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Joint Fault Diagnosis of Legged Robot based on Acoustic Processing

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***Abstract*— In legged robot system, certain types of joint faults can lead the entire system unstable since predefined controller cannot function properly after getting damaged. Therefore, the fault diagnosis is an important operation to prevent systems from failures. In this paper, the acoustic-based fault diagnosis for legged robots (AFL) is developed by employing the FFT and fuzzy logic as a feature extraction and a classification, respectively. In the benchmark, the results indicate that the proposed method can detect and inspect the faults of joint efficiently by means of sound, meaning that AFL method is feasible to be utilized and applied in real applications.**

I. INTRODUCTION

Fault diagnosis is a significant feature for mechanical systems to prevent from unexpected actions caused by failures. Generally, additional sensors (e.g., current sensors) are integrated to the system to inspect the abnormal behaviors – for instant, unusual load current or load torque. However, in order to get the system response, certain types of sensors are required to install inside the systems, such as a tachogenerator, which can lead to minor losses. To overcome this issue, some researchers employ acoustic processing to determine the failures. It is beneficial that acoustic processing can operate independently from the main systems as the sensing devices are not necessary to attach on the systems, and therefore it is widely used in machine health monitoring system as well.

Typically, fault diagnosis of machinery systems is done by means of feature extraction and classification. In [1], sound of the system and responses of vibration sensors are combined in cooperation to detect the vibration of the system. The result shows that it can detect the vibration frequency correctly. Acoustic analysis is also applied with induction motor to identify the faults [2]. The Fast Fourier Transform (FFT) and Spectral Analysis are implemented to detect the bearing and unbalance faults successfully in the experiments. The faults of automobile engine are detected by using FFT and Correlation-based Feature Selection as feature extraction methods [3]. Support Vector Machine (SVM) is employed to perform the fault classification, subsequently. This approach can identify the faults correctly by 88 percent accuracy. Besides aforementioned extracting methods, the Wavelet Transform (WT), the well-known method for frequency and time response, is implemented in [4]. The abnormality is distinguished effectively by using energy ratio of frequency-band. In [5], multi-class SVM is operated to classify the imperfection of the systems with wavelet packet entropy. In traditional techniques of classifying process, not only SVM acts as a classifier but other classical methods, i.e., Artificial Neural Network (ANN), are also used extensively to distinguish between two sets of behaviors – healthy and unhealthy. Certain types of ANN are further implemented successfully in [6]–[7].

In robotic field, fault identification methods have been developed likewise. In case of legged robots, some types of failures (i.e., broken legs) can affect to the entire system. Fault diagnosis is therefore crucial to prevent legged robots from unanticipated event caused by faults. Joint fault problems is one of accidental issues occurring in legged walking robots. The robots will not be able to walk properly when the joints of robots' legs become uncontrollable. In [8], the robot uses current sensors and Inertial Measurement Unit (IMU) to identify the failures of itself. Although the problem statuses indicate correctly in the experiments, a number of current sensors are required to measure the amounts of current spent. Image processing, recognizing artificial markers attached on robots' legs, is developed to detect the defective actions as well [9]. Robot is programmed to execute its legs into three different levels to observe the irregular behaviors. In the event of sightless markers caused by accidents, i.e., concealment of surrounding objects or detachment of artificial markers, this method will diagnosis the fault ineffectively. The Least-Mean-Squares (LMS) filters-based approach is developed so far to discover the reliability of the joints [10]. This manner can identify the locked joints sufficiently; however, the non-linearity of the system is not considered and the outputs of each motor are required to measure for differentiation procedure. Due to the limitations of existing methods as above, acoustic processing can be put into action to perform the joint fault diagnosis.

