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Motorbike Engine Faults Diagnosing System Using Entropy and Functional Link Neural Network in Wavelet Domain

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***Abstract*-The sound of working vehicle provides an important clue for engine faults diagnosis. Endless efforts have been put into the research of fault diagnosis based on sound. It offers concrete economic benefits, which can lead to high system reliability and save maintenance cost. A number of diagnostic systems for vehicle repair have been developing in recent years. Artificial Neural Network is a very demanding application and popularly implemented in many industries including condition monitoring via fault diagnosis. This paper presents a feature extraction algorithm using total entropy of 5 level decomposition of wavelet transform. The engine noise signal is decomposed into 5 levels (A5, D5, A4, D4, A3, D3, A2, D2, A1, D1) using Daubechies "db4" wavelet family. From the decomposed signals, the entropy is applied for each levels and the feature are extracted and used to develop a functional link neural network.**

***Keywords* - Entropy, Wavelet Analysis, Functional Link Neural network.**

I. INTRODUCTION

Identification and diagnosis of vehicle faults on a system has becoming increasingly popular especially for mechanics and automotive manufacturers. It offers reliabilities and potentialities in system monitoring applications through faults diagnosis system. Expert system provide powerful and flexible means for obtaining solution to a variety of problems that often cannot be dealt with by order, more traditional and orthodox methods. The need and the issues related to the development of an expert system for vehicle fault diagnosing is addressed by Ahmad T. Al-Thani [1]. Chen Guojin et al. have developed an intelligent analysis system based on TMS320VC5402 by using eigenvalues of signal in frequency field and time field [2]. Sound quality is also important in term describing an objective measure of the subjective perception to a radiated sound. Knowledge about how people perceive sounds has been applied to engine noise, since this noise can considerable influence on potential buyers. A novel approach to the widespread problem of evaluating the quality of noise of a vehicle engine was presented by G. Pinero, A. Gonzales and M.de Diego [7].

The faults in the vehicle engine may be due to various reasons. The faults may be termed as intermittent failure, or permanent. Both the failures can further be classified according to the suddenness with which failure occurs. For diagnosing variety of faults in the vehicle, the engine faults diagnosis using neural network is presented [3]. The system developed is based on a fault table for the engine. The wavelet neural network is a new neural network model depended on the great breakthrough in wavelet analysis technology recently. A model of wavelet neural networks is constructed based on wavelet frame theory and neural networks technology [4]. A fault diagnosis system based on Discrete Wavelet Transform (DWT) technique for internal combustion engine using sound emission signals is proposed by Juan Da Wu and Chiu Hong Liu [6]. In this paper, the noise signals emanated from the motorbike engine are decomposed into five level using wavelet transform. Energy levels from the 5 level decomposed signals are obtained using filter banks and these data are used as a feature vector to classify the fault present in the motorbike engine.

The application of the artificial neural network (ANNs) has been very extensive in recent years, such as in prediction, classifier, pattern recognition, control filter. Artificial Neural Network (ANNs) provides alternative form of computing that attempts to mimic the functionality of the brain [8]. Feed forward ANNs trained with backpropagation (BP) training algorithm are commonly used in engineering applications for dealing non-linear or complex systems. In this paper, the discrimination of energy levels in different sub-band frequencies is used as a training feature and to classify the faults in the motorbike.

II. DISCRETE WAVELET TRANSFORM

Wavelet analysis has practically become a ubiquitous tool in signal processing. Two basic properties, space and frequency localization and multi-resolution analysis, make this a very attractive tool in signal analysis. The wavelet transform method processes perfect local property in both time space and frequency space and it use widely in the region of vehicle faults detection and identification. The general definition of the wavelet transform is given as [9]:

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) dt \quad (1)$$

where a and b are real and * denote complex conjugate and $\psi(t)$ is the wavelet function. In this research work, Daubechies [10] wavelet class of 4 and decomposition is done until level 5.

