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An unmanned marine vehicle thruster fault diagnosis scheme based on OFNDA

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Abstract: For a number of years there has been a growing interest in the use of fault analysis techniques in recent years in unmanned marine vehicles (UMVs) owing to their significant impact on marine operations. This study presents a novel approach to the diagnosis of unbalanced load (blades damage) faults in an electric thruster motor in UMV propulsion systems based on orthogonal fuzzy neighbourhood discriminative analysis (OFNDA) for feature dimensionality reduction. The diagnosis approach is based on the use of discrete wavelet transforms (DWTs) as a feature extraction tool and the optimal number of mother wavelet function and levels of resolution by analysing the vibration and current signals. As a result of analysis and comparisons, the Deubechies 12 (db12) wavelet and level 8 were chosen. A dynamic recurrent neural network (DRNN) was chosen for fault classification and level of fault severity prediction was implemented. Four faulty conditions were analysed under laboratory conditions and these were recreated by damaging the blades of a motor. The results obtained from the simulation demonstrate the effectiveness and reliability of the proposed methodology in classifying the different faults with greater speed and accuracy compared to existing methods.

KEY WORDS: Unmanned marine vehicles, fault analysis, dynamic recurrent neural network, feature extraction and reduction, OFNDA.

INTRODUCTION

End users of unmanned marine vehicles (UMVs) are now demanding longer mission lengths coupled with increasing vehicle autonomy. With an escalation in autonomy comes the need for higher reliability in such vehicles in order for them to better cope with unexpected events. In a large number of cases, the present generation of UMVs use electric thruster motors. The timely isolation of faults in a motor will thus ensure the integrity and safety of a vehicle while not adversely affecting the overall system performance.

Omerdic & Roberts (2004) propose the general concept of fault diagnosis as essential task models. They then define them as:

- Fault detection and diagnosis (FDD): detection and localisation of faults.
- Fault analysis or identification (FA): determination of the type, cause and severity of faults, and prediction of the possible future faults and time frames in which these could develop, using available data and knowledge about the behaviour of the diagnosed process, mathematical, quantitative or qualitative.

Robust FA including the diagnosis of faults and predicting their level of severity is necessary to optimize maintenance and improve reliability. Early diagnosis of faults that might occur in the supervised process renders it possible to perform important preventative actions, especially important for critical applications.

FA for nonlinear systems has not been fully explored and there is still a big gap between FA theories and their application. Work in this paper has successfully attempted to fill the gap by developing an integrated FA system structure. Many pattern recognition approaches have been implemented for condition monitoring and fault diagnosis of electrical machinery such as artificial intelligence (AI), signal processing, model based and hybrid techniques. Recently AI has been introduced as an approach for condition monitoring and fault diagnosis purposes where accurate mathematical models are difficult to develop. AI aims to generate classifying expressions simple enough to be understood easily by humans (Yusuf et al. 2013). AI include techniques based on Fuzzy Logic Systems (FLSs), neural networks (NNs) (Gacto et al. 2011), genetic algorithms (GAs), adaptive neuro fuzzy inference systems (ANFIS) and support vector machines (SVMs). With FLS, as complexity of the data driven fuzzy models can be reduced with so-called merging algorithms (Hyun Cheol et al. 2010). Furthermore, a fuzzy model offers some sort of interpretability (Gacto et al. 2011) and adapting their parameters and structures over time (Lughofer et al. 2011).

A NN is an effective motor fault detection method which does not need a mathematical model. Furthermore, NNs can recognize patterns even at high noise levels (Lughofer 2011). Almost all previous work in literature is based on using static NNs as fault classifiers, whilst most industrial systems are dynamic and nonlinear in nature, and hence

during their identification it seems desirable to employ the models which can represent the dynamics of the system. Recently great attention has been paid to the development of dynamic recurrent neural networks (DRNNs) owing to their capabilities for modelling nonlinear dynamical systems. Yusuf et al. (2013) and Hyun Cheol et al. (2010) have shown that the DRNN is an attractive method for fault diagnosis in electrical machines. DRNN allows improved fault prediction accuracy of condition monitoring systems which are more powerful than static NN. In addition, DRNNs are more versatile and provide the capability to learn the dynamics of complicated nonlinear systems, while conventional static NN cannot (Wang & He 2005).

This paper aims to develop a new bearing FA scheme for UMV thrusters, which can accurately detect faults and provide useful information about the severity of the fault. In this paper, the fault indications were obtained from vibration and current signals and passed through to discrete wavelet transform (DWT) to extract the useful features, and then a feature reduction technique is implemented to avoid redundant features.

