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Unmanned Marine Vehicles Motor Fault Classifier Based on Nonlinear Autoregressive with Exogenous

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Abstract- Unmanned underwater vehicles (UUVs) are now being employed by the scientific, offshore and naval sectors to perform a multitude of different tasks. This study presents a novel approach to the diagnosis of unbalanced load faults in an electric thruster motor. The type of motor being typically employed in propulsion systems for small electric powered craft such as UUVs. The diagnosis approach is based on the use of discrete wavelet transforms (DWTs) as a feature extraction tool and a nonlinear autoregressive with exogenous input (NARX) neural network for fault classification. To make the fault detection much simpler the DWT was implemented for signal denoising. The NARX classifies the healthy and faulty conditions of the motor by analysing the vibration signal.

The results obtained from the real-time simulation demonstrate the effectiveness and reliability of the proposed methodology in classifying the different faults with greater speed and accuracy.

INTRODUCTION

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. 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. 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.

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 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.

In general the concept of fault diagnosis consists of the following three essential task models [1]:

- 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.

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 [4]. Almost all previous work 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 network (DRNN) due to their capabilities for modelling nonlinear dynamical systems. Yusuf et al and Hyun [2 and 3] 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 [5].

2 Approach

Figure 1 represents the diagram of the fault diagnosis process, where the machine represents a trolling motor and vibration signals are measured in the signal measurement block. The feature extraction block includes the use of DWT to extract features from the measured signals and the dimensionality reduction tool OFNDA for mapping and selecting the best features. The reduced feature set is then fed into a fault decision block where the NARX classifies the faults. For effective condition monitoring, the wavelet transform base de-noising method is implemented to denoised signal with the following specification: (sym 4) mother wavelet, threshold value (4.5). Then this signal is decomposed using DWT. Extracting the most significant features is crucially important for pattern recognition problems**.** To extract the useful information, DWT, a signal analysis method that provides the time and frequency information of the signal was applied. DWT has the ability explore signal features with different time and frequency resolutions [6]. The best selected features are then used to train a NN for fault classification. The total data, after feature reduction, was divided into three sets: 70% were used for training of the NN, 15% for validation and 15% for testing purposes.

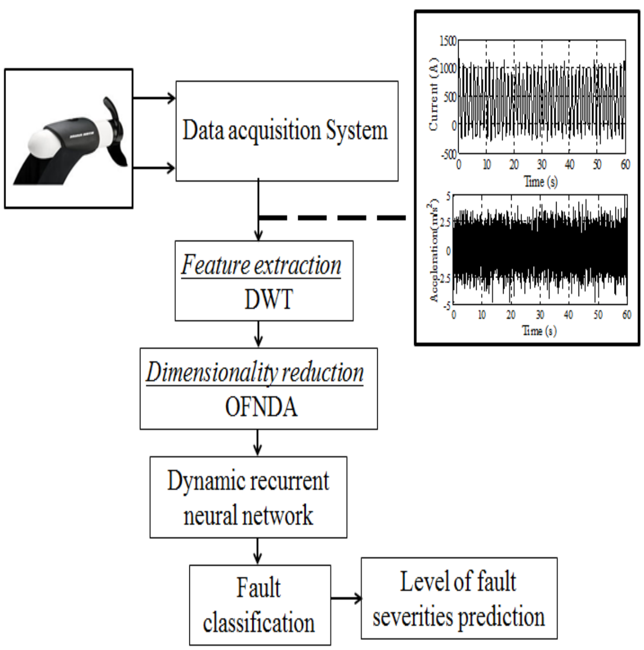

Fig.1. fault diagnosis process

3 Results and Discussion

series of high pass filters to analyse the high frequencies, and it is also passed through a series of low pass filters to analyse the low frequency components of the signal. The DWT decomposes the signal into detail and approximate energy coefficients at different scales expressed in Eqs 1 and 2 respectively:

Mathematically, the wavelet and scaling functions can be represented .

$$x(t) = \sum_{n=-\infty}^{\infty} c(n)\emptyset(t-n + \sum_{n=0}^{\infty}\sum_{n=\infty}^{\infty} d(j,n)2^{j/\pi}\gamma(2^j t-n) \qquad (1)$$

The scaling $c(n)$ and wavelet $d(j,n)$ coefficients are computed as (for level j) [39].

$$c(n) \int_{-\infty}^{\infty} x(t)\,\emptyset(t-n)dt \qquad (2)$$

$$d(j,n) = 2^{j/2}\int_{-\infty}^{\infty} x(t)\,\emptyset(t-n)dt \qquad (3)$$

To emphasize computational efficiency, DWT can achieve such requirement. The DWT can be expressed as

$$dwt(j,k) = \frac{1}{\sqrt{2^j}}\int x(t)\gamma^*\left(\frac{t-k2^j}{2^j}\right)dt \qquad (4)$$

DWT approach is successfully applied to detect and locate faults together with identification of the severity of the faults the same approach can be extended to identify the other faults with a significant reduction in the computation time. The three levels discrete wavelet decomposition is shown in figure.2. At each level, the original signal $(A_o(k))$ is decomposed into separated using low $g[n]$and high pass filters $h[n]$ into a detail (d_j) component which is the high frequency components and approximation (a_n) , which is the low frequency components, by correlating the scaled and shifted versions of the wavelet (as in Eq5). The correlation between the signal and the wavelet at each level of scaling and shifting is termed the wavelet coefficient. The resolution of the signal, which is a measure of the amount of detail of information in the signal, is changed by the filtering operations, and the scale is changed by changed the size window of signals. Resulting from the DWT decomposition, a set of wavelet energy signals (d_j) and (a_j) are obtained .

