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Vibration Based Fault Diagnosis of a Hydraulic Brake System using Variational Mode Decomposition (VMD)

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Abstract: In automobile, brake system is an essential part responsible for control of the vehicle. Vibration signals of a rotating machine contain the dynamic information about its health condition. Many research papers have reported the suitability of vibration signals for fault diagnosis applications. Many of them are based on (Fast Fourier Transform) FFT, which have their own drawback with non-stationary signals. Hence, there is a need for development of new methodologies to infer diagnostic information from such non stationary signals. This paper uses vibration signals acquired from a hydraulic brake system under good and simulated faulty conditions for the purpose of fault diagnosis. A new approach called Variational mode decomposition (VMD) was used in this study. VMD decomposes the signal into various modes by identifying a compact frequency support around its central frequency, such that adding all the modes reconstructs the original signal. VMD finds intrinsic mode functions on central frequencies using alternating direction multiplier method (ADMM). Descriptive statistical features were extracted from VMD processed signals and classified using a machine learning algorithm. For classification J48 decision tree algorithm was used. The results were compared with the statistical features extracted from raw signal using decision tree classifier.

Keywords: Brake fault diagnosis, decision tree algorithm, variational mode decomposition, alternating direction multiplier method, statistical features.

1 Introduction

Brakes are the most important control components in automobile responsible for the stability of the vehicle. The main function of the brake is to decelerate or de-

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crease the speed of a vehicle in order to bring the vehicle to rest within a reasonable distance. The rate of retardation should be proportional to the pedal effort. Hence the brake system should provide the highest degree of safety. It is very important that the brake system must be maintained. The brake system may get faulty due to various reasons, like pad wear, air leak, mechanical fade, etc. which reduces the effectiveness of the brake system. It is essential that the brake system and brake components should be monitored all the time and diagnosed when faults occur. The malfunction of the brake system can be identified through its symptoms or some warning sign. Therefore certain physical parameters such as vibration have been focused in detection incipient faults.

Vibrations generated by moving machine elements often facade the features of fault related signals generated by the machine elements such as gears [Wuxing, Tse, Guiicai, and Shitielin., (2004)], bearings [Zvokelj, Zupan and Prebil (2010); Li and Ma (1997)] and cams [Tinta et al. (2005)]. When these vibration signals are analyzed using fast Fourier transform (FFT), the frequency components are distributed due to overlapping of harmonics and noise in addition to the frequency components. The non-stationary nature of the signals makes the situation further worse by changing the frequency component itself. Hence analysis of the above signals in faulty operating conditions becomes difficult. Conventional application of measurement of statistical parameters may not be useful under such conditions.

In this context researchers are forced to pay their attention on signal processing methods for improving the accuracy of the fault classification tools. In recent years Empirical Mode Decomposition (EMD) was used to detect incipient faults in gears and in bearings [Ricci and Pennachhi (2011); Loutridis S. J. (2004); Yu, Cheng and Yang (2005)] along with intrinsic mode functions (IMF). The IMF may not suitable non-stationary signals. Lei et al. used EMD to extract features from signals for classifying the different modes and degrees of gear faults [Lei, Zuo and He (2010)]. Hence, these EMD feature analysis will provide the information required to make a decision when intervention is required for maintenance. The results of such analysis are used for failure analysis in order to determine the original cause of the fault. This feature analysis can be done using a machine learning approach [Jegadeeshwaran and Sugumaran (2013)].

Many reports illustrated a fuzzy [Wang and Chen (2007)], Neural Network [Rajakarunakaran, Venkumar, Devaraj, and Surya Prakasa Rao (2008)], support vector machines (SVM) [Sakthivel, Sugumaran and Nair (2010)], proximal support vector machines (PSVM) [Sugumaran, Muralidharan and Ramachanran (2007)], decision tree (DT) and best first (BF) tree [Jegadeeshwaran and Sugumaran (2013)] for fault diagnosis study to classify faults in various machine components such as roller bearing, ball bearing, gears and in a single point cutting tool and brakes etc.