To reduce additional computational time for fault classification, an accurate dimensionality reduction tool is needed to select the most informative features from the wavelet feature set. Different feature reduction methods such as principle component analysis (PCA) (Widodo & Yang 2007), linear discriminate analysis (LDA) (Ciabattoni et al. 2015) and empirical mode decomposition (EMD) (Camarena-Martinez et al. 2014) have been used to reduce features redundancy. This paper uses the orthogonal fuzzy neighbourhood discriminative (OFNDA) approach and to the authors' knowledge it has only been used in medical data analysis (Khushaba et al. 2010) and not used in electrical motor fault diagnosis systems. Results show that OFNDA has better classification accuracy compared to both PCA and LDA.

With regards to the structure and content of the paper, following on from this introductory material, the next section presents the novel fault diagnosis system being considered herein. This is followed by a description of the feature extraction and dimensionality reduction approach. Next an innovative fault classification procedure based on a DRNN architecture is reported. Finally conclusions complete the paper.

FAULT DIAGNOSIS SYSTEM

Proposed scheme

The proposed diagnostic procedures used in this work include three main stages, as illustrated in Fig 1. In the first stage, the physical data (current and vibration) are collected and then a DWT is used to extract the useful features in time and frequency domains. In the second stage, the features are reduced using OFNDA to remove redundancy and to decrease the training time. An inaccurate reduction feature tool may remove useful information and will jeopardise the overall performance, and thus the feature reduction stage represents the critical stage in the diagnosis process, the final stage is fault classification using a DRNN.

Figure 1 here

Experimental arrangement

The propulsion system consists of two propellers powered by a set of 24V, 334N Minn Kota Riptide transom mounted saltwater thruster motors. The timely isolation of faults in a motor will ensure the integrity and safety of a vehicle whilst not adversely affecting the overall system performance. In practice when undertaking a mission, if necessary, a fault detection and diagnosis can be instigated on board UUVs whilst at the same time using telemetry to supply its mission control centre with a status report.

Propellers on the thruster motors are durable but not indestructible. Hard surfaces can damage blades partly or fully and can imbalance the operation of a thruster motor, causing significant damage to the internal parts. The diagnoses of these faults are thus necessary for the healthy operation of the thruster motors and critical for UUVs operations. A laboratory prototype motor has been built for the experimental setup, the proposed technique was used to show the behaviour of the motor under normal operating condition and four faulty conditions in 10% (F1), 25% (F2), half (F3) and full cut (F4) as shown in Fig 2.

A linear current sensor was used to measure the stator current and 3-axis accelerometer (ADXL325) with a full-scale range of ± 5 g and bandwidth of 0.5 Hz to 1600 Hz was mounted on the flat surface of the propeller to record the vibration data. Sensor outputs were logged into a PC via a data acquisition card (NI USB-6009 multifunction I/O device) and the motor was powered by 24V battery supply. The MATLAB environment was used to change the duty cycle of the pulse width modulation signals via the motor driver. An operational amplifier (MCP604) has been used in the circuit driver. This microchip is suitable for working with low power. Data was gathered for five cases: no fault F0 (normal operating condition), F1, F2, F3 and F4 fault at a sampling rate of 3 kHz for duration of 30s. Total of 30,000 sample points using a MATLAB software environment were collected representing motor performance under low speed (500rpm) and high speed (3000rpm) conditions.

Figure 2 here

FEATURES EXTRACTION AND DIMENSIONALITY REDUCTION USING OFNDA

After data collection of the essential sensor signals, features are often extracted and selected to analyse the signals from all these embedded sensors, to assess the condition of the system. Feature extraction is usually the first step in any pattern recognition system. Irrelevant features will affect the learning process by increasing the computational cost and sample size,

and may lead to over-fitting. In order to increase the robustness of the classifier and to reduce the data processing load, dimensionality reduction is necessary. Many extraction techniques have been proposed in several domains including time-domain methods, frequency-domain methods, and time-frequency methods.

The DWT is an advanced time and frequency signal processing technique with a growing number of applications in rotating machine fault diagnosis (Abed et al. 2015). The windowing of a DWT is adjusted automatically for low and high frequencies, i.e. it uses short time intervals for high frequency components and long-time intervals for low frequency components. To extract the useful information, here a DWT, was applied.

The selection of optimum levels of decomposition and mother wavelet is crucial to the working of a DWT. In this work, the data-independent selection (DIS) approach is used to determine optimal number of wavelet levels (Phinyomark, Phukpattaranont and Limsakul 2012) whereas minimum description length (MDL) (Hamid & Kawasaki 2002) is used for the selection of a mother wavelet. Table 1 shows the MDL coefficients obtained on the collected data for the available orthogonal or non-orthogonal wavelets in order to select the optimal mother wavelet and the orthogonal wavelet filter 'db12' of the Daubechies family is chosen as the optimal mother wavelet. DIS approach is then applied to obtain the optimum level of decompositions which was equal to 8.

