g)] \tag{8}$$

2.2. Bi-dimensional empirical mode decomposition

The BEMD is extended of EMD which was originally proposed for one-dimensional data. It is similar to sifting process of EMD, excepted that the curve fitting such as cubic spline interpolation or linear interpolation is replaced by surface fitting for creating envelopes. The detail description of BEMD could be found in [19]. Given the digital image $I = f(x,y)$, $x = 1,\ldots, M$, $y = 1,\ldots, N$, the sifting process of BEMD is summarized as follows.

Step 1: Identify the extrema involved maxima and minima of the image *I*.

Step 2: Generate the upper envelope and lower envelope by connecting maxima points and minima points using surface interpolation, respectively. Determine the local mean surface function m by averaging the upper and lower envelopes.

Step 3: Subtract out the mean surface from the image to get a residue $h = I - m$, judge whether h is an IMF; if it is, go to step 4. Otherwise, repeat step 1 and step 2 using the residue *h* until the latest residue turns to be an IMF.

Step 4: Input the residue *h* to the loop from step 1 to step 3 to get the next remained IMFs until it cannot be decomposed further.

The stopping condition used to judge whether the residue *h* is an IMF and when to stop the loops is defined as:

$$SD=\sum_{k=0}^{M}\sum_{i=0}^{N}\frac{\left|h_{i(j-1)}(k,l)-h_{ij}(k,l)\right|^{2}}{h_{i(j-1)}(k,l)^{2}} \tag{9}$$

2.3. Generalized discriminant analysis (GDA)

The goal of discriminant analysis is to combine features of the original data in a way which most effectively discriminates between classes. When combining features, the dimension of the data is reduced so that most effectively preserves its cluster structure. Linear discriminant analysis (LDA) is a traditional method of this theory and has been fruitfully proven on classification problems. However, LDA was unsuccessful in solving nonlinear problem. Therefore, generalized discriminant analysis (GDA) was proposed to replace LDA for dealing with nonlinear discriminant analysis using kernel function operator. GDA method provides a mapping of the input vectors into high dimensional features space. The detailed description of GDA could be found in [20].

2.4. Support vector machines (SVMs)

SVMs are a relatively new computational learning method based on the statistical learning theory presented by Vapnik [21]. In SVMs, original input space maps into a high-dimensional dot product space so called a feature space, and in the feature space the optimal hyperplane is determined to maximize the generalization ability of the classifier. The maximal hyperplane is found by exploiting the optimization theory, and respecting insights provided by the statistical learning theory. The traditional SVM was proposed for dealing with binary classification where the class labels can take only two values: 1 and −1. However, more than two classes commonly encounters in the real world problem. For examples, in fault diagnosis of rotating machinery, there are several fault classes such as mechanical unbalance, misalignment, bowed shaft, bearing faults, etc. Two algorithms used for multi-class classification are one-against-all (OAA) and one-against-one (OAO). These algorithms could be further read in [22].

3. BEMD BASED IMAGE ENHANCEMENT AND PROPOSED FAULT DIAGNOSIS SYSTEM

BEMD iteratively decomposes the original images into IMFs which are reduced the frequency information gradually. At each level of decomposition, the high-frequency information part being IMF and low-frequency information part being the residue are obtained. The former expresses the image texture whilst the latter expresses the content of the image. In the BEMD-based enhancement method, the high-frequency part is expanded to be clearer and more prominent by multiplying with factor k which is set in $1< k< 3$. In case of high *k* value, the highest frequency augments too much, hence, the borders become too ridge. On contrary, if *k* value is smaller than 1, the loss of borders is eminent. The expanded part is then fused with the residual parts by using principal component analysis fusion detailed in [23]. Finally, the enhanced image is obtained from reconstruction process.