In all the feature classification approaches, the maximum classification accuracy is a challenging one. Since the classification accuracy fully depends on the condition of the signal, the raw signal obtained from the brake setup cannot be used directly for analysis due to noise. It is very essential to improve the condition of the signal through some preprocessing techniques. Hence a new preprocessing technique was developed to decompose the signal into various modes or IMFs using calculus variations. The modes have compact frequency support around the central frequency. ADMM was used as optimization tool to find such central frequencies concurrently [Konstantin Dragomiretskiy and Dominique Zosso (2014)]. The main purpose of decomposing a signal is to identify various components (descriptive statistical features) of the signal. This work focuses on a new algorithm - variational mode decomposition (VMD), which extracts different modes present in the signal. The extracted statistical feature modes were then classified using J48 decision tree algorithm.

The vibration of the brake system depends on various parameters like, brake force, rotational speed of the rotor etc. The focus of this study is to identify a suitable 'feature-classifier' set for the brake fault diagnosis. Hence a static brake test setup with constant brake force or load and constant speed were considered in this study.

The paper is structured as follows:

The experimental setup, experimental procedure and fault simulation procedure have been described in Section 2. Vibration signal acquisition, feature extraction process has been discussed in Section 3. Feature selection process has been described in Section 4. The theory about VMD features have been discussed in Section 5. The classification accuracy of decision tree algorithm with VMD processed statistical process have been evaluated and compared with the statistical features (without VMD analysis) in Section 6. Section 7 summarizes the main findings of this paper. The decision tree (DT) classifier with VMD processed statistical features have been proposed as a suitable classifier for the brake fault diagnosis.

2 Experimental studies

The experimental study was conducted on a static hydraulic brake test setup. A commercial passenger car's (Model: Maruti Suzuki - Swift) hydraulic brake system was fabricated as the brake test rig as shown in Figure 1. The vibration signals were acquired by using a piezoelectric type accelerometer (an uni-axial type, 50g range, 100mV/g sensitivity and 40 kHz resonant frequency). It was connected to a data acquisition system (DAQ system - NI USB 4432 model, sampling rate of 102.4 kilo samples per second, 24 bit resolution) through a signal conditioning unit, where the analog signal is converted to a digital signal using an analog to digital converter

(ADC).

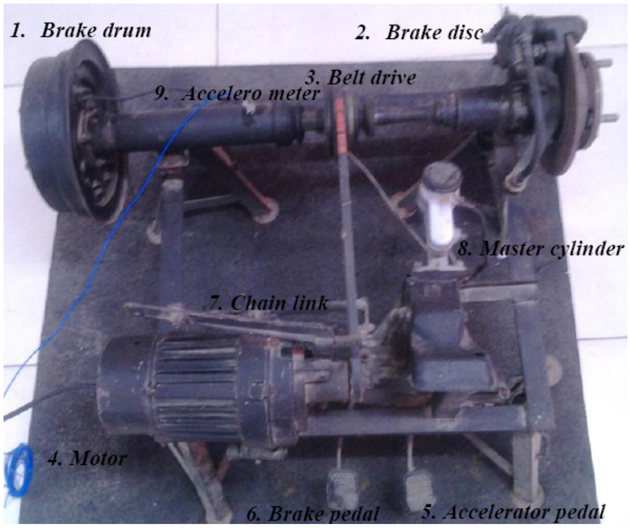

Figure 1: Experimental setup.

Initially the test rig was assumed to be in good condition and the vibration signal was acquired. The frequently occurred nine most important fault conditions namely, air in the brake fluid, brake oil spill on disc brake, drum brake pad wear, disc brake pad wear (even) – inner, disc brake pad wear (even) – inner and outer, disc brake pad wear (uneven) – inner, disc brake pad wear (uneven) – inner and outer, reservoir leak, drum brake mechanical fade were simulated for testing. Under different simulated fault conditions the vibration signals were acquired from the hydraulic brake system working under constant braking condition (Original Speed 667 rpm, Brake load 67.7 N). From the accelerometer, the vibration signals for different fault conditions were taken with the following settings [Jegadeeshwaran and Sugumaran (2013)].

1. Sample length: 1024 (arbitrarily chosen)
2. Sampling frequency: 24 kHz (as per the Nyquist sampling theorem)
3. Sample size: Minimum of 55 samples was taken for each conditions of the braking system.

The acquired vibration signals in digital form were stored directly in the computer through NI LabVIEW graphical program (Figure 2). These vibration signals were processed to extract the statistical features.

