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Fault Diagnosis of Monoblock Centrifugal Pump Using Stationary Wavelet Features and Bayes Algorithm

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***Abstract* - Fault diagnosis of monoblock centrifugal pump is conceived as a pattern recognition problem. There are three important steps to be performed in pattern recognition namely feature extraction, feature selection and classification. In this study, Stationary wavelet transform (SWT) is used for feature extraction from the input signals and Bayes net classifier is used for classification. A WEKA implementation of Bayes net algorithm is used. The different fault conditions considered for the present study are Cavitation (CAV), Impeller fault (FI), Bearing Fault (BF) and both Impeller and Bearing Fault (FBI). The representative signal is acquired for all faulty conditions, Features are extracted, classified and the results are presented. The experimental setup and the procedure for conducting the experiments are discussed in detail.**

***Keywords:* Stationary wavelets transform, fault diagnosis, wavelet feature, Bayesnet.**

I. INTRODUCTION

In a monoblock centrifugal pump, defective bearing, defect on the impeller and cavitation cause a very serious problems. Cavitation results in undesirable effects, such as deterioration of hydraulic performance (drop in head capacity and efficiency). Fault detection is achieved by comparing the signals of monoblock centrifugal pump running under normal and faulty conditions. Vibration signals are widely used in condition monitoring of centrifugal pumps. For the measurement of the vibration levels for each condition, seismic or piezoelectric transducers along with data acquisition system is used. From the vibration signal relevant features are extracted using Stationary Wavelet Transformations (SWT) and classification is done using bayesnet classifier and the results are presented.

V. Muralidharan and V. Sugumaran (2012) have reported the comparative study of bayes classifier and bayes net classifier for pump data using discrete wavelet transform features (DWT features). Finally, concluded that bayes net classifier seem to be good for DWT features. The same authors (2013) also investigated in detail with J48 algorithm and support vector machines for continuous wavelet and DWT features. Jiangping Wang, Hong Tao Hu (2006) focuses on a problem of vibration-based condition monitoring and fault diagnosis of pumps. The vibration-based machine condition monitoring and fault diagnosis incorporate a number of machinery fault detections and diagnostic techniques. They used fuzzy logic principle as a fault diagnostic technique to describe the uncertain and ambiguous relationship between different fault symptoms and classify frequency spectra representing various pump faults. Fansen Kong, Ruheng Chen (2004) proposed a new combined method based on wavelet transformation, fuzzy logic and neuro-networks for fault diagnosis of a triplex pump. The failure characteristics of the fluid and dynamic-end can be divided into wavelet transform in different scales. Therefore, the characteristic variables can be constructed making use of the coefficients of Edge worth asymptotic spectrum expansion formula and fuzzified to train the neuro-network to identify the faults of fluid- and dynamic-end of triplex pump in fuzzy domain. Tests indicate that the information of wavelet transformation in scale 2 is related to the meshing state of the gear and the information in scales 4 and 5 is related to the running state of fluid-end. Good agreement between analytical and experimental results has been obtained. V. Muralidharan *et al.,* discussed that classification capability of J48 algorithm and SVM algorithm with DWT features. The similar types of faulty conditions were considered and the experiments were performed. Also, they have performed an experiment with rough set theory and support vector machine algorithms. However, there is a scope for conditional probability based algorithms in the field of fault diagnosis. Hence, this work has been taken up with stationary wavelet transforms and bayesnet algorithm for fault diagnosis of monoblock centrifugal pump in order to fill the gap.

II. EXPERIMENTAL STUDIES

The main idea of this study is to find whether the monoblock centrifugal pump is in good condition or in faulty condition by a systematic procedure following certain steps. If the pump is found to be in faulty condition then the next step is to segregate the faults into Cavitation (CAV), Impeller fault (FI), Bearing Fault (BF) and both Impeller and Bearing Fault (FBI)defect together.

A.Experimental Setup Description

The monoblock centrifugal pump is taken for this study. The motor (2HP) is used to drive the pump. Piezoelectric type accelerometer is used to measure the vibration signals. The accelerometer is mounted on the pump inlet using adhesive and connected to the signal conditioning unit where signal goes through the charge amplifier and an analog to digital converter (ADC) and the signal is stored in the memory. Then the signal is processed from the memory and it is used to extract the features.