In this paper, the acoustic-based fault diagnosis for legged robots (AFL) is developed to detect the abnormalities of joints. Sound of servo motors are recorded simultaneously while a walking legged robot is executed to perform specific actions. The recorded signals are normalized afterward before analyzing frequency response with FFT. The energy of each frequency band will be calculated for feature extraction process. For classifier, the fuzzy logic classifier (FLC) is selected to avoid a drawback of conservative method, such as ANN, which can be overfitting in complicated model. In addition, the results of the AFL method are compared with ANN-based approach, and they show that the proposed method can provide preferable outcome in term of accuracy. Lastly, it can be concluded that the AFL method is feasible to utilize in the domain of fault detection on legged robots.

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Fig. 1. The quadruped robot used in the experiment and study.

II. System Description

The legged walking robot used in this study consists of four legs with 2 degrees of freedom per each leg as illustrated in Fig.1. Eight servo motors are built-in to act as actuator for each joint. The robot is connected directly to computer to execute the assigned action. In the experiments, the acoustic signals of the robot are recorded via the USB microphone allocating on the center of the robot. There are two types of joint diagnosis in this study, healthy and unhealthy joints. The healthy joints are defined as normal joints that can function properly in the practical situation; whereas, unhealthy joints are uncontrollable joints, i.e., locked joints, non-powered joints and broken-gear joints.

III. Theoretical Background

A. Fast Fourier Transform (FFT)

Fourier Transform (FT) is extensively used in digital signal processing to analyze the frequency response. In this study, the sound of motor is collected as a discrete signal; as a result, the FT is calculated by force of circumstance in discrete domain, called as Discrete Fourier Transform (DFT). The FFT is an efficient computation of the DFT, namely

$$X(k) = \sum_{n=0}^{N-1} x(n) W_N^{kn}, \tag{1}$$

$$W_N = e^{-j2\pi/N}, \tag{2}$$

where $X(k)$ is the kth coefficient of a length N sequence $\{x(n)\}$ and $k = 0, ..., N-1$ [11]. The amplitude of frequency spectrum $X(k)$ can be calculate by

$$A(k) = \frac{|X(k)|}{N} = \frac{\sqrt{\mathrm{Re}(X(k)^2) + \mathrm{Im}(X(k)^2)}}{N}, \tag{3}$$

with corresponding frequency:

$$f(k) = \Delta f \cdot k, \tag{4}$$

where $\Delta f = f_s/N$ and f_s is the sampling frequency.

B. Fuzzy Logic Classifier (FLC)

In order to label the data, there are several types of classifiers that can be utilized to cluster the groups of data in different manners. The advantage of fuzzy classifier is that it allows linguistic labels which is equivalent to what human used in real life, such as warmer, warm, cold, colder and etc., [12]. The dissimilarity between fuzzy classifier and non-fuzzy classifier is illustrated in Fig. 2. For non-fuzzy classifier, the data can be in either one set or the other, whereas it can belong to two sets in fuzzy classifier. For example, the $27°\mathrm{C}$ can be labeled in only one set, $warm$ or hot, for non-fuzzy classifier. On the other hand, the $27°\mathrm{C}$ can be a member of both $warm$ and hot sets but with different weights(w) as $27°\mathrm{C} \in warm$ with $w = 0.2$ and $27°\mathrm{C} \in hot$ with $w = 0.8$.

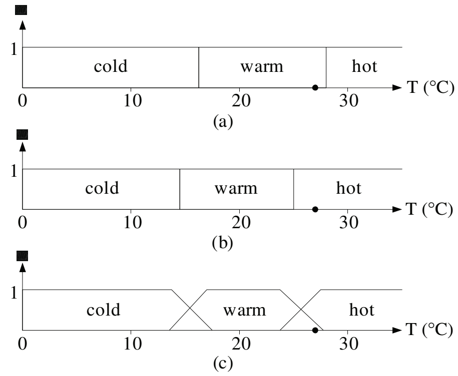

Fig. 2. Example of non-fuzzy and fuzzy classification: (a) $27°\mathrm{C} \in warm$, (b) $27°\mathrm{C} \in hot$ and (c) $27°\mathrm{C}$ belongs to both $warm$ and hot sets with $w = 0.2$ and $w = 0.8$, respectively.