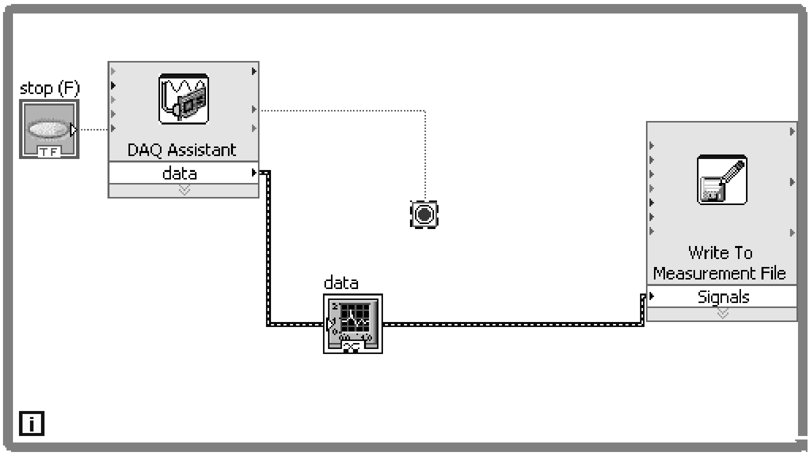

Figure 2: NI LabVIEW Graphical Program.

3 Feature extraction

Feature extraction is the process of computing some meaningful measures that represent a signal. The vibration signal may consist fairly a number of statistical parameters. Using a suitable pre-processing technique these statistical features can be extracted.

3.1 Feature extraction through Variational Mode Decomposition (VMD)

The extracted vibration signal was decomposed in to modes using variational mode decomposition (VMD) approach. The decomposed signal was used to generate decision tree. From the decision tree the most important features were selected. They are standard error1, standard error2, sample variance2, sample variance4, sample variance6, kurtosis1, and kurtosis2. These seven features were selected for classification. The definitions of statistical features were described by Jegadeeshwaran and Sugumaran [Jegadeeshwaran and Sugumaran (2013)].

Standard error: The standard error is a measure of the amount of error in the prediction of y for an individual x in the regression, where x and y are the sample means and 'n' is the sample size.

$$\text{Standard error} = \sqrt{\frac{1}{n-2}\left[\sum (y-\bar{y})^2 - \frac{\sum[(x-\bar{x})(y-\bar{y})]^2}{\sum (x-\bar{x})^2}\right]} \tag{1}$$

Sample variance: It is variance of the signal points and the following formula was used for computation of standard variance.

$$\text{Sample variance} = \frac{n\sum x^2 - \left(\sum x\right)^2}{n\left(n-1\right)} \tag{2}$$

Kurtosis: Kurtosis indicates the flatness or the spikiness of the signal. Its value is very low for good condition of the brake material and high for faulty condition of the brake material due to the spiky nature of the signal.

$$\text{Kurtosis} = \left\{ \frac{n\left(n+1\right)}{\left(n-1\right)\left(n-2\right)\left(n-3\right)} \sum \left(\frac{x_i - \bar{x}}{S}\right)^S \right\} - \frac{3\left(n-1\right)^2}{\left(n-2\right)\left(n-3\right)} \tag{3}$$

where, 'S' is the sample standard deviation; S_d is the sample standard deviation.

Standard deviation: This is a measure of the effective energy or power content of the vibration signal.

$$\text{Standard deviation} = \sqrt{\frac{n\sum x^2 - \left(\sum x\right)^2}{n\left(n-1\right)}} \tag{4}$$

The selected modes of the extracted vibration signals were classified using the J48 decision tree algorithm.

3.2 Feature extraction through statistical parameters

A fairly twelve set of statistical parameters were extracted from the raw signals. They are mean, median, mode, standard error, sample variance, kurtosis, skewness, minimum, maximum, standard deviation and count. The process of extracting statistical features using statistical tool was described by Sugumaran et al., [Sugumaran and Ramachandran (2007)]. The extracted features were used to generate decision tree. From the decision tree the most important features were selected. These selected features were then classified using decision tree algorithm.

Skewness: Skewness characterizes the degree of asymmetry of a distribution around its mean.

$$\text{Skewness} = \frac{n}{\left(n-1\right)\left(n-2\right)} \sum \left(\frac{x_i - \bar{x}}{S_d}\right)^3 \tag{5}$$

Maximum: Maximum signal point value in a given signal.