B.Procedure

The pump was allowed to rotate at a speed of 2880 rpm at normal working condition and the vibration signals are measured. The sampling frequency of 24 KHz and sample length of 1024 were considered for all conditions of pump. The sample length was chosen arbitrarily to an extent; however, the following points were considered. After calculating the wavelet transforms it would be more meaningful when the number of sample is more. On the other hand, as the number of sample increases, the computation time increases. To strike a balance, sample length of around 1,000 was chosen. The specification of the monoblock centrifugal pump is given as below.

TABLE I SPECIFICATION OF THE PUMP UNDER STUDY

Rotational Speed	2880 rpm
Pump Size	50 mm x 50mm
Current	11.5 A
Discharge	392 lps
Head	20m
Power	2 hp

In the present study the following faults were simulated as described below.
Cavitation - by intentionally closing the suction gate valve partially.
Impeller fault - chipping to dislodge one material to simulate pitting.
Bearing fault – a thin cut through wire cut EDM.
Bearing and Impeller fault together.
The faults were introduced one at a time and vibration signals were taken.

III. FEATURE EXTRACTION

Stationary Wavelet Transform (SWT) has been widely used and provides the physical characteristics of time-frequency domain data. The advantage of using SWT is that it avoids the down sampling process and hence one can preserve the length of the signal for analysis. SWT of different versions of different wavelet families have been considered. The following wavelet families and their sub families have been tried for the present study. Daubechies wavelet, Coiflet, bi-orthogonal wavelet, reversed bi- orthogonal wavelet, symlets and Meyer wavelet. Basian algorithms are used for validation of the output.

IV. FEATURE DEFINITION

Feature extraction constitutes computation of specific measures, which characterize the signal. The stationary wavelet transform (SWT) provides an effective method for generating features. The collection of all such features forms the feature vector.

A feature vector is given by

$$v^{swt} = \left\{ v_1^{swt}, v_2^{swt}, \dots v_8^{swt} \right\}^T \quad (1)$$

A component in the feature vector is related to the individual resolutions by the following equation

$$v_i^{swt} = \frac{1}{n_i} \sum_{j=1}^{n_i} w_{i,j}^2 \ , i = 1, 2, \dots 8 \quad (2)$$

Where, v_i swt is the i^{th} feature element in a SWT feature vector. n_i is the number of samples in an $w^2_{i,j}$ individual sub-band.

V.CLASSIFICATION

Bayesian decision making refers to choosing the most likely class given the value of feature or features. Consider the classification problem with two classes C_1 and C_2 based on a single feature x. From the training sets of the two classes, histograms can be prepared and the respective a priori probabilities determined. Information extracted there from can be used to carry out classification based on the feature x. The parameters of classification and confusion matrix pertaining to the best one is presented in Table 2.

TABLE II BAYES NET PARAMETERS FOR SWT FEATURES

Test Parameter	**Values**
Test mode	10-fold cross-validation
Time taken to build model	0.06 seconds
Total Number of Instances	1250
Correctly Classified Instances	1025 (82 %)
Incorrectly Classified Instances	125 (18 %)
Mean absolute error	0.0932
Root mean squared error	0.2365

VI. RESULTS AND DISCUSSION

All the wavelet families and its sub-groups were used to find the stationary wavelet transform which form the feature vectors. The extracted features were then given as an input to the classifier (Bayes NET algorithm) and the classification accuracies were found. Fig.1. will describe the classification accuracies among the different families of wavelet. One can easily understand that the classification accuracy of reverse bi-orthogonal family is high. The performance among the reverse bi-orthogonal wavelet and its versions is presented in Fig.2. Form Fig. 2, one can easily understand the maximum classification accuracy is 82% which is against rbio3.1. This means that the 3.1 version of reverse bi-orthogonal wavelet performs relatively better than any other versions of the wavelet families. The detailed classification detail for rbio 3.1 is given below in the form of confusion matrix in Table. 3.