IV. Methodology

The AFL method is divided into two processes, feature extraction and classification, conventional processes used in existing methods. The algorithm begins with recording the sounds of motors attached on the legged robot, while robot is performing specific actions – activating each joints individually. In the feature extraction, the acoustic signals will be transferred to the next processes, normalization, FFT and energy calculation, sequentially. The decision making of fault detection will be done afterward by using fuzzy classification. The overall processes of AFL algorithm is shown in Fig. 3.

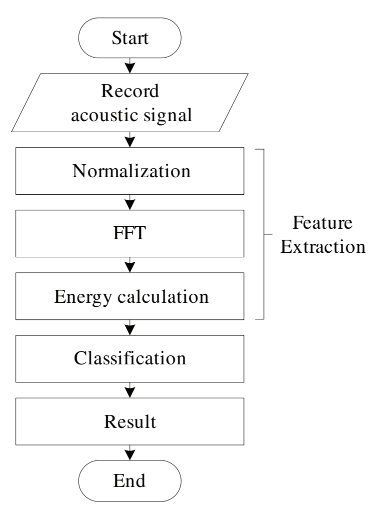

Fig. 3. Procedure of acoustic-based fault diagnosis for legged robots (AFL).

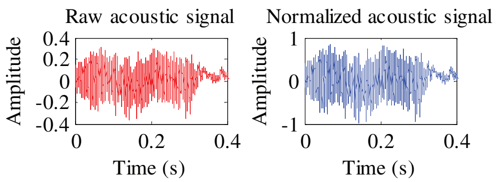

Fig. 4. Raw signal and normalized signal of healthy joint.

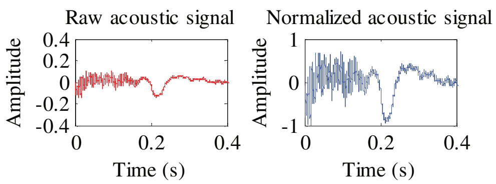

Fig. 5. Raw signal and normalized signal of unhealthy joint.

A. Feature Extraction

After collecting acoustic data, the feature of each signal will be extracted using three main processes as follows:

1) Normalization:: In order to avoid the effect of various intensity of sound, all of the acoustic signals will be normalized by maximum peak – divided the waveform by the peak value. Fig.4 and Fig.5 illustrate the examples of normalization results of both healthy and unhealthy joint signals.

2) FFT:: As aforementioned, there are several ways to extract the feature of sound signals. The FFT is employed to perform this procedure in this study by the reason of sufficient information provided. The frequency responses of healthy and unhealthy (locked joint) signals are shown in Fig.6 and Fig.7, respectively. Since there are so many frequency spectrum provided by FFT, meaning that some data are redundant, these data will be processed in the next step to minimize the number of features.

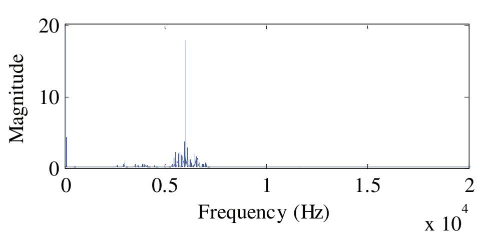

Fig. 6. The frequency spectrum of healthy joint acoustic signal.

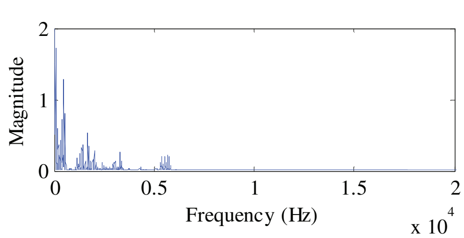

Fig. 7. The frequency spectrum of unhealthy joint acoustic signal.