III. Wavelet Entropy

A signal can be expended in different ways and the number of binary subtrees may be very large. It is necessary to find an optimal decomposition by using a convenient algorithm. Entropy is commonly method in many fields, especially in signal processing applications. Entropy indicates the amount of information which is stored in observed signal. There are more different entropy types such as Shannon, low energy, sure, threshold, etc. The entropy 'E' must be an additive information cost function such that E(0) = 0 and

$$\sum_i E(s_i) \quad (2)$$

The entropy for observed signal in */p* norm with $p \geq$ can be expressed as,

$$E(si) = |si|^p \quad (3)$$

and

$$E(s) = \sum_i |si|^p \quad (4)$$

The Shannon entropy is defined as

$$E(s) = \sum_i s_i^2 \log(s_i^2) \quad (5)$$

Where '*Si*' represent coefficient of signal '*s*' in an ortho-normal basis (Wavelet Toolbox Guide 2007). If entropy value is greater than one, the component has a potential to reveal more information about the signal and it needs to be decomposed further in order to obtain simple frequency component of the signal. The using of entropy provides distinctive features about the signal and reduces the size of feature vector as compared with the using of node coefficients alone [12].

III. Feature Extraction

The Discrete wavelet transform has particular advantages for characterizing signals at different localization levels in time as well as frequency domains. Discrete wavelet transform "db4" is used to decompose the signal into two frequency sub-bands such as low frequency band (approximate coefficients) and high frequency band (detail coefficients) through high pass and low pass filtering. In this paper, a five level decomposition is performed through "db4" wavelet function. The frequency band of each wavelet decomposition level is given by Parameshwaiah and Cox [11]. The frequency sub-bands and center frequency of each decomposition level performed in this work are given in Table 1.

Table I
Band And Center Frequency Of Each Level

Level of Decomposition	Frequency band (Hz)	Center frequency (Hz)
0 (A5)	0 - 689.06	344.53
1 (D5)	689.06 -1378.12	1033.59
2 (D4)	1378.12 - 2756.24	2067.18
3 (D3)	2756.24 - 5512.48	4134.36
4 (D2)	5512.48 - 11024.96	8268.72

Table 2
Sub Band Frequencies For Each Level In Hz

Sub bands Levels	1	2	3	4
0(A5)	1- 172.27	172.27 - 344.53	344.53- 516.80	516.80- 689.06
1(D5)	689.06- 861.33	861.33- 1033.59	1033.59- 1205.86	1205.86- 1378.12
2(D4)	1378.12- 1722.65	1722.65- 2067.18	2067.78- 2411.71	2411.71- 2756.24
3(D3)	2756.24- 3445.30	3445.30- 4131.36	4134.36- 4823.42	4832.42- 5512.48
4(D2)	5512.48- 6890.6	6890.60- 8268.75	8268.75- 9648.84	9648.84- 11024.96

After five level of decomposition, the approximation coefficients of 5^{th} level and detailed coefficients of D2~D5 are considered for extracting the energy features. The frequency bands corresponding to the above level are further divided into four sub-frequency bands using band pass filter which are tabulated in Table 2. At each wavelet decomposition level, the entropy at four frequency sub-bands is computed and then its equivalent entropy is calculated. The entropy values of these levels are used as a feature vector for training the functional link neural network.

IV. Experimental Set-up And Methodology

The condition of the vehicle is examined by a panel of experts and the details of faults like carburetor problem, carbon problem, chain problem and spark plug problem are obtained and recorded for each motorbike. A digital sound recorder (SONY ICD-300) is used to record the sound signal from the motorbike engine. The position of recorder is kept 1 meter above the ground level and 1.3 meter from the center of the motorbike engine to measure the noise signal based on the Acoustical International Standard (ISO 9614 & ISO 3745). The recorded signal is saved as .dvf format and this sound signal is converted into wave format using Sony Digital Sound Editor Software. The above experiment is conducted on eighty different motorbikes of same model. Figure 1 shows the methodology of this work. In this experiment, the noise emanated from the motorbike engine is recorded at four different gear conditions and sampled at a sampling frequency of 44.1 kHz. Throughout the experiment, the motorbike engine speed is maintained constant at 2000 rpm and kept at stationary condition. The engine noise signal are digitized and decomposed into 5 levels of decomposition using "db4" wavelet transform. The approximation and detail coefficients for five level decompositions are obtained for various engine fault signals; carburetor problem, carbon problem, chain problem and spark plug problem, which are shown in Figure 2, Figure 3, Figure 4, Figure 5, Figure 6, Figure 7 Figure 8 and Figure 9 respectively. The entropy values are normalized using bipolar normalization and used for training the neural network.