Table 1 here

Figs 3 and 4 show the original vibration signal, DWT details coefficients of the signal for level-8 decompositions (d1-d8) and approximate coefficient (a8) under normal and faulty operating condition, respectively.

Figure 3 here

Figure 4 here

The DWT decomposition gives a clear idea about how the original signal is reconstructed using the approximations and details at various levels. However, the DWT yields a high dimensional feature vector (Phinyomark, Phukpattaranont and Limsakul 2012) and in some cases the number of features is relatively larger than the number of training samples. This is usually referred as the ‘curse of dimensionality’, adversely affecting training and testing speed. An accurate dimensionality reduction tool is thus needed to remove redundant features information (Prieto et al. 2013). Feature reduction is an important task in machine learning and it facilitates classification, compression, and visualization of high-dimensional data by mitigating undesired properties of high-dimensional spaces by removing redundant features information that may lead to over fitting.

As such, it is obvious that the main goal of feature dimensionality reduction is to reduce the number of features without compromising the quality of classification. Generally, dimension reduction approaches can be classified into linear, and nonlinear methods (Lin and Guo 2015). The choice of linear and nonlinear techniques will be determined by the nature of the classification problem. The linear case is the simplest classification problem in which both linear and nonlinear techniques are expected to classify all the data correctly. For nonlinear case, classes of data can be separated using nonlinear separating planes, where using linear techniques in this case would misclassify a large portion of the data.

Here feature reduction method attempts to determine the best combination of original wavelet coefficients. OFNDA has been recently proposed by Khushaba et al (Khushaba et al. 2010) as a new approach for feature reduction. The algorithms which are fully described in their paper works on the basis to maximize the distance between features belong to different classes (S_B) whilst minimize the distance between features in the same class (S_w).

The feature reduction technique of OFDNA described in this section was applied to the four fault conditions and was able to reduce the number of wavelet features, originally

from 16 to 8 enabling faster computation. Fig 5 shows the distribution of OFNDA features and indicates that it classified the different features with clearly distinct regions which will help in better classification of the faults using a DRNN as described next.

Figure 5 here

DYNAMIC NEURAL NETWORK FOR REAL TIME FAULT CLASSIFICATION

Most industrial systems are dynamic and non-linear in nature, and hence during fault identification it seems desirable to employ those models which can represent the dynamics of the system, to increase operational reliability and to optimize preventative maintenance. It is therefore necessary to develop an efficient tool for analysis and process monitoring, in real time. NNs can be classified into dynamic and static. Static NNs have no feedback and delays, and the output is calculated directly from the input through feed-forward connections. In dynamic NNs (DNNs), the output instead depends on the current and previous inputs, outputs, or states of the network. Generally, DNNs are more powerful than static NNs. Studies have shown that their use can improve the fault prediction accuracy of electrical motor condition monitoring systems (Hyun et al. 2010).

In this paper, DRNN based on non-linear autoregressive classifier with exogenous data (NARX) model is chosen. A NARX response at any given time depends not only on the current input, but on the history of the input sequence. NARX neural networks are computationally powerful in theory, but they also have several advantages in practice. For example, it has been reported that gradient-descent learning can be more effective in NARX networks than in other recurrent architectures. NARX is commonly used in time series modelling. In addition, the architecture of NARX will reduce the computational cost. In this work, four time-delayed selected from the input and output were fed back as inputs to the network. After the dimensionality reduction stage the wavelet features were reduced from 16

to 8 features that forms the NN inputs. The network used is a logistic classifier that incorporates sigmoid activations in all the hidden and output units and uses back-propagation (BP) method as presented in McClelland et al. (1986) for training to compute the weights between connected processing elements, so that the difference between the actual output and the desired output is minimized.

Input to the NN consists of the eight OFNDA features, x_1^{OFNDA} , x_2^{OFNDA} , and x_3^{OFNDA} ... x_8^{OFNDA} and the output of the network consists of five units, used to indicate particular blades normal and faulty conditions as shown in Table 2. 60% of the OFNDA features were used as a training data set and 20 % as testing and validation set respectively.

Table 2 here

Fig 6 indicates the performance of DRNN for a thruster motor operating under different severity of blades fault (F1, F2, F3, and F4). Fig 6 also shows a misclassification occurs when the actual value does not coincide with the desired value.