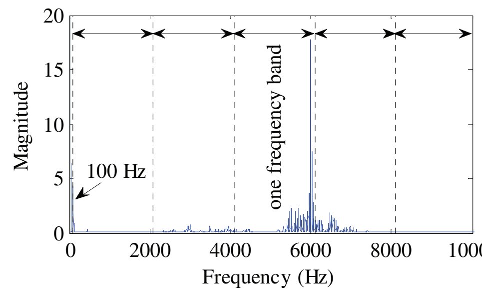

Fig. 8. Energy calculation of each frequency band, set as 2000 Hz.

3) Energy calculation:: The energy of each frequency band is manipulated as a feature for classification process which can be calculated as follows:

$$Energy = \sum_{k \in S} |A(k)|^2 , \tag{5}$$

where

$$S = \{k : f_L \leq f(k) < f_H\}, \tag{6}$$

f_L and f_H are low and high frequencies of the frequency bandwidth, respectively. In this study, the frequency bandwidth is set as 2000 Hz. According to the experiments, there are various kinds of system noises occurred while operating. In order to make this system become more precise, the values allocating under 100 Hz are not included in this operation as shown in Fig.8, meaning that the parameters f_L and f_H of the 1st band are set as 100 and 2100 Hz, severally. The bands corresponding to frequency range can be seen in Table I, and the examples of feature extraction of healthy and unhealthy joints are illustrated in Fig.9.

B. Classification

The AFL method employs the concept of fuzzy logic to classify the status of the joints of legged robot. In recent year, the fuzzy logic is used to detect the fault of induction

TABLE I

THE f_L AND f_H CORRESPONDING TO FREQUENCY BAND

Serial number	f_L-f_H (kHz)	Serial number	f_L-f_H (kHz)
1	0.1-2.1	5	8.1-10.1
2	2.1-4.1	6	10.1-12.1
3	4.1-6.1	7	12.1-14.1
4	6.1-8.1	8	14.1-16.1

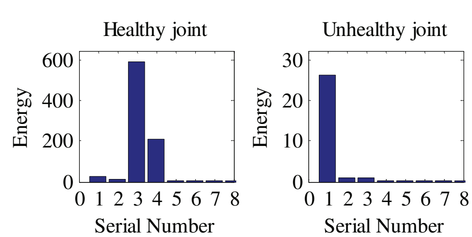

Fig. 9. Example energy of each frequency bands calculation of healthy and unhealthy joint sounds.

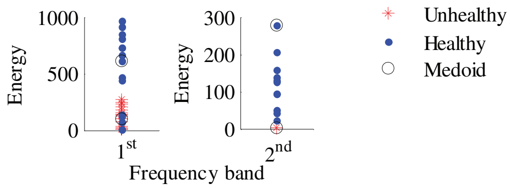

Fig. 10. The labeled data of the 1st and 2nd frequency bands, preprocessed experimentally as database of classification.

TABLE II
FUZZY RULE FOR CLASSIFICATION OF HEALTHY AND UNHEALTHY JOINTS OF LEGGED ROBOTS

Fuzzy Rule	Area
if x_1 is $small$ and x_2 is $large$ then Class 1	***A***
if x_1 is $large$ and x_2 is $large$ then Class 1	***B***
if x_1 is $small$ and x_2 is $small$ then Class 2	***C***
if x_1 is $large$ and x_2 is $small$ then Class 1	***D***

motor in [13] and to monitor the status of vehicle online in [14], successfully. The advantage of the fuzzy logic classifier (FLC) is that it is more practicable than the conventional learning-based approaches (e.g., ANN) which is not only delicate to analyze but also the slow speed of training process [15]. However, the FLC can be operated with a limited number of input variables due to the fact that the input space will be divided into fuzzy regions. For AFL method, the energies of first-five frequency bands are selected as a feature vector. As shown in Fig. 9, there is a significant disparity between the healthy and unhealthy values allocated in the first-five frequency bands. There is two fuzzy sets, $small$ and $large$, defined for each feature. According to the pre-collected database, in certain features, it is improper to separate the region efficiently due to the overlapping region, as illustrated in Fig. 10. In such case, the small and large sets are predefined by concerning of the medoid points of each labeled feature, guaranteeing that most of data are still classified correctly.

