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APPLICATION OF THERMAL IMAGE: MACHINE FAULT DIAGNOSIS USING PCA AND ICA COMBINE WITH SVM

Ali Md. Younus, Achmad Widodoa, Bo-Suk Yang

School of Mechanical Engineering, Pukyong National University,Busan, South Korea

ABSTRACT
A new approach for fault diagnosis of rotating machine based on thermal image investigation using image histogram features is proposed in this paper. By using thermal image, the information of machine condition can be investigated; it is easier than other conventional methods of machine condition monitoring. In the current work, the behavior of thermal image is investigated with different condition of machine. A test-rig that represents the machine in industry was set up to produce thermal image data in experiment. Some significant features have been extracted and selected by means of PCA and ICA and other irrelevant features have been discarded. The aim of this study is to retrieve thermal image by means of selecting proper feature to recognize the fault pattern of the machine. The result shows that classification process of thermal image features by SVM and other classifier can serve for machine fault diagnosis.

Keywords: Thermal image, Features, Condition Monitoring, Pattern Recognition.

1. INTRODUCTION
Among the excellent condition monitoring tools, infrared thermograph (IRT) is one of the important tool which can assist in the reduction of maintenance time and cost of industry. IRT allows for inspection of mechanical machinery for thermal pattern on pump, motors, bearings, fans, pulleys and other rotating machinery [1]. For new approach of machine condition monitoring, IRT has significant part due to frequently fault diagnosis. Indeed, thermal image is able to indicate whether the machine condition is normal or abnormal. For example, the support bearing contains very useful information on the subject of machine condition so the condition monitoring (CM) data in real application should be experimented on them. Infrared (IR) imaging approach is used in the industry as a part of non-destructive evaluation of machine condition especially to check misalignment, bend shaft and rolling element bearing fault based on thermography (temperature) data [2-4]. Hence, data analysis technique is essential in every approach for machine condition identification.

Fault diagnosis of rotating machinery can be handled as a task of pattern recognition that consists of three steps: data acquisition, feature extraction and final condition identification is the demandable issue of fault diagnosis. In order to obtain correct information whether normal or abnormal, it is important to complete all step of signal processing whatever the signal type such as vibration, image, current, acoustic signal and so on. In this study, the image histogram features have been chosen for pattern classification and condition monitoring because all thermal image features are not useful to fault diagnosis. Images play with many features such as shape, histogram, colour, spectra texture and others [5]. Fault pattern classification specially for image is typically included of image acquisition, pre-processing, segmentation, feature extraction or dimension reduction, feature selection, classification and decision steps. It is the task of exploring the model that generated the patterns that we must concern with.

Histogram based features such as standard deviation, skew, variance, energy, entropy etc. as dimensionless parameters are effective and practical in fault diagnosis of rotating machinery due their relative sensitivity to early faults and robustness to various load and speed. Here, dimensionless parameters are extracted from the raw IRT data which have unfortunately large dimensionality that may increase the computational burden of a subsequent classifier and degrade the generalize capability of the classifier. Therefore, to overcome these difficulties, a few original features which apparently characterize the machine operating condition need to be selected feature from all features. The methods such as distance evaluation technique [6], genetics algorithm [7, 8], conditional entropy [9] are applied to seek the proper features to established machine characteristics. So after getting normalized features by extracting method, the extracting features are fed into the classification algorithm to identify the machine status as the final step of condition monitoring. Widodo & Yang et al [6] and J.-D. Son et al.[10] used support vector machines(SVM) classifier for vibration and current signal which performed very well to fault diagnosis. Nui & Yang et al. [11] introduced multi-agent decision fusion using several classifier together and B.S Yang et al. [12] showed the new approached of fault classification which is adaptive resonance theory kohonen neural network (ART-KNN).

This report provides a fault diagnosis scheme for rotating machinery based on thermograph signal by employing histogram features of image. In this experiment, four machine conditions were measured to acquire data. Acquiring data is processed as follows: firstly, features of thermal images are calculated based on Histogram features of Image. Secondly, the feature extraction is conducted by pre-processing techniques by PCA and ICA. Lastly, the extracted data are used for input of the classification algorithms such as support vector machines (SVM), Fuzzy k-Nearest Neighbour (Fk-NN), Adaptive Resonance theory- KOHONEN neural network (ART-KNN) and The Parzen Probabilistic Neural Network (PPNN). The propose method is tested through characterize the different condition of machine fault simulator (MFS). The result from this method validates for assessing the machine state.