Figure 6 here

Several trial and error steps are used to optimize the number of hidden neurons and in this case 25 was found suitable. Table 3 compares the prediction of faults using a DRNN with PCA, LDA and OFNDA features on test data set and shows that DRNN with OFNDA features outperforms in classifying and predicting the severity of these faults in comparison to PCA and LDA. PCA performs better than LDA but there were many misclassifications compared to OFNDA features in this case as shown in Fig 7 and thus is not suitable for on-line classification.

Table 3 here

Figure 7 here

The superiority of the proposed algorithm is also tested with some existing algorithms in literatures and comparative results are shown in Table 4. The results show that mean

classification accuracy using the proposed approach is 97% which is much better than most of the existing techniques. Many techniques only used one signal as a fault indicator and thus limiting the accuracy in classifying the severity of the faults.

Table 4 here

Conclusions

This paper proposes a new methodology for FA of a thruster motor under different operating conditions based on OFNDA for feature reduction. DWT was used as an efficient feature extraction method. However, these features alone are not capable of a good fault classification performance. OFNDA was applied to obtain the best features for fault classification, and the results show that better classification accuracy was obtained. These features were fed to a DRNN for fault classification, enabling the fault classifier to incorporate a dynamic component. The application of these techniques to real data has shown that they constitute an effective fault classifier in practice, capable of detecting and classifying different type of thruster faults fairly accurately. These indications in real time will greatly improve the reliability of the operations and reducing overall maintenance costs. These technologies in future can be used to predict remaining useful life time of a thruster providing longer hassle free endurance of autonomous marine vehicles.

REFERENCES

- A. Phinyomark P. Phukpattaranont, C. Limsakul AN. 2012. Feature Extraction and Reduction of Wavelet Transform Coefficients for EMG Pattern Classification. *Electr Electron Eng.* 122:27–32.
- Abed W, Sharma S, Sutton R, Motwani A. 2015. A Robust Bearing Fault Detection and Diagnosis Technique for Brushless DC Motors Under Non-stationary Operating Conditions. *J Control Autom Electr Syst [Internet]*. 26:241–254. Available from:

<http://dx.doi.org/10.1007/s40313-015-0173-7>

Alok, S., Kuldip, K., and Godfrey, C. (2006) Class-dependent PCA, MDC and LDA: A combined classifier for pattern classification, *Pattern Recognition*, 39 (7), 1215 - 1229.

Camarena-Martinez D, Valtierra-Rodriguez M, Garcia-Perez A, Osornio-Rios RA, Romero-Troncoso R de J. 2014. Empirical Mode Decomposition and Neural Networks on FPGA for Fault Diagnosis in Induction Motors. *Sci World J [Internet]*. 2014:17. Available from: <http://dx.doi.org/10.1155/2014/908140>

Ciabattoni L, Cimini G, Ferracuti F, Freddi A, Ippoliti G, Monteriu A. 2015. A novel LDA-based approach for motor bearing fault detection. In: *Ind Informatics (INDIN), 2015 IEEE 13th Int Conf.*; p. 771–776.

David L. McClelland ER and J. 1986. *Parallel distributed processing: explorations in the microstructure of cognition, vol. 1: foundations*. Group CPR, editor. MIT Press.

Gacto MJ, Alcalá R, Herrera F. 2011. Interpretability of linguistic fuzzy rule-based systems: An overview of interpretability measures. *Inf Sci (Ny) [Internet]*. 181:4340–4360. Available from: <http://www.sciencedirect.com/science/article/pii/S0020025511001034>

Hamid EY, Kawasaki ZI. 2002. Wavelet-based data compression of power system disturbances using the minimum description length criterion. *Power Deliv IEEE Trans*. 17:460–466.

Hyun Cheol C, Knowles J, Fadali MS, Kwon Soon L. 2010. Fault Detection and Isolation of Induction Motors Using Recurrent Neural Networks and Dynamic Bayesian Modeling. *Control Syst Technol IEEE Trans*. 18:430–437.

Kankar PK, Sharma SC, Harsha SP. 2011. Fault diagnosis of ball bearings using continuous

wavelet transform. *Appl Soft Comput* [Internet]. 11:2300–2312. Available from:

<http://www.sciencedirect.com/science/article/pii/S1568494610002139>

Khushaba RN, Al-Ani A, Al-Jumaily A. 2010. Orthogonal fuzzy neighborhood discriminant analysis for multifunction myoelectric hand control. *IEEE Trans Biomed Eng* [Internet].

57:1410–1419. Available from: <http://www.ncbi.nlm.nih.gov/pubmed/20172801>

Khushaba, N., Al-Ani, A., and Al-Jumaily, A. (2010) Orthogonal Fuzzy Neighborhood Discriminant Analysis for Multifunction Myoelectric Hand Control, *IEEE Transactions on Biomedical Engineering*, 57(6), 1410-1419

Lin Y and Guo Y. 2015. Optimal Uncorrelated Unsupervised Discriminant Projection. *Appl Mech Mater*. 701-702:54–57.