In this study, there are four methods developed to classify the abnormality of joints based on the fuzzy classification.

1) Fuzzy Rule (FR):: The method is functioned along with the general concept of fuzzy logic by isolating the input space into fuzzy regions. Fig. 11 shows the input space of two frequency bands, i.e., the 1st and 2nd frequency bands, with 20 data points of healthy joints and 20 data points of unhealthy joints. It is noted that there are more points of healthy joints allocated out of range illustrated in the figure. For this aspect, the fuzzy rule is simply defined, as shown in Table II, in which x_1 is a member of the 1st frequency band and x_2 is a member of the 2nd frequency band. As stated by the fuzzy rule, it is noticeable that two classes can be classified efficiently with two sets of features. However, it will become more complicated to classify the data when the number of features is higher than two in consonance with Fig.12.

2) Mean of Fuzzy Set (MF):: To avoid the complexity of determining fuzzy region in an input space, the MF method uses the fuzzy values – the degrees of truth and probabilities range between 0 and 1 – to identify whether healthy or unhealthy by calculation the mean value of five features. Since there are two fuzzy sets for each feature, the $small$ and $large$ sets are directly defined as unhealthy and healthy sets, consecutively. The result of classification is governed by comparing the mean values of probabilities between two sets, as Eq.(7),

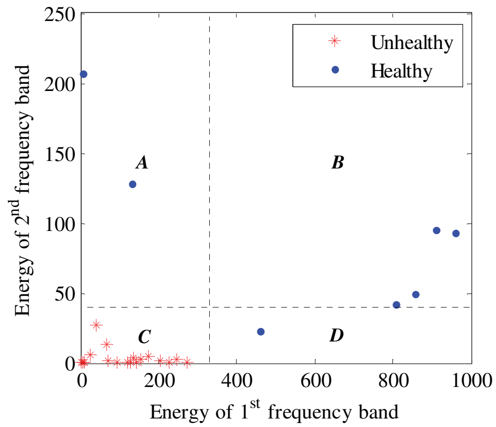

Fig. 11. The input space of data from two frequency bands.

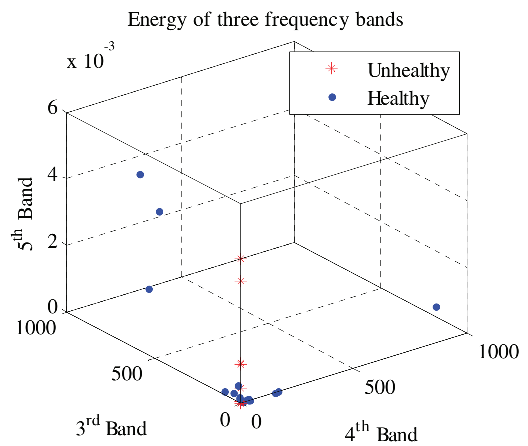

Fig. 12. The input space of data from three frequency bands.

$$output = \begin{cases} \frac{prob_h+1}{2}, & \text{if } prob_h > prob_u \\ \frac{1-prob_u}{2}, & \text{if } prob_h < prob_u \\ -1, & \text{otherwise} \end{cases}, \quad (7)$$

where $prob_h$ and $prob_u$ are set as the mean values of probabilities of healthy and unhealthy, sequentially.

3) Medoid of Fuzzy Set (MDF):: Medoid is a value of elements in the set which represents the center of clustering. This method is similar to the MF method, but the medoid value is used instead of mean value. Additionally, the final output is also calculated using Eq.(7).