The proposed system for machine fault diagnosis using thermal image is shown in Fig. 1. This system consists of consequent modules: image preprocessing, image enhancement mentioned above, histogram feature representation, feature extraction, and classification. Thermal images captured from the machine conditions which are normal condition, misalignment, mass unbalance, and bearing fault are utilized as the input for this system. These images are processed by the preprocessing module to remove the noise, enhance the contrast of image using HE algorithm, and crop the region of interest (ROI). Then, these preprocessed images are passed through the feature representation module where histogram features are extracted. However, as fore-mentioned, this feature data are normally high dimension and have a large amount of redundant features that will be significantly decreased the performance if they are directly inputted into the classifier. Therefore, GDA-based feature extraction should be employed to choose the appropriate features and transform the exiting feature data into lower dimensional space. Finally, these features will be split into training and testing data to generate the diagnosis model through learning process and validating this model, respectively.

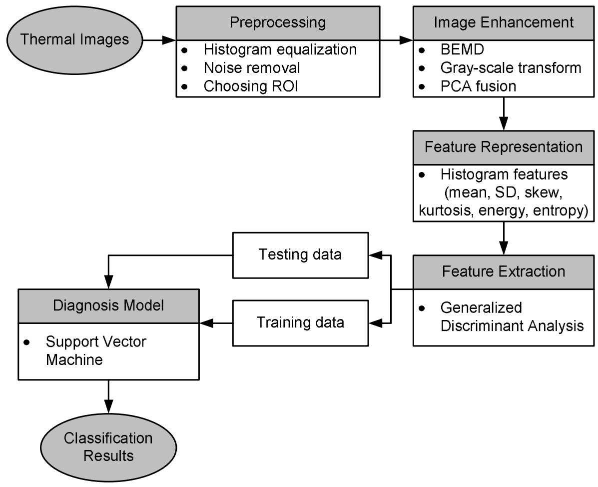

Fig. 1 Proposed system for thermal image based fault diagnosis

4. EXPERIMENTAL SETUP AND IMAGE ACQUISITION

To validate the proposed system, experiment was carried out using simulator which consists of driving motor, shaft, disks, PC for saving data, and thermal camera as shown in Fig. 2. The short shaft which is of 30 mm diameter and is supported by two ball bearings at the ends was attached to the shaft of the motor through a flexible coupling to minimize the effects of misalignment and transmission of vibration from motor. The coupling is also used to adjust the misalignment condition on the fault simulator. In order to create the unbalance condition, the disks with many available thread holes to add extra mass were attached on the shaft. The variable speed DC motor (0.5 HP) with speed up to 3450 rpm was used to drive the motor. Table 1 shows the main specifications of thermal camera and fault simulator. This camera used in the experiments was a long-wave infrared camera from FLIR with a thermal sensitivity of 0.08 °C at 30 °C.

The thermal camera is the major key device and some its parameters requires to be set due to their importance for data acquisition, especially for thermal image data. The most important parameter is emissivity and the other parameters are relative humidity, scale temperature, focal length of camera, and distance. All of these parameters are chosen according to experiment condition. In this study, all of conditions were used same setting parameters to accomplish the experiment.

The experiment for each machine condition was carried out as followings: the speed of the motor was increased gradually up to 900 rpm. This speed was held for five minutes to which the machine reached its stable condition, and then the process of image acquisition was begun. The detailed descriptions of image data in four machine condition experiments are shown in Table 2.