Lughofer E, Bouchot J-L, Shaker A. 2011. On-line elimination of local redundancies in evolving fuzzy systems. *Evol Syst* [Internet]. 2:165–187. Available from:

<http://dx.doi.org/10.1007/s12530-011-9032-3>

Lughofer E. 2011. *EVOLVING FUZZY SYSTEMS – METHODOLOGIES, ADVANCED CONCEPTS AND APPLICATIONS*. Springer Berlin Heidelberg.

Omerdic E, Roberts G. 2004. Thruster fault diagnosis and accommodation for open-frame underwater vehicles. *Control Eng Pract* [Internet]. 12:1575–1598. Available from: <Go to ISI>://000224015100010

Prieto MD, Cirrincione G, Espinosa AG, Ortega JA, Henao H. 2013. Bearing Fault Detection by a Novel Condition-Monitoring Scheme Based on Statistical-Time Features and Neural Networks. *Ind Electron IEEE Trans*. 60:3398–3407.

Samanta B, Al-Balushi KR, Al-Araimi SA. 2004. Bearing fault detection using artificial

neural networks and genetic algorithm. EURASIP J Appl Signal Process. 2004:366–377.

Wang X, He Y. 2005. Diagonal recurrent neural network based on-line stator winding turn fault detection for induction motors. In: Electr Mach Syst 2005 ICEMS 2005 Proc Eighth Int Conf. Vol. 3., p. 2266–2269 Vol. 3.

Widodo A, Yang B-S. 2007. Application of nonlinear feature extraction and support vector machines for fault diagnosis of induction motors. Expert Syst Appl [Internet]. 33:241–250. Available from: <http://www.sciencedirect.com/science/article/pii/S0957417406001382>

Xu Z, Xuan J, Shi T, Wu B, Hu Y. 2009. Application of a modified fuzzy ARTMAP with feature-weight learning for the fault diagnosis of bearing. Expert Syst Appl [Internet]. 36:9961–9968. Available from:

<http://www.sciencedirect.com/science/article/pii/S0957417409001080>

Yusuf SA, Brown DJ, Mackinnon A, Papanicolaou R. 2013. Application of Dynamic Neural Networks with Exogenous Input to Industrial Conditional Monitoring. 2013 Int Jt Conf Neural Networks [Internet]. Available from: <Go to ISI>://000349557200055