4) Voting of Fuzzy Set (VF):: The voting method is adapted to used as a decision making process in this approach. It is noted that the values of probability that is higher

TABLE III

RESULT OF CLASSIFICATION IN HEALTHY ROBOT CASE

	Joint Number							
	1	2	3	4	5	6	7	8
Actual	◯	◯	◯	◯	◯	◯	◯	◯
ANN	◯	◯	◯	◯	◯	◯	◯	◯
FR	◯	◯	◯	◯	◯	◯	◯	◯
MF	◯	◯	◯	◯	◯	◯	◯	◯
MDF	◯	◯	◯	◯	◯	◯	◯	◯
VF	◯	◯	◯	◯	◯	◯	◯	◯

◯ = Healthy, × = Unhealthy

than 0.75 are also counted in voting process. For example, the result of voting for set $A = \{0.8, 1, 0.5, 0, 0.9\}$ is 1.

V. EXPERIMENTAL SETUP

In the first step, the acoustic databases of 20 data of healthy and 20 data of unhealthy joint sounds are collected by using the quadruped robot in Fig.1 to design the classification strategy. In the experiment, the AFL is operated with different three situations, i.e., healthy robot, one leg locked and one leg non-powered. Furthermore, the 40 random acoustic signals of healthy and unhealthy joints are experimented as well to measure the accuracy of the proposed method. All of the experiments conducted are compared to the ANN with same set of databases. The ANN is constructed with 5 hidden layers with 5 nodes per layer, and it is trained with back-propagation learning method. Moreover, the types of faults are also inspected in the experiment.

VI. RESULTS AND DISCUSSIONS

In the experiment, there are four cases conducted to evaluate the robustness of the classification. The output of classification process will be allocated between 0 and 1, referring to healthy and unhealthy class. If the output is close to 0, it means that the joint will be arranged in the healthy class. On the contrary, the joint will be sorted into the unhealthy class if the output gets close to 1. The performance of each method will be appraised by calculating Mean Square Error (MSE), and the accuracy of each method will be determined as well.

A. Healthy robot

According to Table III, the results show that all algorithms can classify the class efficiently. However, there are some minor errors – according to the numerical results – with ANN and MF methods as 0.0008 and 0.005, respectively. The error occurring with ANN's output is possibly caused by the improper training process; yet, the result is acceptable. The overlapping region of classes slightly leads the insignificant mistake in MF method. Conversely, the FR, MDF and VF can avoid the problem of overlapping region successfully.

B. One leg locked

In this experiments, all algorithm can operate properly except ANN with the similar problem as seen in Table IV. The ANN network can become overfitting if the traninng process is not treated in a good manner. While testing the training set with this ANN network, it can classify the data into the correct classes successfully in the experiments. Thus, it can be concluded that the error occurred because of overfitting network. The MF produces less error than ANN, and the results are therefore acceptable. Again, the FR, MDF and VF still provide the good results in terms of errors.

TABLE IV

RESULT OF CLASSIFICATION IN ONE LEG LOCKED CASE

	Joint Number							
	1	2	3	4	5	6	7	8
Actual	◯	◯	×	×	◯	◯	◯	◯
ANN	◯	◯	×	×	◯	◯	◯	×
FR	◯	◯	×	×	◯	◯	◯	◯
MF	◯	◯	×	×	◯	◯	◯	◯
MDF	◯	◯	×	×	◯	◯	◯	◯
VF	◯	◯	×	×	◯	◯	◯	◯

◯ = Healthy, × = Unhealthy

TABLE V

RESULT OF CLASSIFICATION IN ONE LEG NON-POWERED CASE

	Joint Number							
	1	2	3	4	5	6	7	8
Actual	◯	◯	◯	◯	◯	◯	×	×
ANN	◯	◯	◯	◯	◯	×	×	×
FR	◯	◯	◯	◯	◯	◯	×	×
MF	◯	◯	◯	◯	◯	◯	×	×
MDF	◯	◯	◯	◯	◯	◯	×	×
VF	◯	◯	◯	◯	◯	◯	×	×

◯ = Healthy, × = Unhealthy

C. One leg non-powered

Similar to previous two experiments, only ANN and MF method generate the errors as 0.125 and 5.875×10^{-5}, respectively, while FR, MDF and VF are still functioning sufficiently with 0.000 error. Table V shows the experimental results of this test case.