2. FEATURE EXTRACTION AND EVALUATION

Feature extraction is one of the most important parts used for condition monitoring and fault diagnosis, whose aim is finding a simple and effective transform of original signals. Important features contain in the signal can be extracted for machine condition monitoring and fault diagnosis. The selected features will be the major factor that determines the complexity and success of signal pattern classification process. Detail has been discussed about image features by Umbaugh & Scott [5]. For thermal image analysis, Histogram features of image have been used because data structure of thermograph in temperature scale is similar to the image gray level distribution as like array structure.

2.1 Histogram Features

The histogram features can be considered as statistical based features which provide us information about the characteristic of the gray level distribution for the image. Notated that, for thermal image the gray level of image depends on temperature that always varies with temperature. Now let us consider a image I, thus the first-order histogram probability P(g) can be expressed as

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

Where M is the number of pixel in the image I or sub image considering that's entire dimension is NxN and N(g) is the number of gray level g.

The mean is the average value which gives some information about general brightness of the image. As the colour distribution varies on temperature so the thermal image can be classified according to its colour intensities. We will use L as total number of gray level available range from 0 to 255 for image but for thermograph signature which is comparable with maximum and minimum temperature as may be mentioned 0^0K to maximum value of temperature. Therefore, mean can be defined as follows

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

Variance is defined as a measure of the dispersion of a set of data points around their mean value.

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

The standard deviation, which is also known as the square root of the variance, tells us something about the contrast. It describes the spread in the data, so a high contrast image will have a high temperature distribution over image. Using this we can be able to classify various of machine conditions thermal images. Standard deviation is termed as follows

$$\sigma_g = \sqrt{\sum_{g=0}^{L-1} (g-\bar{g})^2 P(g)} \tag{4}$$

The skew S measures the asymmetry about the mean in the gray level distribution. It is defined as

$$S = \frac{1}{\sigma_g^3} \sqrt{\sum_{g=0}^{L-1} (g-\bar{g})^3 P(g)} \tag{5}$$

The energy E tells us something about how the gray levels are distributed

$$E = \sum_{g=0}^{L-1} [P(g)]^2 \tag{6}$$

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

The entropy E_t is a measure that tells us how many bits we need to code the image data, and is given by

$$E_t = \sum_{g=0}^{L-1} P(g) \log_2 [P(g)] \tag{7}$$

As the pixel values in the image are distributed among more gray levels, the entropy increases. A complex image has higher entropy than a simple image.

The kurtosis K is just the ratio of the fourth central moment and the square of the variance.

$$K = \sum_{g=0}^{L-1} \frac{(g-mean)^4}{\sigma^4} \tag{8}$$

2.2 Feature Extraction and classification

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called *features extraction*. If the features are carefully extracted then it is expected that the features set will contain the relevant information from the input data in order to perform the desired task. Two types of feature extraction method have been applied in this current work which are Principal component analysis (PCA) and Independent component analysis (ICA). PCA is a classical statistical method and is often used to machine fault diagnosis and pattern classification. And ICA is a technique that transform multivariate random signal into a signal having components that as mutually independent in complete statistical sense. For classification, SVMs, ARTKNN FKNN, PPNNs and e.tc. algorithms are used for machine condition diagnosis.

3. EXPERIMENT AND MEASUREMENTS

3.1 Experimental setup

Figure1 show the fault simulator with thermo-cam sensor that is apart and a short shaft of 30 mm diameter is attached to the shaft of the motor through a flexible coupling; this minimizes effects of misalignment and transmission of vibration from motor. Using coupling we can set misalignment condition of the fault simulator. The shaft is supported at its ends through two ball bearings. A disk is attached with the shaft that is used for making balanced and unbalanced condition of fault simulator. To get unbalanced extra mass is to add on the disk. A variable speed DC motor (0.5 HP) with speed up to 3450 rpm is used as the basic drive. Table 1 shows the main specification of thermo cam and fault simulator. The sensor used in the experiments for this study is a long-wave IR camera from FLIR with a thermal sensitivity of 0.08 °C at 30 °C.