Figures and Tables

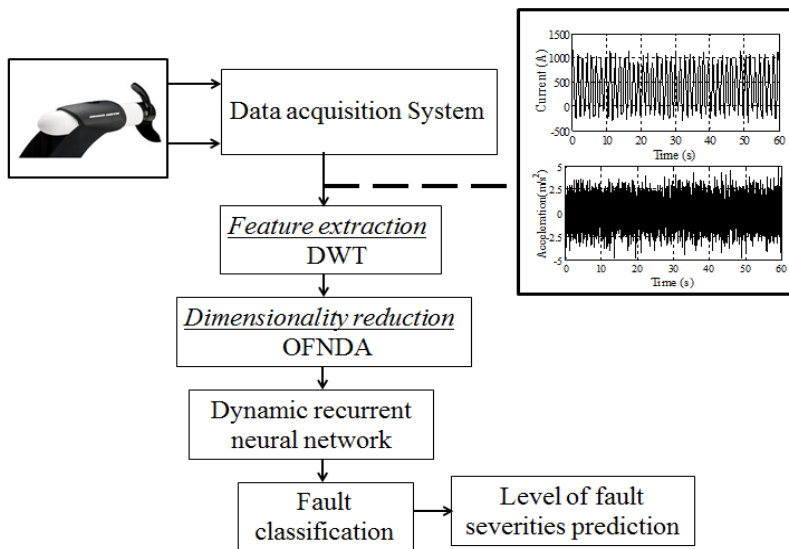


Fig 1: Proposed diagnostic procedures

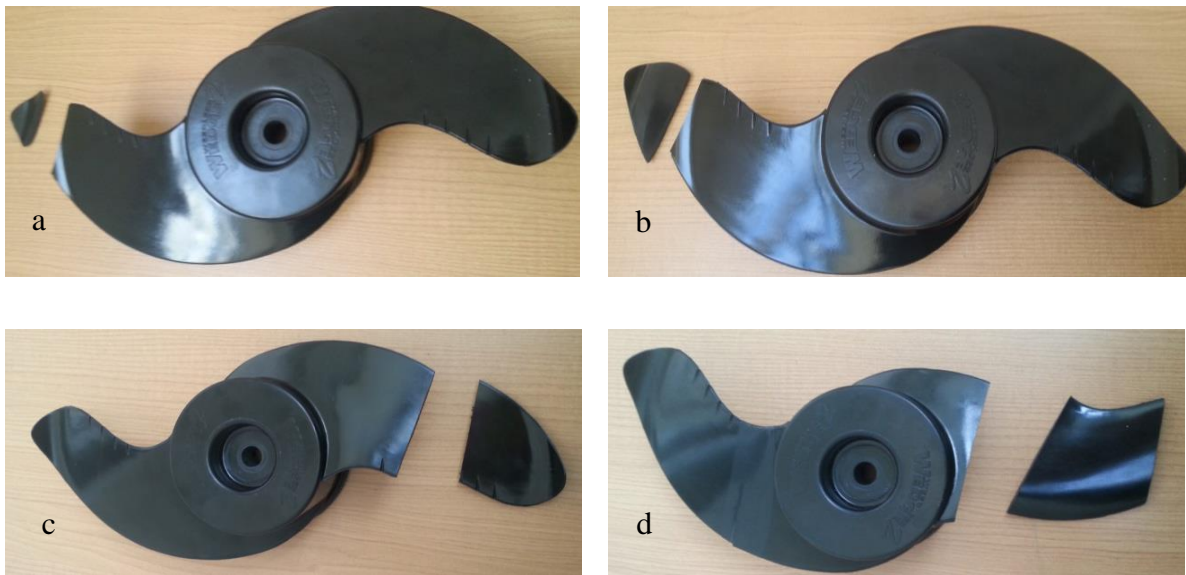


Fig 2: Blades fault with four severities (a) F1 -10%, (b) F2- 25%, (c) F3- 50% and (d) F4- 100%