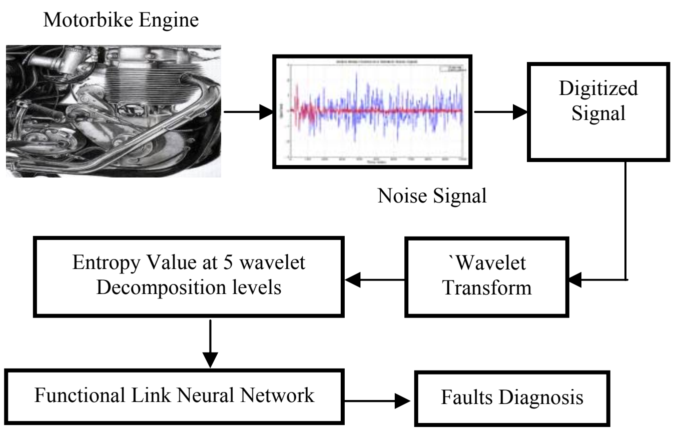


Fig. 1. Methodology for engine fault detection

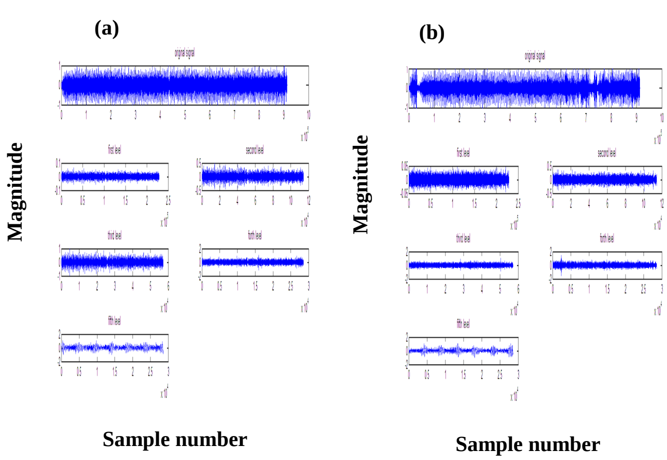


Fig. 2. Original and decomposed signal of motorbike without (a) and with (b) carbon problem.

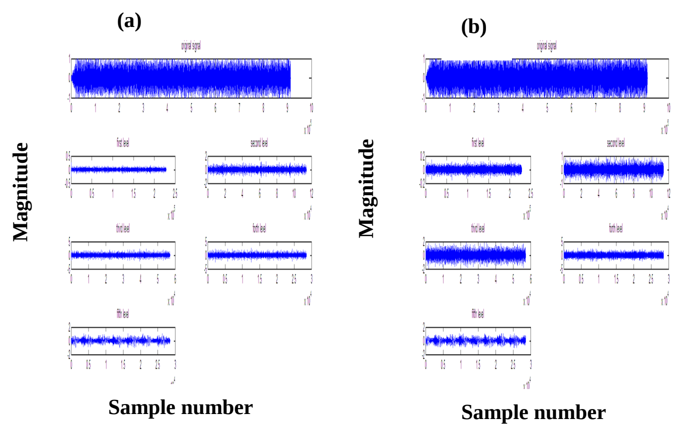


Fig. 3:.Original and decomposed signal of motorbike without (a) and with (b) chain problem.

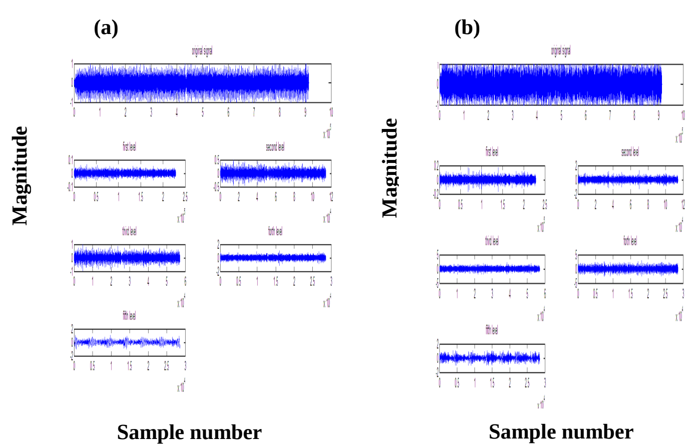


Fig. 4. Original and decomposed signal of motorbike without (a) and with plug problem (b).