D. The 40 acoustic signals of healthy and unhealthy joints

This experiment is conducted to measure the accuracy of the proposed methods. Forty random acoustic signal of healthy and unhealthy joints (20 signals for each class), are set to extract the feature and feed to the input of classifier. Fig. 13 illustrates the confusion matrix of all methods tested in the benchmark. It is noticed that MF, MDF and VF have the equivalent confusion matrix so that they are belonged to the same matrix. In addition, the variables, TP, FP, FN and TN, are referred to True Positive, False Positive, False Negative and True Negative, serially. The accuracy of the classification can be determine as

$$Accuracy = (TP + TN)/Total\ population. \quad (8)$$

The ANN provides poor results compare to others in terms of accuracy as 0.95 while FR can classify the faults better than ANN with 0.975. On the other hands, MD, MDF and VF can perform efficiently with 100 percent accurate.

(a)

		Actual: Healthy	Actual: Unhealthy
Predicted	Healthy	TP 18	FP 2
Predicted	Unhealthy	FN 0	TN 20

(b)

		Actual: Healthy	Actual: Unhealthy
Predicted	Healthy	TP 20	FP 0
Predicted	Unhealthy	FN 1	TN 19

(c)

		Actual: Healthy	Actual: Unhealthy
Predicted	Healthy	TP 20	FP 0
Predicted	Unhealthy	FN 0	TN 20

Fig. 13. The confusion matrix of classification: (a) ANN, (b) FR and (c) MF, MDF and VF.

E. Types of faults classification

The types of faults are detected in this experiment. There are three types of fault tested that are broken gears, non-powered and locked joints. The ANN and FR methods are employed to cluster the types of faults. According to the Fig. 14, it is complicated to classify the types of faults since some data are extremely overlapped. In this case, the ANN with with 5 hidden layers of 5 nodes cannot be trained successfully so that the 10 hidden layers are constructed to perform in place. For FR method, the three basic fuzzy rules are utilized to overcome this problem. The results show that FR method can classify the types of faults more accurate than ANN method with 5% detection error. Although the network was trained properly, the ANN method cannot perform well with 40% detection error. Additionally, the error occurred in this experiment are caused by the fact that some data are quite similar.

VII. Conclusions and Future Works

This paper presents the novel methods of fault diagnosis of joint by means of acoustic processing. The process has been done by extracting the features of sounds with the FFT and the energy of frequency band. The classification process was operated based on the concept of fuzzy logic. Four different classification are conducted in this paper. According to the experiments, it can be concluded that the proposed methods, FR, MDF and VF, can detect the fault of joint efficiently. Due to the simplicity, the VF method is the best manner to diagnose the faults. The MDF method is also operated successfully without error, but it is costly to find the medoid. Even MDF can provide the same level of accuracy, some minor errors occur with output. Moreover, the FR method is feasible to employ with non-complex and small set of cluster which is more simple than conventional learning system. In order to prevent from the overlapping region in an input space, it is planed to apply the fuzzy classification by weight which employs optimization algorithms to avoid the bad interpretability in the future. Moreover, additional sensor will be integrated to increase the performance and accuracy.

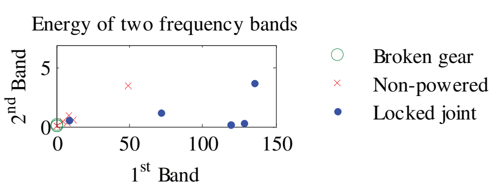

Fig. 14. The data of three different types of faults.