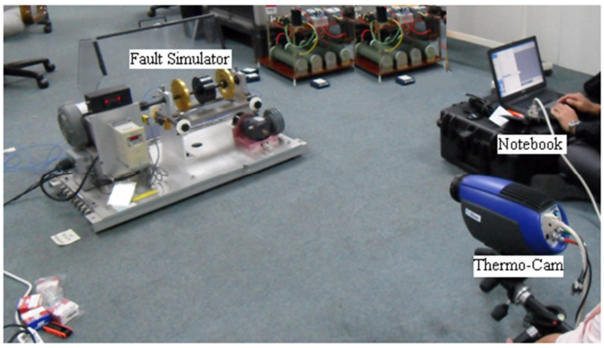

Fig. 2 Experimental setup

Table 1 Specification of Thermal Camera and Fault Simulator

Devices	*Specification*
Thermal camera (FLIR-A 40 series)	• Solid state, uncooled micro bolometer detector, 7.5 to 13 µm • –40 °C to +70 °C storage temperature range • Solid object materials and surface treatments exhibit emissivity • ranging from approximately 0.1 to 0.95. • For short distance, humidity is default value of 50 % • 0.08 °C at 30 °C thermal sensitivity • IP 40 (Determined by connector type)
Fault simulator	• Shaft diameter: 30 mm • Bearing: Two ball bearings • Bearing housings: Two bearing housings, aluminum horizontally split bracket for simple and easy changes, tapped to accept transducer mount • Bearing housing base: Completely movable using jack bolts for easy misalignment in all three planes • Rotors: Two rotors, 6" diameter with two rows of tapped holes at every 20° (with lip for introducing unbalance force)

Table 2 Specification of Thermal Camera and Fault Simulator

Label of Classes	*Machine Condition*	*No. of Samples*	*No. of Training Samples*	*No. of Testing Samples*
C1	Normal	20	10	10
C2	Misalignment	20	10	10
C3	Bearing fault	20	10	10
C4	Mass unbalance	20	10	10

5. RESULTS AND DISCUSSIONS

5.1 Image preprocessing

Fig. 3 shows one of the original thermal images of machine condition. Due to the focus on fault diagnosis in rotating machinery and reduction in the computation of image processing, ROI is chosen from original image as the rectangle where the size is 150×20. This size is likewise applied for other images of all machine conditions. The HE algorithm is subsequently employed for these ROIs to enhance the contrastIn the paper, all authors are required to use the SI unit.

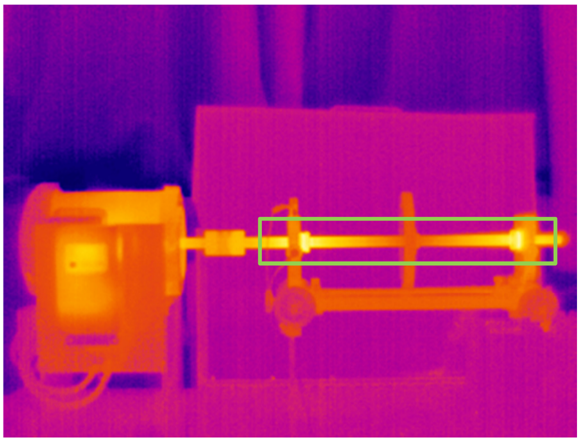

Fig. 3 Original thermal image and ROI

5.2 Feature representation

In this procedure, histogram feature calculation is carried out to describe the characteristics of machine conditions. Totally, 480 feature values (80×6) have been extracted from the ROIs. From now on, the images after enhancing by HE technique and their features are called original images and original features, respectively. As shown in Fig. 4 which depicted the three first original features, the features of machine conditions are not well clustered and overlapped with each other even though the images have been enhanced by HE. This decreases significantly the accuracy of classification result which leads to the misunderstood of real machine condition. Obviously, HE algorithm is not adequate to improve the images for achieving good diagnosis result. Therefore, the enhancement method based on BEMD is used to ameliorate the image quality. The stopping criterion using for BEMD and the k factor are chosen as 0.1 and 1.35,

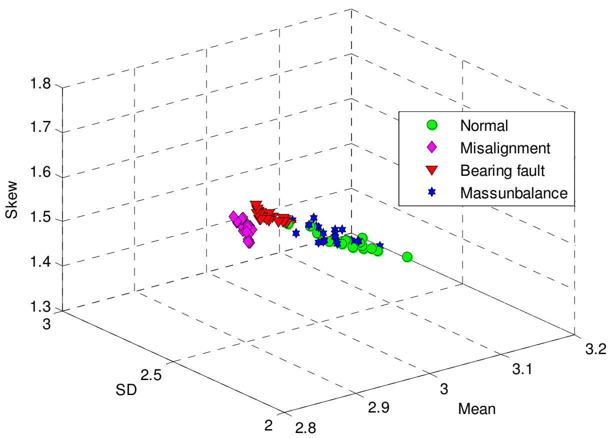

Fig. 4 Original features

respectively. Similarly, histogram features are also extracted from these enhanced images in which the three first features are plotted in Fig. 5. Evidently, after enhancing, the features are well separated. This enables the accuracy of classification to increase considerably.