Minimum: Minimum signal point value in a given signal.

Range: Difference in maximum and minimum signal point values for a given signal.

Mean: The arithmetic average of a set of values or distribution.

Median: Middle value separating the greater and lesser halves of a data set.

Mode: Most frequent value in a dataset.

Count: Number of data points in the signal.

4 Variational Mode Decomposition

Variational Mode Decomposition (VMD) decomposes the signal into various modes or intrinsic mode functions using calculus of variation. Each mode of the signal may have compact frequency support around a central frequency. VMD tries to find out these central frequencies and intrinsic mode functions centered on those frequencies concurrently using an optimization methodology called ADMM [Konstantin Dragomiretskiy and Dominique Zosso (2014)]. The original formulation of the optimization problem is continuous in time domain.

VMD is formulated as; Minimize the sum of the bandwidths of k modes subject to the condition that sum of the k modes is equal to the original signal. The unknowns are k central frequencies and k functions centered at those frequencies. Since part of the unknowns is function, calculus of variation is applied to derive the optimal functions.

Bandwidth of an AM-FM signal primarily depends on both, with the maximum deviation of the instantaneous frequency $\Delta f \sim \max\left(\left|\omega_k(t) - \omega_k\right|\right)$ and the rate of change of instantaneous frequency. Dragomiretskiy and Zosso (2014) proposed a function that can measure the bandwidth of a intrinsic mode function $u_k(t)$. At first they computed Hilbert transform of $u_k(t)$. Let it be $u_k^H(t)$. Then formed an analytic function $\left(u_k(t) + ju_k^H(t)\right)$. The frequency spectrum of this function is one sided (exist only for positive frequency) and assumed to be centered on ω_k . By multiplying this analytical signal with $e^{-j\omega_k t}$, the signal is frequency translated to be centered at origin. The integral of the square of the time derivative of this frequency translated signal is a measure of bandwidth of the intrinsic mode function $u_k(t)$.

$$\text{Let} \quad u_k^M(t) = \left(u_k(t) + ju_k^H(t)\right) e^{-j\omega_k t} \tag{6}$$

It is a function whose spectrum is around origin (baseband). Magnitude of time derivative of this function when integrated over time is a measure of bandwidth. Hence,

$$\Delta\omega_k = \int \left(\partial_t \left(u_k^M(t)\right)\right) \overline{\left(\partial_t \left(u_k^M(t)\right)\right)} dt \tag{7}$$

where, $\partial_t \left(u_k^M(t)\right) = \partial_t \left[\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)\right]$.

The integral can also expressed as a norm.

$$\Delta\omega_k = \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] \right\|_2^2 \tag{8}$$

The sum of bandwidths of k modes is given by $\sum_{k=1}^{K} \Delta\omega_k$.

The resulting variational formulation is as follows:

$$\min_{u_k,\omega_k} \left\{ \sum_k \left\| \partial_t \left[\left(\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right) e^{-j\omega_k t} \right] \right\|_2^2 \tag{9}$$

$s.t.$ $\sum_k u_k = f$, where f is the original signal.

The augmented Lagrangian multiplier method converts this into an unconstrained optimization problem. The following algorithmic approach has used for VMD:

Final algorithm for VMD:

initialize $\hat{u}_k^1,\ \hat{\omega}_k^1,\ \hat{\lambda}^1$, n $\leftarrow 0$

repeat

$n \leftarrow n+1$

for $k = 1 : K$ do

Update $\hat{u}_k$ for all $\omega \geq 0$

$$\hat{u}_k^{n+1} \leftarrow \frac{\hat{f} - \sum_{i<k} \hat{u}_i^{n+1} - \sum_{i>k} \hat{u}_i^n + \frac{\hat{\lambda}^n}{2}}{1 + 2\alpha(\omega - \omega_k^n)^2} \tag{10}$$

Update ω_k:

$$\omega_k^{n+1} \leftarrow \frac{\int_0^\infty \omega \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega}{\int_0^\infty \left| \hat{u}_k^{n+1}(\omega) \right|^2 d\omega} \tag{11}$$

end for

Dual ascent for all $\omega \geq 0$:

$$\hat{\lambda}^{n+1} \leftarrow \hat{\lambda}^n + \tau(\hat{f} - \sum_k \hat{u}_k^{n+1}) \tag{12}$$

$$\text{until convergence:} \quad \sum_k \left\| \hat{u}_k^{n+1} - \hat{u}_k^n \right\|_2^2 \Big/ \left\| \hat{u}_k^n \right\|_2^2 < \varepsilon \tag{13}$$