The DWT approach has been successfully applied to detect and locate faults together with identification of the severity of the faults .The signal is passed through a

$$A_o(k)) = \sum \vartheta_i^m.\theta_i^m(t) + \sum_{j=1}^{m}\sum_i \alpha_i^j.\varphi_i^j \qquad (5)$$
$$= a_n\ (t) + d_n(t) + \cdots + d_1$$

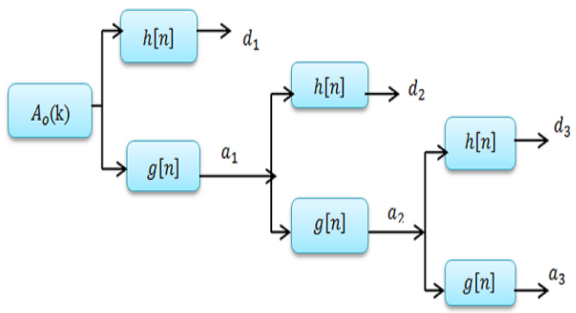

Fig.2. Discrete Wavelet decomposition

Commonly, dimensionality reduction methods can be implemented as methods of feature projection and feature selection. In this paper only the projection method is considered. The feature projection method attempts to determine the best combination of original wavelet. Coefficients and additionally, the features reduced are different from the original features. OFNDA has been recently proposed. OFNDA as a new approach for feature reduction , it works to maximize the distance between features belong to different classes (S_b) whilst minimize the distance between features in the same class (S_w) while taking into account the contribution of the samples to the different classes OFNDA has been successfully applied to classify 4 classes of rolling element bearing defects and normal conditions working under variable speed and load conditions on other hand OFNAD have been overcome the singularity problems for linear discriminate analysis (LDA). There are no accounts in the literature of using the intelligent features of OFNDA for feature reduction in the fault diagnosis of an electrical motor Eqs (6-8) are illustrated the OFNDA process, the first step is to apply principle component analysis to remove any redundancy that may cause singularity before staring discriminate analysis and keep all principle components to prevent loss any useful information. Then the computation of the proposed fuzzy neighborhood discriminant analysis (FNDA) proceeds by calculating the S_w *and* S_b . the transformation matrix is calculated.

$$S_w = \sum_{i=1}^{c} \sum_{k=1}^{l_i} \mu_{ik}\left(X_k - X_j\right)\left(X_k - X_j\right)^T \quad (6)$$

$$S_b = \sum_{i=1}^{c} \mu_{ik}(\mathrm{U_i} - \mathrm{X_x})(\mathrm{U_i} - \mathrm{X_x})^{\mathrm{T}} \quad (7)$$

$$G = G_{FNDA} \cdot G_{PCA} \quad (8)$$

where μ_{ik} Is the membership of pattern k in class i, $X_k$is the K_{th} sample, and U_i is the mean of the patterns that belong to class i and $G_{FNDA}.G_{PCA}$ *is the* Transformation matrix related to PCA and FNDA respectively. The feature reduction techniques mentioned above were able to reduce the original number of wavelet features from 6 to 2, enabling faster computation. It can be observed from Figure 4 that boundaries between different operating conditions are more distinct when using the OFNDA technique.

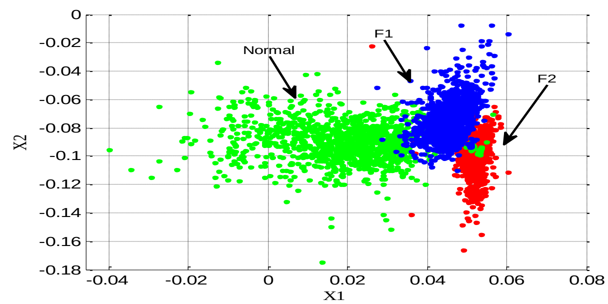

Fig.3. OFNDA features

Figure. 4 shows that fault F1 and fault F2 were correctly classified by the proposed technique within less than 0.5 sec of the occurrence of the fault.

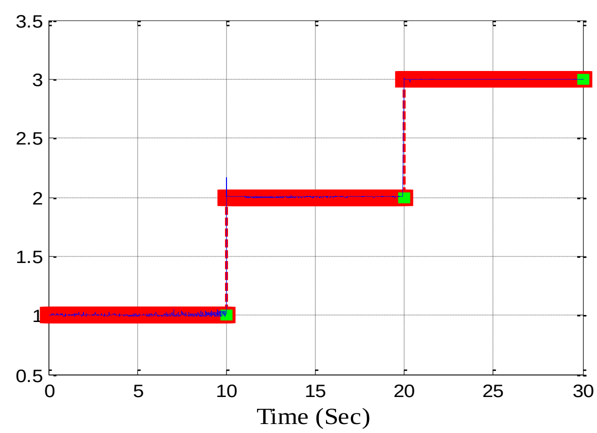

Fig.4. DNN performance

4 Conclusion

This paper proposes a new methodology for fault diagnosis of a trolling motor under two unbalanced load operating conditions. A DWT was used as a feature extraction tool to obtain a better resolution of the signal in time and frequency domains and then feature reduction based on OFNDA was applied to obtain the best features for fault classification. These features were then fed into a NARX for classifying the faults and results showed that better classification accuracy was obtained with OFNDA techniques.

Further tests simulating the real operating behaviour of the trolling motor under normal and faulty conditions also confirmed the superiority of the proposed method which can easily be appiled to real time fault detection and classification on board the *Springer* UUV. The proposed technology is portable to other types of autonomous vehicle

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Biography

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