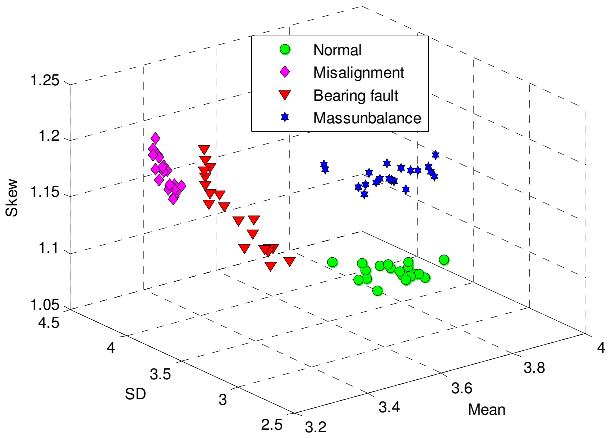

Fig. 5 Enhanced image features

5.3. Feature extraction

The features obtained from previous procedure are normally high dimension and have a large amount of redundant features. It is of necessity to reduce the dimension for increasing computational effect, avoid the disorder of features, and select the prominent features which can precisely characterize the machine condition. For these reasons, GDA is commonly used after feature calculation process. In this study, the number of features is reduced from 6 to 3 after employing GDA which is depicted in Figs. 6 and 7. As shown in Fig. 6, the features obtained from GDA are vastly superior to the original ones in clustering as in Fig. 4. However, there exists the overlap between normal condition and bearing fault condition. This definitely leads to the misclassification in the next step. In comparison with the features obtained from GDA of enhanced images as depicted in Fig. 7, all conditions are separately clustered and there is no any overlap between machine conditions. This helps the classification process to be easier and more accurate.