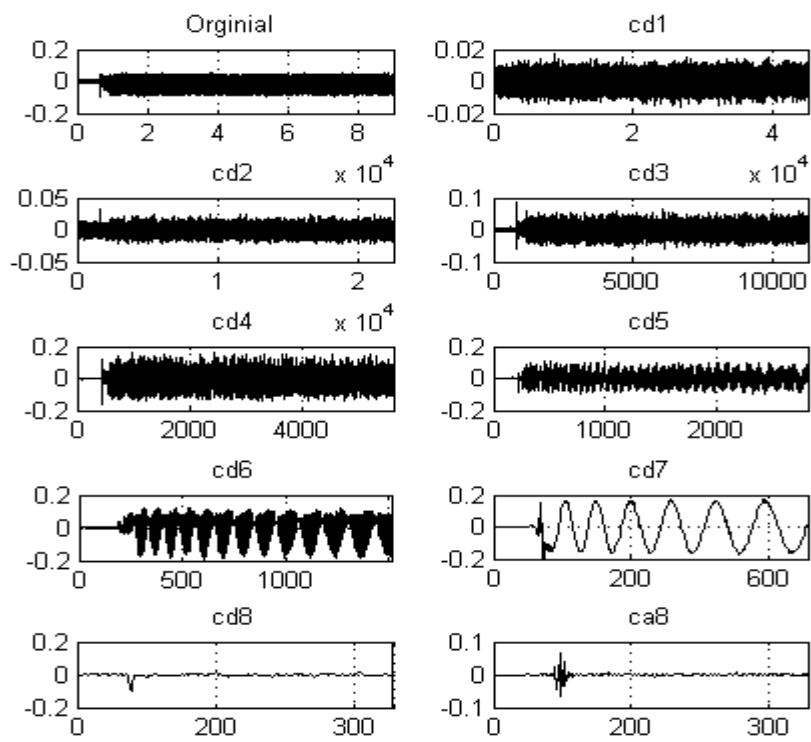


Fig 3: Vibration signal under normal operation

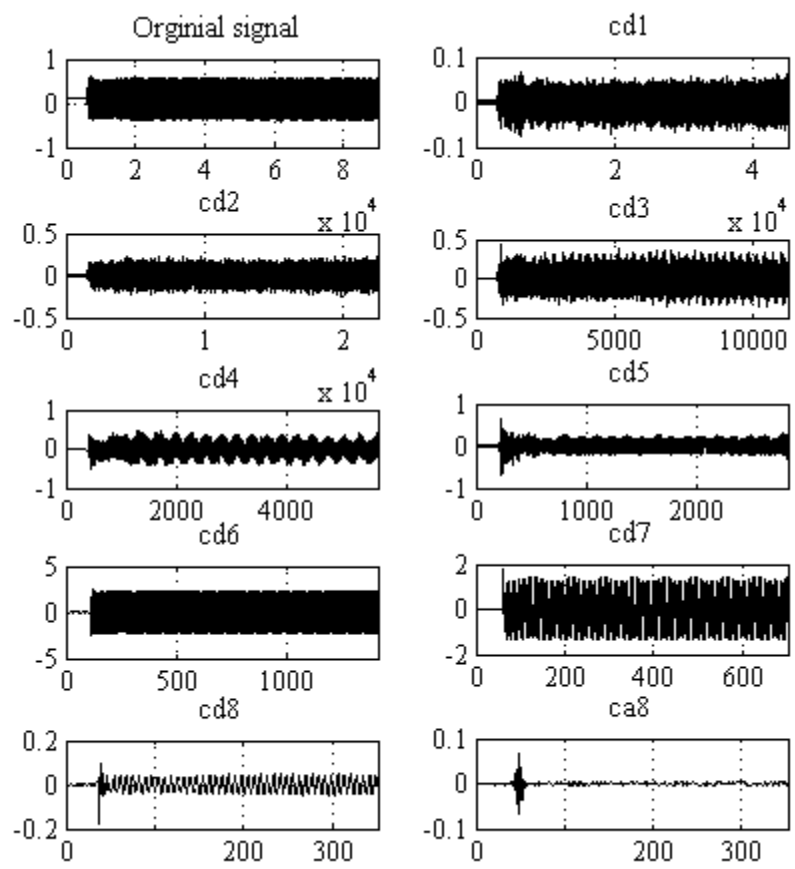


Fig 4: Vibration signal under faulty operation

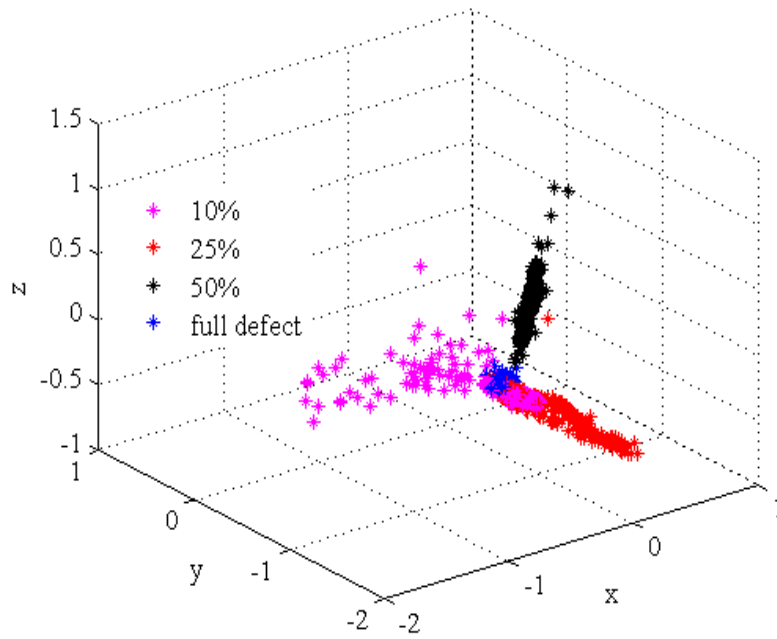


Fig 5: OFNDA features under different severities of blades fault

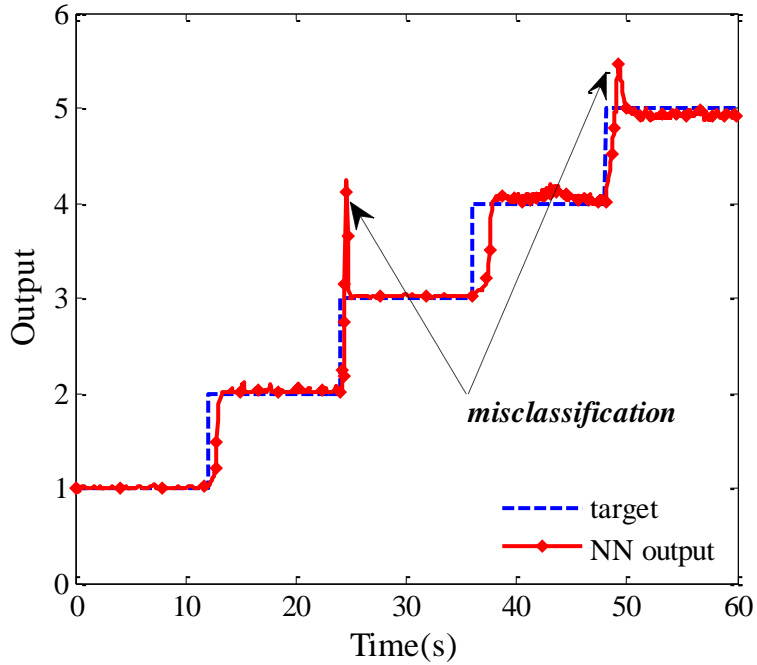


Fig 6: Overall fault diagnosis tests for motor operating under different severity of blades faults using OFNDA