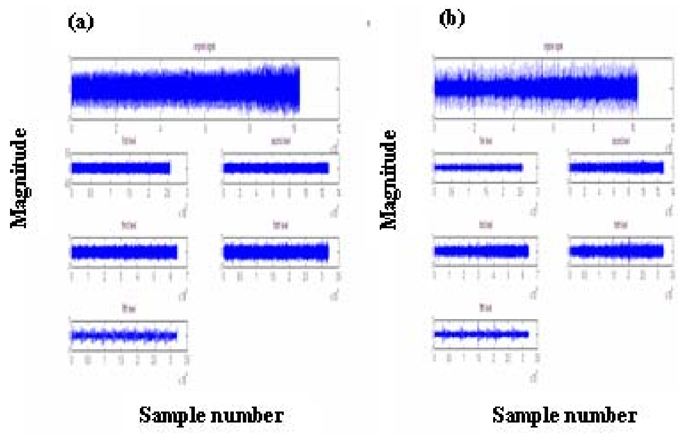
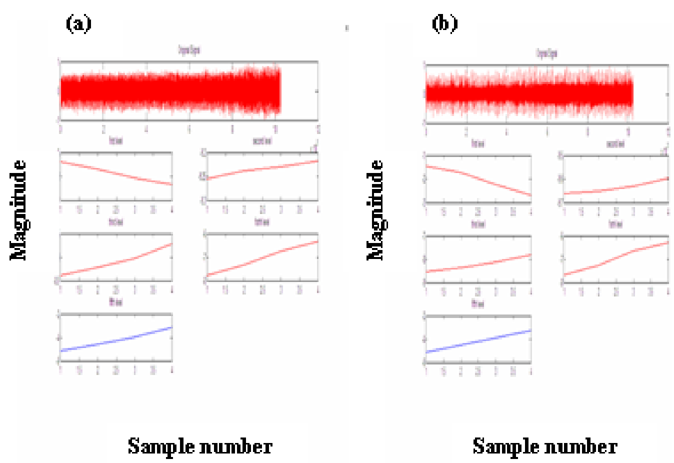


Fig. 5.Original and decomposed signal of motorbike without (a) and with (b) carburetor problem.



Fig, 6:.Entropy signal of using wavelet transform "db4" without (a) and (b) with carburetor problem

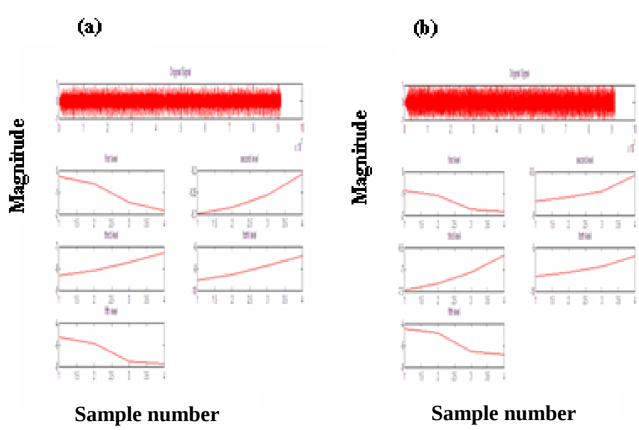


Fig. 7. Entropy signal of using wavelet transform "db4" without (a) and (b) with carbon problem