The confusion matrix can be interpreted as follows. The diagonal elements in the matrix are correctly classified instances and non-diagonal elements are incorrectly classified data points. From the matrix it can be easily understood how it was misclassified. The classification accuracy was calculated accordingly. Therefore, for rbio3.1, the classification accuracy was found to be 82%.

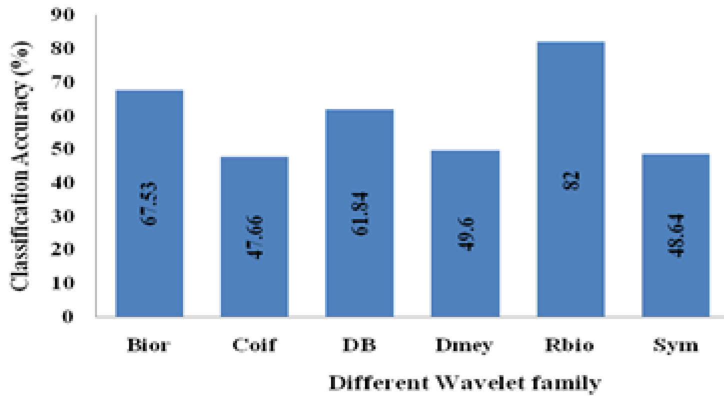

Fig.1 Histogram for classification accuracies for different wavelet families

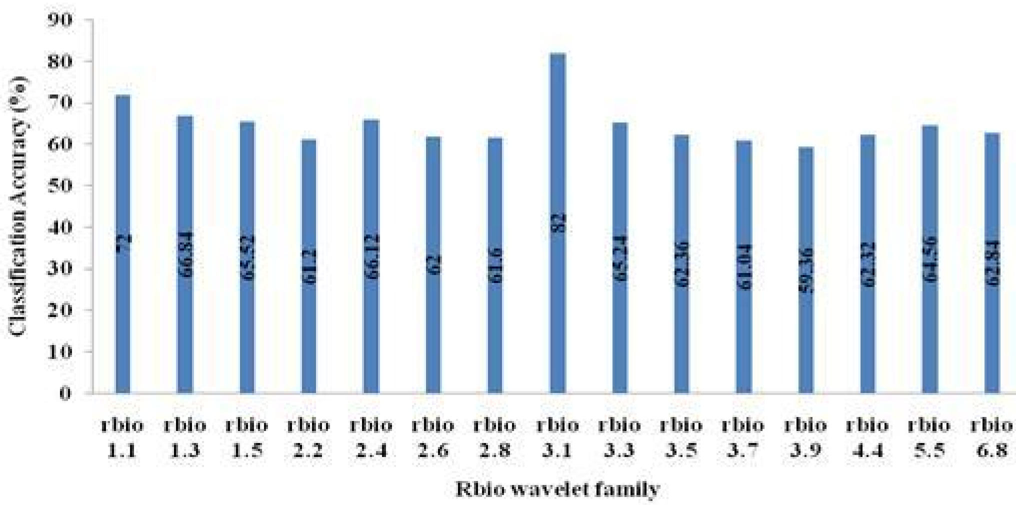

Fig.2 Histogram chart for classification accuracies of rbior wavelet and its versions

TABLE.III. CONFUSION MATRIX FOR RBIO3.1

	Good	CAV	FB	FI	FBI
Good	208	9	0	30	3
CAV	5	215	0	26	4
FB	0	0	246	1	3
FI	84	36	12	118	0
FBI	0	9	3	0	238

A – Good; B –Cavitation; C – Impeller Fault (FI); D – Bearing Fault (FB); E –Bearing and Impeller Fault (FBI).

VII. CONCLUSION

In the present study monoblock centrifugal pump was taken for the study. Stationary Wavelet features were extracted and classified using bayesnet algorithm to study the fault discriminating capabilities of wavelets for vibration signal. From the results and discussion one can confidently say that the best wavelet for this application is reversed bi-orthogonal wavelet 3.1 and whose classification accuracy is found to be 82%. Therefore, to conclude, the SWT features with bayesnet algorithm based classification also very much suited for real time applications.

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