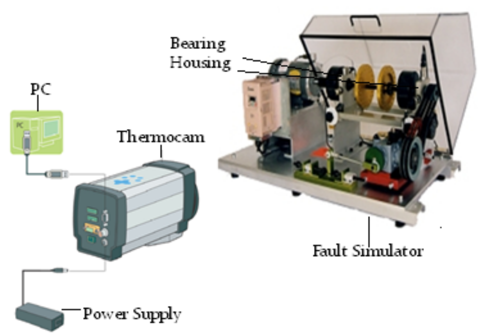

Fig 1. Experimental setup

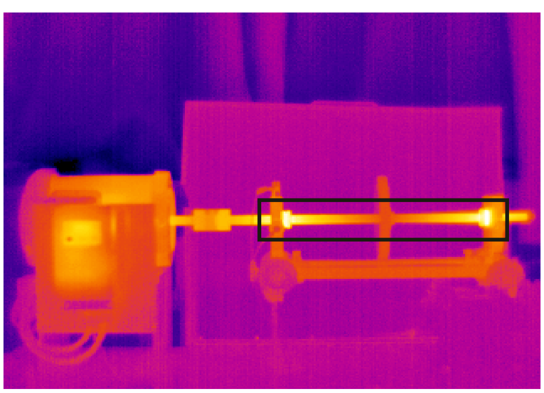

Fig 2. Original Thermal Image

misalignment and transmission of vibration from motor. Using coupling, we can set misalignment condition of the fault simulator. The shaft is supported through two ball bearings at its ends. Disks are attached on the shaft used to make balanced and unbalanced condition of fault simulator. To get unbalanced, extra mass is added on the disks. A variable speed DC motor (0.5 HP) with speed up to 3450 rpm was used as the basic driver. Table 1 shows the main specification of thermo cam and fault simulator. The sensor used in the experiments for this study is a long-wave IR camera from FLIR with a thermal sensitivity of 0.08 °C at 30

3.2 Experimental procedure

In this experiment, the thermo-cam is the major key device that some parameters are set for data accusation. Some specifications of the thermo cam have been given in the prior section where we can get some idea, regarding thermo-cam. Herein, some parameters are very important to obtain data is emissivity of the object that plays fundamental role for image (signal) accusation but those parameters are put automatically functioning of thermo-cam and all machine's materials about to same. Others parameter of objects, for example, relative humidity, scale temperature, focal length of camera and distance are set as our requirement of experiment. All of these parameters are chosen according to our experiment condition. For all four normal, mass unbalance , misalignment and bearing fault condition, we have put same parameter for accomplished the experiment.

In the current study, we try to analyze different types of faulty condition machine by this experiment. Firstly, the normal condition of machine was set, afterward speed of the motor been increased gradually up to 900 rpm. And then, machine was run for five minutes to get its stable condition then data acquisition was lunched. We conducted experiment of normal, misalignment and mass unbalance condition of machine successively. Data from thermo-cam was saved directly to the notebook or PC. The image from thermo-cam is shown in Figure 2. which carrying only visual inspection of machine condition. Figure 3. shows the data structure from thermo-cam in Kelvin scale which has been processed for fault diagnosis.

....	....	....	....	....	...	...	...	...	....	...
....	....	....	....	...	...	....	....	...	....	...
....	....	315.58	315.79	315.39	315.12	314.83	311.94	304.97	....	....
....	....	315.72	316.35	315.87	315.51	315.16	312.65	305.41	....	...
....	....	316.51	316.62	316.05	315.69	315.23	312.84	305.46	....	....
....	....	316.45	316.80	316.41	316.13	315.55	313.55	305.86	....	...
....	....	316.22	316.41	316.32	316.44	315.87	313.77	306.26	....	...
....	....	315.89	316.44	316.49	316.60	316.18	314.08	306.23	....	...
....	....	315.36	316.12	315.90	316.15	316.18	314.51	307.18	....	...
....	....	315.67	315.82	315.72	315.82	315.94	316.02	314.34	....	...
....	....	315.10	315.57	315.72	315.74	315.67	322.69	331.09	....	...
....	....	315.21	315.64	315.95	315.84	316.97	324.40	334.91	....	...
....	....	....	....	....	...	...	...	...	....	...
....	....	....	....	...	...	....	....	...	....	...