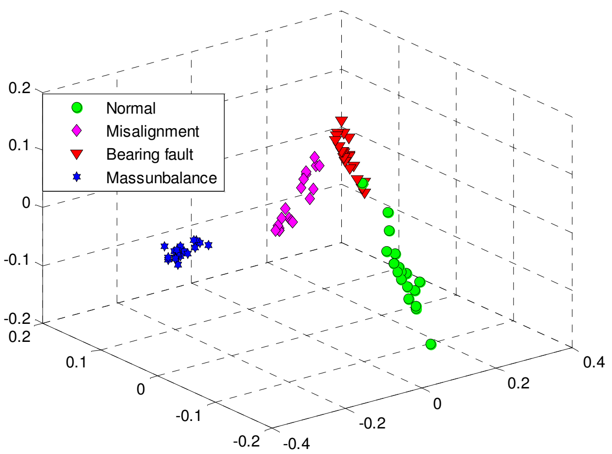

Fig. 6 Original features obtained from GDA

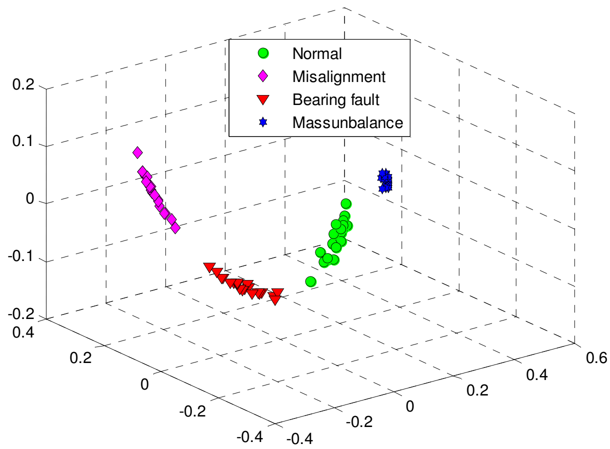

Fig. 7 Enhanced image features obtained from GDA

5.4. Classification results

The next procedure following feature extraction is classification. In this procedure, the features attained from GDA become the inputs of classifier, which SVM is employed here in which two algorithms involved one-against-one (OAO) and one-against-all (OAA) are used. Furthermore, some parameters are predefined e.g. the RBF kernel is used as the basis function of SVM, C and γ are set to 100 and 0.001, respectively. Firstly, the classifiers must be trained by training data before they are used for classifying the machine conditions. Commonly, 50% samples for each condition (10 samples) is utilized as training data and the remaining samples are belong to testing data. The training and testing classification results for OAO and OAA are respectively tabulated in Table 3

Table 3 Results of classification

Features	*Process*	*Classification Accuracy (%)*	
		OAO	*OAA*
Original images	Training	100	100
	Testing	97.5	95
Enhanced images	Training	100	100
	Testing	100	100

In training process, the SVM classifiers applied OAO and OAA method achieve 100% accuracy without any misclassification out of 40 samples of training data for both original features and enhanced features. After training, these classifiers are tested against the testing data. For original features, the classification accuracy of OAO and OAA are respectively as 97.5% and 95% due to the overlap of machine condition features. For features of enhanced images, the accuracy is 100% for all classifiers. The confusion matrix showing the classification results is given in Table 4. In confusion matrix, each cell contains the number of samples that is correctly classified corresponding to the outputs classifiers and actual designs. For example, the number is shown as 9 in the first cell (the first column and the first row of confusion matrix) means that there are 9 outputs belonged to normal condition (C1). It is similar to the other cells in the diagonal of confusion matrix. The other cells that are not in the diagonal of confusion matrix indicate the misclassifications. For example, the cell being in the third column and the first row has the value as 1 shows that one subject should have belonged to class C1 has been classified as subjects of bearing fault condition (C3), etc. In the case of enhanced image features, the entire cell in the diagonal has the value as 10 whilst other cells are zero. This means all machine conditions have been accurately classified. Therefore, it can be concluded that the enhancement method based on BEMD has assisted significantly in increasing the accuracy of machine fault diagnosis.

Table 4 Confusion matrix of testing results

Features	Output/ desired	Confusion Matrix							
		OAO				OAA			
		C1	C2	C3	C4	C1	C2	C3	C4
Original	C1	9	0	1	0	9	0	1	0
	C2	0	10	0	0	0	10	0	0
	C3	0	0	10	0	1	0	9	0
	C4	0	0	0	10	0	0	0	10
GDA	C1	10	0	0	0	10	0	0	0
	C2	0	10	0	0	0	10	0	0
	C3	0	0	10	0	0	0	10	0
	C4	0	0	0	10	0	0	0	10

6. CONCLUSIONS

In this study, the BEMD based image enhancement method and the machine fault diagnosis system using thermal images have been presented. The thermal images captured from machine conditions are firstly preprocessed by using the histogram equalization to enhance the image contrast, removing noise, and cropping to obtain the ROI. These images are further enhanced by enhancement method based on BEMD. Then, the histogram feature representation and the GDA feature extraction are severally carried out to extract the features of enhanced images and reduce the high dimension of feature data. Lastly, the SVM classifiers based on OAO and OAA methods are implemented for these features to classify the machine conditions. The results show that the proposed enhancement method is capable of increasing the accuracy of classification and efficiently assisting in machine fault diagnosis.

REFERENCES

[1] T. Toutountzakis, C.K. Tan, and D. Mba, "Application of acoustic emission to seeded gear fault detection", *NDT & E International*, Vol. 38, pp. 27-36, 2005.

[2] J. D. Wu and C.Q. Chuang, "Fault diagnosis of internal combustion engines using visual dot patterns of acoustic and vibration signals", *NDT & E International*, Vol. 38, pp. 605-614, 2005.

[3] B.S. Yang and K.J. Kim, "Application of Dempster–Shafer theory in fault diagnosis of induction motors using vibration and current signals", *Mechanical Systems and Signal Processing*, Vol. 20, pp. 403-420, 2006.