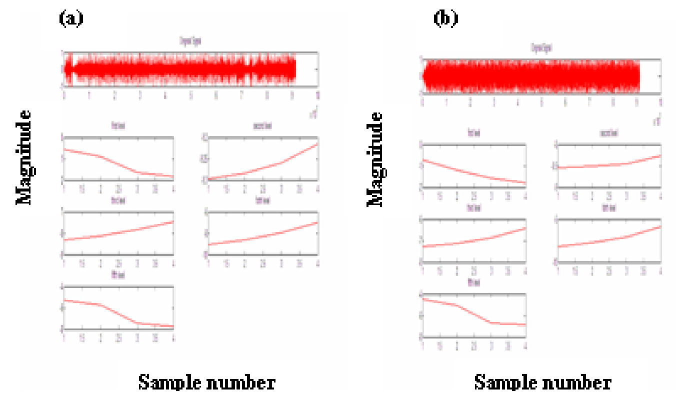
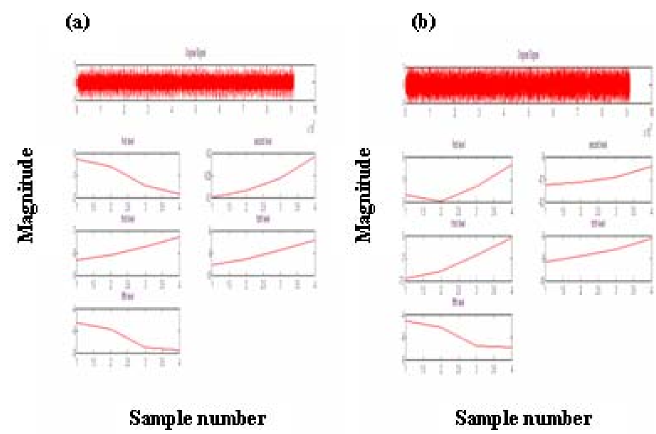


Fig. 8:.Entropy signal of using wavelet transform "db4" without (a) and (b) with chain problem



Fig, 9:.Entropy signal of using wavelet transform "db4" without (a) and (b) with plug problem

TABLE 3
TRAINING RESULTS – MEAN OF CLASSIFICATION RATE AND MEAN OF EPOCH NUMBER

<table>
<tr><td colspan="5">Number of input neurons: 17, Number of Hidden Neurons: 16,
Number of output neuron:1
Activation Function: 1/(1+exp(-v/q)),
Learning Rate: 0.31 Momentum Factor:0.94
Training Tolerance: 0.01 q_h=1.0 q_o=1.0
Testing Tolerence:0.15
Number of samples used for training: 176
No. samples used for testing: 220</td></tr>
<tr><td>Trial no</td><td>Mean Classification Rate-I</td><td>Mean Classification Rate-II</td><td>Mean Classification Rate-III</td><td>Mean Classification Rate-IV</td></tr>
<tr><td>1</td><td>80.23</td><td>80.38</td><td>81.72</td><td>87.50</td></tr>
<tr><td>2</td><td>79.71</td><td>80.65</td><td>81.58</td><td>88.70</td></tr>
<tr><td>3</td><td>80.29</td><td>80.66</td><td>81.14</td><td>89.40</td></tr>
<tr><td>4</td><td>80.29</td><td>80.58</td><td>82.14</td><td>89.00</td></tr>
<tr><td>5</td><td>80.35</td><td>80.67</td><td>82.50</td><td>88.93</td></tr>
</table>

V. Neural Network Training

Four neural network models are considered in this paper to diagnose the motorbike engine faults. The neural network has three layers namely input layer, hidden layer and output layer. For training the neural network, the input layer has 17 input neurons representing the entropy value at various critical band frequencies. The hidden layer has 16 hidden neurons, and the output layer has 1 output neurons. The first functional link neural network model is used to classify the carburetor problem, the second, third and forth models are used to identify the spark plug, chain and carbon problem respectively.

The hidden and input neurons have a bias value of 1.0 and are activated by binary sigmoidal activation function. Five trials are considered for each fault. For each trial, the network is trained with 50 different weight samples. The training tolerance and testing tolerance are fixed as 0.15. The learning rate and momentum factor are chosen as 0.31 and 0.94 respectively. The training results are tabulated in Table 3.

The number of mean classification rate for training the functional link neural network models are tabulated in Table 3. The number of mean epoch for training a functional link neural network models lies between 64 and 173. From this table, it can be observed that the minimum classification rate is 79.71% and the maximum classification rate is 89.40%.

VI. Conclusion

In this paper, the identification of motorbike engine faults using entropy wavelet transform is presented. A simple procedure is developed to extract the features from the motorbike engine noise signal. Subsequently, a simple functional link NN model is developed to identify the faults like carburetor, spark plug, chain and carbon problem. The significance of entropy value of a signal after wavelet transformation is also analyzed. The experimental results show that the different faults of the vehicle engine can be identified using the proposed method. In the future work, it is proposed to implement the feature extraction and the NN model in an embedded system.

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