Fig 3. Temperature in Kelvin Scale at each pixel of thermal image

Table 1: Specification of thermo-cam and fault simulator

Thermo-cam	• Solid state, uncooled micro

(FLIR-A 40 series)	bolometer detector, 7.5 to 13 µm • -40 °C to +70 °C storage temperature range • Solid object materials and emissivity: 0.1 to 0.95. • For short distance, humidity is default value of 50 %. • 0.08 °C at 30 °C thermal sensitivity
Fault simulator	• Shaft diameter: 30 mm • Bearing: Two ball bearings • Bearing housings: Two bearing housings, • 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°.

4. RESULT AND DISCUSSION

4.1 Feature representation and Feature extraction

In the following feature extraction process, histogram based image features of thermal image data have been used which a new approach to machine condition monitoring.

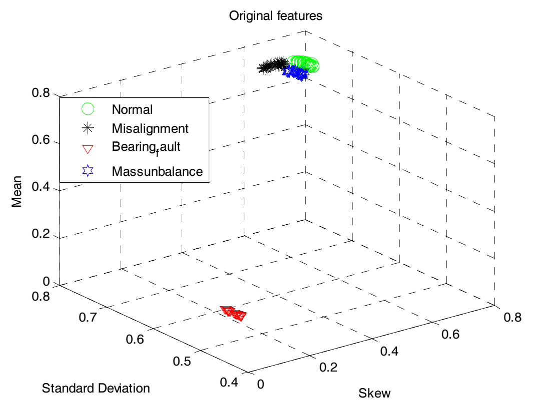

Fig 4. Original features selected randomly

In fact, the original features data could not be possible to cluster well because it is high dimension data structure and being overlapped each other. This phenomenon is shown in the Figure 4, the three features from the original features data(120) has been chosen manually without applying any feature extraction algorithm. The representation of features in figure has possessed as scattered due to large size of data only limited number data having to present. Also different type of faults in figure is overlapped each other. So, these data cannot be separated and also not possible to directly processed into classifier because it will degrade the performance of classifier