4.1 Discretization of frequency

It is first assumed that length of the mirrored signal in the time domain is 1. If total length of the mirrored signal in terms of number of discrete values is T, then sampling interval is $1/T$. The discrete frequency ω is assumed to vary from -0.5 to +0.5 so that it represents normalized discrete frequency. It must be noted that algorithm construct Fourier transform of different mode function values for positive frequencies only. The other half can be easily created by conjugating and reflecting on the left side.

Once all the mode functions in the frequency domain are obtained, then obtain the time domain mode functions by taking inverse Fourier transform. These mode functions correspond to mirrored signal. Then cut off the appended (reflected portions) part of the signal to obtain the desired intrinsic mode functions.

5 Feature classification using J48 Decision tree Algorithm

In the preset study a decision tree classifier has been used. A decision tree is a statistical classifier which transforms the data to a tree called decision tree (Quinlan, 1986). A standard tree consists root, nodes, branches and leaves (Figure 3). One branch is a chain of nodes which involves one attribute. The occurrence of an attribute provides the information about the importance of the associated attribute. The procedure of forming the Decision Tree and feature selection has been explained in detail by Sugumaran [Sugumaran and Ramachandran (2007)]. The selected features were classified using J48 decision tree algorithm.

6 Results and Discussion

The vibration signals were acquired for good and nine other fault conditions of the hydraulic brake system. Totally 550 samples were collected; 55 signals from each class. The statistical features were treated as features and act as input to the algorithm. The corresponding status or condition of the classified data will be the required output of the algorithm. This input and corresponding output together forms the dataset.

6.1 Classification using Decision Tree algorithm with Statistical Features (Without VMD processed features)

The dataset is used with decision tree J48 algorithm for generating the decision tree for the purpose of feature selection and classification. From the twelve extracted features, the top five features namely minimum, standard error, sample variance, kurtosis and skewness were selected from the decision tree shown in Figure 4. The

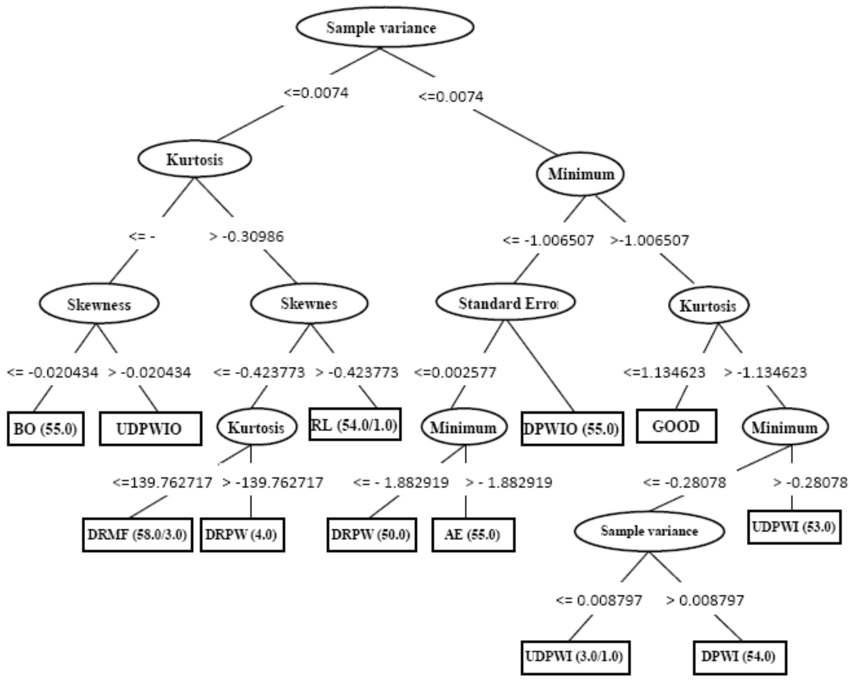

Figure 3: Decision tree with Statistical features (without VMD).

selected features were classified using J48 decision tree algorithm [Jegadeeshwaran and Sugumaran (2013)]. J48 decision tree algorithm gives the maximum classification accuracy as 97.45 % for a selected number of features.