[4] J. Wang and H. Hu, "Vibration-based fault diagnosis of pump using fuzzy technique", *Measurement*, Vol. 39, pp. 176-185, 2006.

[5] A. Widodo and B.S. Yang, "Application of nonlinear feature extraction and support vector machines for fault diagnosis of induction motors", *Expert System with Applications*, Vol. 33, pp. 241-250, 2007.

[6] B.S. Yang, T. Han, and J.L. An, "ART-Kohonen neural network for fault diagnosis of rotating machinery", *Mechanical Systems and Signal Processing*, Vol. 18, pp. 645-657, 2004.

[7] S.K. Lee and P.R. White, "Higher-order time-frequency analysis and its application to fault detection in rotating machinery", *Mechanical Systems and Signal Processing*, Vol. 11, pp. 637-650, 1997.

[8] J. Cheng, Y. Yang, and D. Yu, "The envelope order spectrum based on generalized demodulation time-frequency analysis and its application to gear fault diagnosis", *Mechanical Systems and Signal Processing*, vol. 24, pp. 508-521, 2010.

[9] C. Meola and G.M. Carlomaggo, "Recent advance in the use of infrared thermography", *Measurement Science and Technology*, Vol. 15, pp R27-R28, 2004.

[10]S. Bagavathiappan, T. Saravanan, N.P. George, J. Philip, T. Jayakumar, and B. Raj, "Condition monitoring of exhaust system blowers using infrared thermography", *Insight*, Vol. 50, pp. 512-515, 2007.

[11]R.C. Gonzalez and R.E. Woods, *Digital image processing*, *3rd ed.*, MA, Addision-Wesley, 1993.

[12]Y.T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization", *IEEE Transactions on Consumer Electronics*, Vol. 43, pp. 1-8, 1997.

[13]D. Menotti, L. Najman, J. Facon, and A.A. de Araujo, "Multi-histogram equalization methods for contrast enhancement and brightness preserving", *IEEE Transactions on Consumer Electronics*, Vol. 53, pp. 1186-1194, 2007

[14]N.E. Huang, et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis", *Proceeding of the Royal Society of London, Series A: Mathematical, Physical and Engineering Sciences*, Vol. 454, pp. 903-995, 1998.

[15]Anna Linderhed, "2D empirical mode decompositions in the spirit of image compression", *Wavelet and Independent Component Analysis Applications IX , SPIE Proceedings*, Vol. 4738, pp. 1-8, 2002.

[16]S.E. Umbaugh, *Computer Imagign: Digital Image Analyis and Processin*g, Taylor & Francis, Boca Raton, 2005.

[17]A. Widodo and B.S. Yang, "Application of nonlinear feature extraction and support vector machines for fault diagnosis of induction motors", *Expert System with Applications*, Vol. 33, pp. 241-250, 2007.

[18]W. Siedlecki and J. Sklansky, "A note on genetic algorithm for large scale feature selection", *Pattern Recognition Letter*, Vol. 10, pp. 246-259, 1989.

[19]J.C. Nunes, Y. Bouaoune, E. Delechelle, O. Niang and Ph. Bunel, "Image analysis by bidimensional empirical mode decomposition", *Image and Vision Computing*, Vol. 21, pp. 1019-1026, 2003.

[20]G. Baudat and F. Anouar, "Generalized discriminant analysis using a kernel approach", *Neural Computation*, Vol. 12, pp. 2385-2404, 2000.

[21]V.N. Vapnik, *The Nature of Statistical Learning Theory*, New York, Springer, 1999.

[22]B.S. Yang and A. Widodo, *Introduction of Intelligent Machine Fault Diagnosis and Prognosis*, New York, Nova Science Publishers, 2009.

[23]H. Hariharan, A. Gribok, M.A. Abidi, and A. Koschan, "Image fusion and enhancement via empirical mode decomposition", *Journal of Pattern Recognition Research*, Vol. 1, pp. 16-32, 2006.