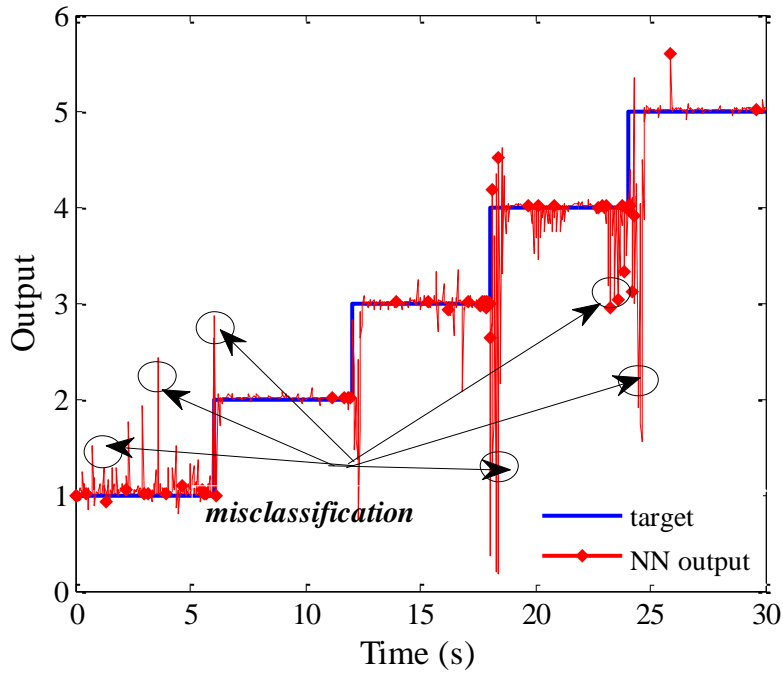


Fig 7: Overall fault diagnosis tests for motor operating under different severity of blade fault using PCA features

Table 1. Mother wavelet optimization based on MDL coefficients

Wavelet	MDL	Wavelet	MDL	Wavelet	MDL
haar	14.78	db10	7.13	sym6	13.10
db2	15.63	db11	5.13	coif1	9.65
db3	15.67	db12	5.04	coif2	13.07
db4	10.07	db13	5.89	coif3	10.27
db5	9.62	db14	6.96	coif4	8.281
db6	9.88	sym2	15.63	demy	9.89
db7	8.17	sym3	15.67	bior1.1	14.78
db8	7.43	sym4	11.04	bior1.3	7.132
db9	7.23	sym5	12.58	bior1.5	11.96

Table 2: DRNN outputs under different blade severities

Output 1	Output 2	Output 3	Output 4	Output 5	Indication
1	0	0	0	0	F0
0	1	0	0	0	F1
0	0	1	0	0	F2
0	0	0	1	0	F3
0	0	0	0	1	F4

Table 3: Comparison of the performance of different feature reduction methods

Speed	Blades identified rate (%) using test data set				
	1	2	3	4	5
PCA (Prieto et al. 2013)					
High speed	97.7	95.9	98.1	78.2	80.0
Low speed	99.1	82.8	77.9	64.2	96.0
LDA (Alok et al. 2006)					
High speed	95.6	95.8	99.2	85.6	85.8
Low speed	51.4	72.4	80.0	80.0	80.0
OFNDA					
High speed	99.0	98.4	96.7	93.6	96.4
Low speed	99.7	98.9	97.6	96.4	98.7

Table 4: Comparison of the proposed method with recent published works

References	Fault Indicator	Feature Extraction Tool	Feature Dimensionality Reduction tool	Classifier	Classification accuracy%
(Prieto et al. 2013)	Vibration signal	Statistical time features	PCA	Static NN	95
(Kankar et al. 2011)	Vibration signal	Continuous Wavelet Transform (CWT)		Static NN SVM SOM	93 93 72
(Xu et al. 2009)	Vibration signal	CWT	FLS		87
(Yusuf et al. 2013)	Vibration signal			DNN NARX	91 95
(Camarena-Martinez et al. 2014)	Current signal	EMD		Static NN	90
(Samanta et al. 2004)	Vibration signal	Statistical time features	GA	Static NN	88
Proposed approach	Current and Vibration signals	DWT	OFNDA	DNN	97