The number of objects required for forming a class was varied from 1 to 100. Refering Figure 4, when the number of objects is 3 the algorithm gives the maximum classification accuracy (97.45%).

When the number of data points is less the algorithm tends to over fit the data and when it is more the algorithm tends to generalize the model built. Hence, it is better to chose minimum value to form a class. The confidence factor was varied from ‘0’ to ‘1’ and found that there is no variation in the classification accuracy (Figure 5). Hence, in the present study it was fixed as ‘0.25’ (default value). The classification accuracy achieved was **97.45 %**.

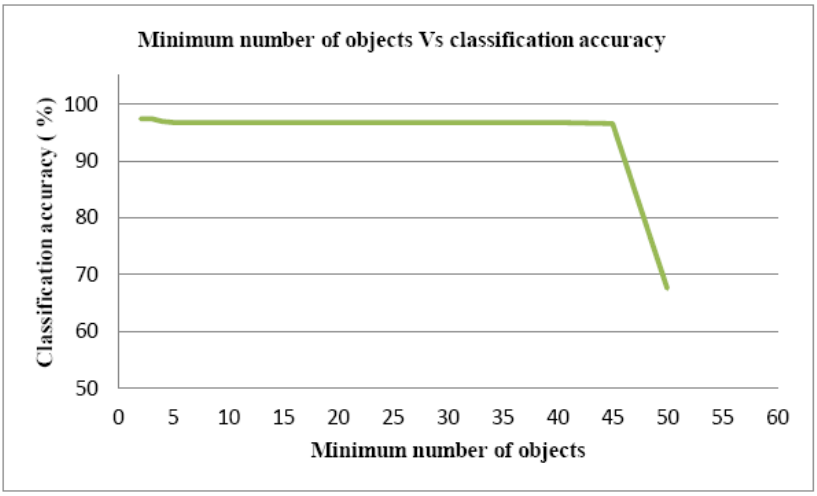

Figure 4: Minimum no. of objects Vs classification accuracy– Decision tree without VMD.

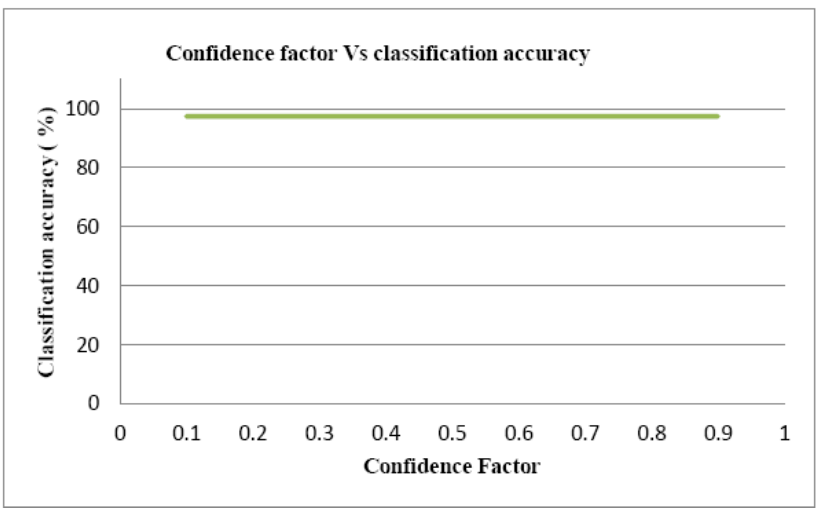

Figure 5: Confidence factor Vs classification accuracy – Decision tree without VMD.

6.2 Classification using Decision Tree algorithm with Statistical Features (With VMD processed features)

The vibration signals are preprocessed using VMD to find out its frequency components. They are also called as intrinsic mode functions. The IMFs are arranged in ascending order of frequencies with each N^{th} mode having the highest frequency and maximum information content. The top five statistical features suggested by the DT algorithm were used for the VMD analysis. Among the 550 data sets, 400 data sets (40 data sets in each class) were kept for training and 150 data sets (15 data sets in each class) were kept for testing. Each feature was decomposed in to 120 modes. Among the extracted features, the top seven features were participated for classification. This was found using the decision tree (Figure 6). The selected seven features are namely StdError1, Kurtosis1, StdError2, Kurtosis2, Variance2, Variance4, Variance6.