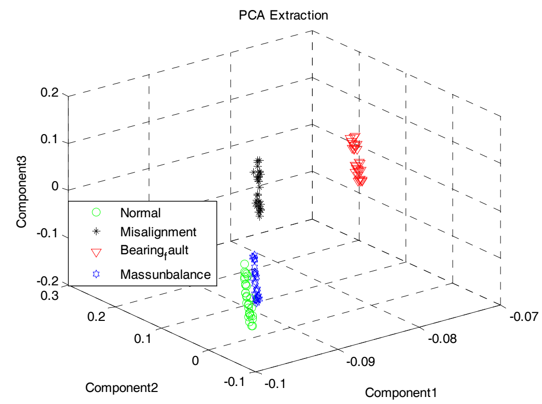

Fig 5. Clustering features by PCA

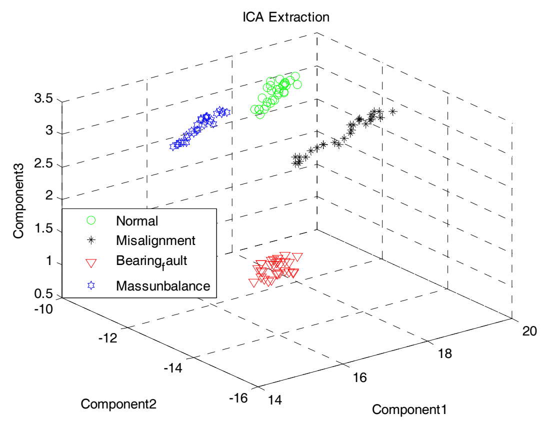

Fig 6. Clustering features by ICA

To overcome these problems and disadvantages, useful features should be extracted and also necessary to reduce the dimension of original data features. Accordingly, the dimension reduction and feature extraction algorithm like PCA and ICA has been employed intending to avoid disorder data. In this study, ICA and PCA is applied based on variation of eigenvalue. The eigenvalues have been chosen according to the biggest value have been selected and remaining were discarded. So, the components of PCA were calculated according to that eigenvalues. The first three principal components of PCA are plotted in Figure 5. It can be mentioned that the different class of data for machine conditions are well separated. If we pay attention to both original features selected randomly (in Figure 4.) and feature by PCA (in Figure 5.), obviously, the using PCA extracting data is showing the better performance than choosing features randomly or manually. The Figure 6. shows the extacting features data by ICA of histogram features of themal image. Also represents the impendent component analysis with four different machine conditions. Data extracting features over ICA compare to PCA and randomly chosen is well. The separation of four types data for machine condition is really appreciable through ICA and every classter data is away eachother in Figure 6.

Table 2: Classifier performance

Features	Data	Classifier Performance			
		Supervised Classifier		Neural Network classifier	
		SVM	FKNN	ARTKNN	PPNN
PCA	Valid	0.9833	0.9167	0.7500	0.8167
	Test	0.8667	0.8333	0.8000	0.7833
ICA	Valid	1.0000	1.0000	0.9660	0.9312
	Test	0.9861	0.9633	0.9425	0.9100
Original Data	Valid	0.7800	0.7837	0.6941	0.6965
	Test	0.7487	0.7600	0.6528	0.6281

4.2 Training and Classification

The relevant parameters setup for the classifier is according to G.Nui et al.[11], Widodo et al. [6], J.-D. Son et al. [10] and B.S. Yang et al.[12]. They have carried out vast and deep researches on classifier for machine fault diagnosis to find out optimum parameters of classifier for achieving good result. With optimum parameters of classifier, in the current work , the RBF kernel is used as the basis function of SVMs which consists of two parameters are C and γ . As optimal value of these arguments, C and γ is defined with values 10 and 2^{-2} respectively. ARTKNN is a classifier of neural networks family whose main parameter is number of neurons and also criterion parameter denoted as ρ . The criterion parameter, ρ >0.96 indicates the optimal number of neurons because it is directly proportional to the neural numbers. In order to achieve satisfactory performance by this networks, the number of neural networks is 27. The performance of FKNN depends on parameter K so that it is a important problem to find a suitable K. To accomplish this job, we have tried the value of k<5 which gives us satisfactory result of classification. In practice, the parameter value of FKNN differs case to case. Here, PPNNs are a simple type of neural network used to classify data vectors.

In classification processes, features data were input as fifty percent for training and remaining were test validation. After performing classification, from the Table 2 the training and testing accuracy of four classifiers can be observed. For thermal image data, it can be seen that the classification performance using ICA data is much better than PCA and original features data with all classifier. Here, two types of classifier have been shown for classifications that are supervised learning method and neural networks classifier. The best classification accuracy is for thermal image data by SVM and FKNN classifier with trained value of 1.000 where SVM and FKNN are belong to a family of supervised classifier. However, only the SVM test performance is very well over other classifiers. ARTKNN and PPNN belong to family of *neural network classifier*. Performance of this is also appreciable as shown in Table 2. It can be concluded that all classifiers which have been used in this work validate for thermal image data on machine condition diagnosis that is not of course for original features.

5. CONCLUSION

By this work, a useful application of thermography in the machine condition monitoring and fault diagnosis area is presented. The thermograph data was taken into account to investigate different types of machine fault. At first, the experiment was carried out for four conditions at the same experimental condition after that raw data was extracted from its original structure to compatibility in data processing technique. Histogram features based on statistical of image were employed as a proper feature for thermal image data. Calculated image features data were taken into feature extraction algorithm due to mass dimensionality. As a result, data extracted by ICA shows better clustering performance compare to PCA. Finally, comparison of classifier accuracy using original, ICA and PCA data shows remarkable result by SVM than other machine learning method.

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7. MAILING ADDRESS

Ali MD. Younus
School of Mechanical Engineering,
Pukyong National University
San 100, Yongdang-dong, Nam-gu, Busan 608-739,
South Korea
Phone: +82-10-8689-7777
E-mail: md.yali@yahoo.com