References

[1] L. Swathy and L. Abraham, “Analysis of vibration and acoustic sensors for machine health monitoring and its wireless implementation for low cost space applications,” in *the First International Conference on Computational Systems and Communications (ICCSC)*, Dec 2014, pp. 80–85.

[2] F. Salazar-Villanueva and O. Ibarra-Manzano, “Spectral analysis for identifying faults in induction motors by means of sound,” in *the International Conference on Electronics, Communications and Computing (CONIELECOMP)*, Mar 2013, pp. 149–153.

[3] H. Ghaderi and P. Kabiri, “Fourier transform and correlation-based feature selection for fault detection of automobile engines,” in *the 16th CSI International Symposium on Artificial Intelligence and Signal Processing (AISP)*, May 2012, pp. 514–519.

[4] Z. Shuai, Q. Yanhuai, and H. Qingkai, “Fault characteristics analysis for rotor systems with misalignment based on wavelet packet decomposition and frequency-band energy ratio analysis,” in *the 30th Chinese Control Conference (CCC)*, Jul 2011, pp. 4331–4335.

[5] A. Jamal and N. Verma, “Automatic fault diagnosis system using acoustic data,” in *the 8th IEEE International Conference on Industrial and Information Systems (ICIIS)*, Dec 2013, pp. 421–426.

[6] Y. Shatnawi and M. Al-khassaweneh, “Fault diagnosis in internal combustion engines using extension neural network,” *Industrial Electronics, IEEE Transactions on*, vol. 61, no. 3, pp. 1434–1443, Mar 2014.

[7] W. Wang, Q. Huang, and Y. Zhang, “On the motor fault diagnosis based on wavelet transform and ann,” in *the 31st Chinese Control Conference (CCC)*, Jul 2012, pp. 5339–5346.

[8] A. Roennau, G. Heppner, T. Kerscher, and R. Dillmann, “Fault diagnosis and system status monitoring for a six-legged walking robot,” in *the IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)*, Jul 2011, pp. 874–879.

[9] F. Seljanko, “Fault detection algorithm for legged walking robot,” in *the IEEE International Conference on Mechatronics and Automation (ICMA)*, Aug 2013, pp. 1211–1216.

[10] M. Mladenov, M. Mock, and K.-E. Grosspietsch, “Fault monitoring and correction in a walking robot using lms filters,” in *the International Workshop on Intelligent Solutions in Embedded Systems*, Jul 2008, pp. 1–10.

[11] K. R. Rao and P. Yip, Eds., *The Transform and Data Compression Handbook*. Boca Raton, FL, USA: CRC Press, Inc., 2000.

[12] J. Jara and R. Acevedo-Crespo, “Crisp classifiers vs. fuzzy classifiers: A statistical study,” in *Adaptive and Natural Computing Algorithms*, ser. Lecture Notes in Computer Science, M. Kolehmainen, P. Toivanen, and B. Beliczynski, Eds. Springer Berlin Heidelberg, 2009, vol. 5495, pp. 440–447. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-04921-7_45

[13] H. Azgomi and J. Poshtan, “Induction motor stator fault detection via fuzzy logic,” in *the 21st Iranian Conference on Electrical Engineering (ICEE)*, May 2013, pp. 1–5.

[14] D. Jaramillo and C. Narvaez, “Vehicle online monitoring system based on fuzzy classifier,” in *the 3rd International Conference on Advances in Vehicular Systems, Technologies and Applications*, Jun 2014, pp. 33–38.

[15] S. Abe and M.-S. Lan, “A method for fuzzy rules extraction directly from numerical data and its application to pattern classification,” *Fuzzy Systems, IEEE Transactions on*, vol. 3, no. 1, pp. 18–28, Feb 1995.