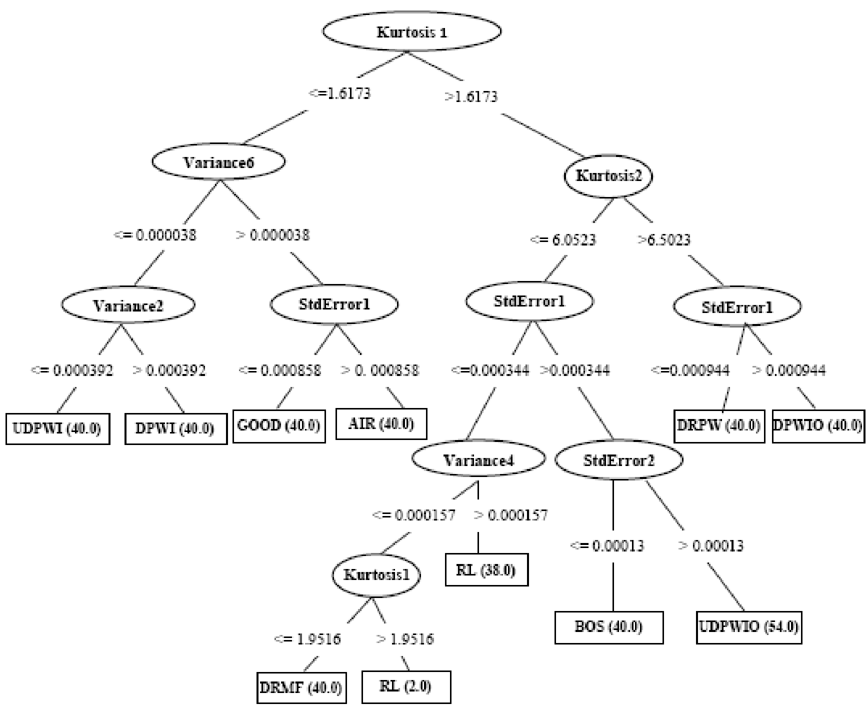

Figure 6: Decision tree with Statistical features (with VMD).

The selected VMD processed statistical features extracted from the modes were classified using J48 decision tree algorithm. Table 1 depicts the confusion matrix for decision tree. The confusion matrix shows the misclassification details (Table 1) was found using the non-diagonal elements in the confusion matrix. The classifier was trained using the train set. The classification accuracy was then tested using test set.

Table 1: Confusion Matrix using C 4.5 decision tree algorithm (with VMD processed features)

Category	1	2	3	4	5	6	7	8	9	10
1	15	0	0	0	0	0	0	0	0	0
2	0	15	0	0	0	0	0	0	0	0
3	0	0	15	0	0	0	0	0	0	0
4	0	0	0	15	0	0	0	0	0	0
5	0	0	0	0	15	0	0	0	0	0
6	0	0	0	0	0	15	0	0	0	0
7	0	0	0	0	0	0	15	0	0	0
8	0	0	0	0	0	0	0	15	0	0
9	0	0	0	0	0	0	0	0	15	0
10	0	0	0	0	0	0	0	0	0	15
1 = GOOD : Brake without any fault; 2 = AE : Air in brake fluid; 3 = BO : Brake oil spill; 4 = DPWI : Disc brake pad wear-Inner; 5 = DPWIO : Disc brake pad wear Inner & outer; 6 = UDPWI : Uneven disc pad wear (Inner); 7 = UDPWIO : Uneven disc pad wear (Inner & Outer); 8 = DRMF : Drum brake mechanical fade; 9 = DRPW : Drum brake pad wear; 10 = RL : Reservoir leak.										

Untrained test set was classified using the trained set. In this fashion the classification accuracy was found using decision tree algorithm. The diagonal elements belong to the correctly classified instances. The classification accuracy achieved by VMD statistical features with decision tree algorithm is **100%**. It is better than the classification accuracy of normal descriptive features (without VMD processed features). This supports the superiority of VMD statistical features over normal statistical features.

Referring Figure 7 and Figure 8, the maximum classification accuracy was achieved when the minimum number of object is 2 and confidence factor is 0.25. The statistical features extracted from the raw signal (without VMD) and the modes (with VMD) are classified using decision tree algorithm and the results are presented in Table 2.

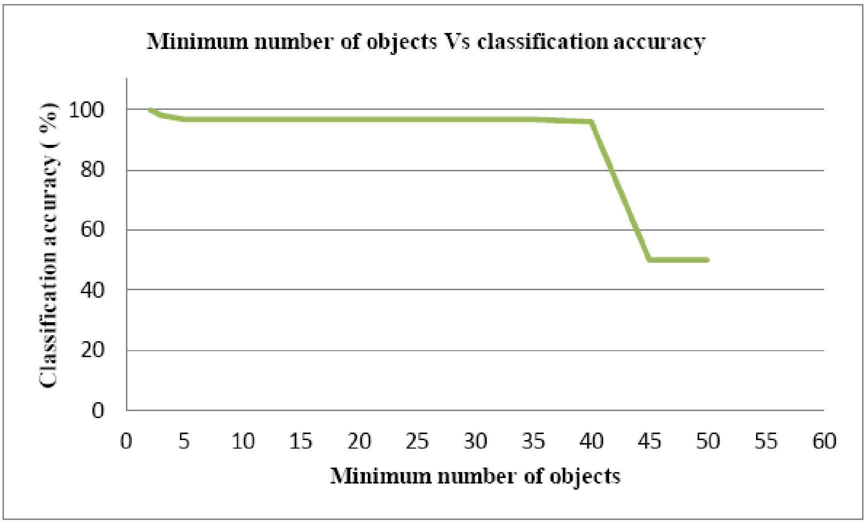

Figure 7: Minimum no. of objects Vs classification accuracy– Decision tree with VMD.

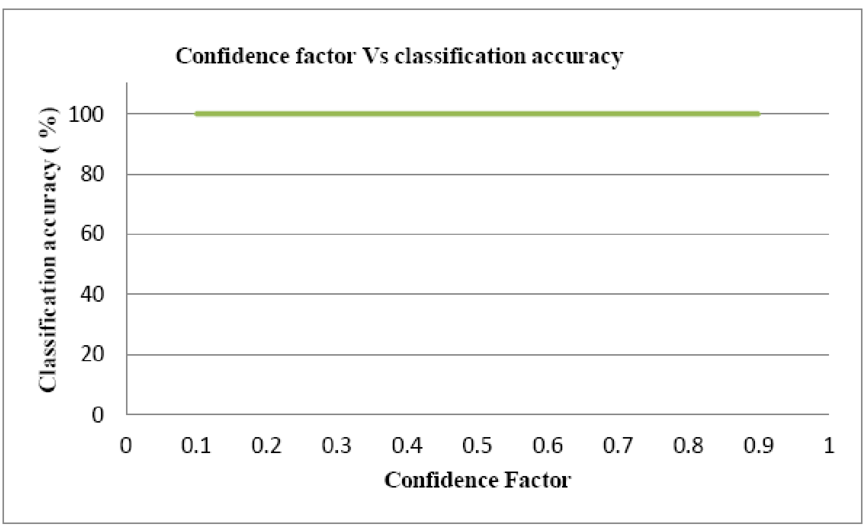

Figure 8: Confidence factor Vs classification accuracy – Decision tree with VMD.

From Table 2, it is found that J48 decision tree algorithm gives the maximum classification accuracy. The achieved classification accuracy for VMD processed statistical features with decision tree was **100 %.**

Table 2: Overall Classification accuracy.

S. No.	Classifier	Classification accuracy (%)
1	DT (without VMD)	**97.45**
2	DT (with VMD)	**100**

7 Conclusion

The paper presented a new signal processing technique for fault diagnosis of brake system called 'Variational mode decomposition' along with decision tree classifier. For bench marking the new features and classier, statistical features extracted from raw signal (without VMD preprocessing and with VMD preprocessing) and decision tree classifier respectively have been taken up. First, the superiority of VMD processed features was established in comparison with conventional statistical features. Then, the classifier performance of the decision tree algorithm was compared to prove the better performance. From the results and discussion, one can conclude that the VMD preprocessed signals with decision tree classifier performs better in fault diagnosis of a hydraulic brake system.

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