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Gear Box Fault Diagnosis Using Hilbert Transform Feature Classification by PSVM

Saravanan Natarajan*
Department of Engineering, Mechanical and Industrial Engineering, Higher College of Technology, Ministry of Manpower, Muscat, Sultanate of Oman

The condition of an inaccessible gear in an operating machine can be monitored using the vibration signal of the machine measured at some convenient location and further processed to unravel the significance of these signals. This paper proposes a fault detection method that combines Hilbert transform and machine learning method namely proximal support vector machines (PSVMs). The statistical feature vectors from Hilbert transform coefficients are classified using J48 algorithm and the predominant features were fed as input for training and testing PSVM and their efficiency in classifying the faults in the Bevel Gear Box was studied. It was observed that the Hilbert transform feature has an ability to capture the condition of the gear box,and can be used in condition monitoring of mechanical equipments.

Keywords: Hilbert Transform, Proximal Support Vector Machine, Machine Learning Method, Bevel Gear Box, Statistical Features, Fault detection.

I. INTRODUCTION

The Hilbert transform plays an important role in many subjects of science and technology such as optics [1], waves in stratified fluids [2] and [3], signal processing and so on. As early as in 1940s, Hilbert transform was used to define the instantaneous frequency of a non-stationary signal by Gabor. The usefulness of Hilbert transform for the definition of the instantaneous frequency was proved by Vakman in 1970's. Not long ago, Huang developed a new method, called Hilbert–Huang transform, for analysing nonlinear and non-stationary data in [4].The gear box with tooth breakage produces non-stationary signals and the author chose Hilbert transform to capture the hidden details in the vibration signals of the gear box under investigation. The Hilbert transform coefficients are used for fault classification using support vector machines (SVM) and were found effective [5].The above mentioned work was carried out by the same author.

The short coming in Fourier analysis to identify the transients developed due to localized faults can be overcome using Hilbert transform and this paper studies its capability to inherent the transient characteristics in it for fault diagnosing a gear box. Fault diagnosis of gearboxes is of crucial importance and has been studied for several decades. A distinct characteristic of gearbox faults is that they often generate vibration signals with amplitude and/or phase modulation. In the frequency domain, this is reflected by the increase of the sideband components around the related meshing frequencies and their harmonics [6]. In general, a fault that has distributed effects, such as gear eccentricity, generates only a few sideband components.

Sideband distance may vary with time. As a result, the spectral composition of the collected vibration signal often changes with time. Fourier analysis is unable to reveal such characteristics [7]. Other approaches are needed to identify early fault features from non-stationary signals. When gear fault occurs, the vibration signals always display non-stationary behaviour. Therefore how to extract the fault characteristic information from the non-stationary vibration signals is the crux of the gear fault diagnosis [8]. Sidebands cannot be detected by spectral analysis [9].The short-time Fourier transform is probably the most widely used time-frequency representation. However, its resolution is often unsatisfactory because of poorly matched windows in signal analysis [10]. Though Wigner–Ville distribution, another time–frequency method, is also used in fault detection [11], the oscillating interference between the signal components often exists when applied to a multi-component signal [7]. The Choi–Williams distribution provides better resolution than the smoothed Wigner–Ville distribution; however, it is still insensitive to the time-scale of signal components [10]. The smoothed instantaneous power spectrum method, which combines the advantages of the spectrogram and the instantaneous power spectrum, gives clearer time–frequency representation of signal [7].The above literature survey shows that various methods has been adopted for fault detection but with some short comings. Hence the need for this work of using Hilbert transform to study the vibration signal of a fault gear box arises.

Support Vector Machine (SVM) is used in many applications of machine learning because of its high accuracy and good generalization capabilities. The raw vibration signal in any mode from a single point on a machine is not a good indicator of the health or condition of a machine. The raw signatures acquired through a vibration sensor needed further processing and classification of the data for any meaningful surveillance of the condition of the system being monitored. The flowchart in Fig 1 explains the process of data acquisition and further processing using PSVM.

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This work deals with extraction of features from the vibration data of a bevel gear box system using Hilbert transform and classification of gear faults using support vector machine (SVM).The vibration signal from a piezoelectric transducer is captured for the following conditions: Good bevel gear, bevel gear with tooth breakage (GTB), bevel gear with crack at root of the tooth (GTC), and bevel gear with face wear of the teeth (TFW) for various loading and lubrication conditions.

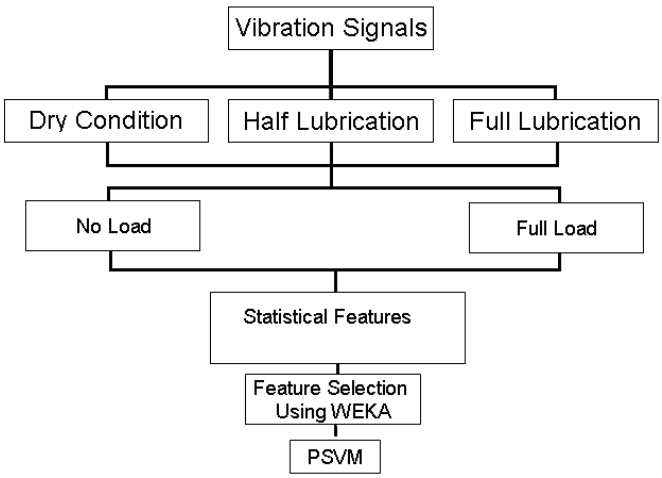

Fig. 1 Flowchart of fault diagnosis system

Fig. 2 Fault simulator setup

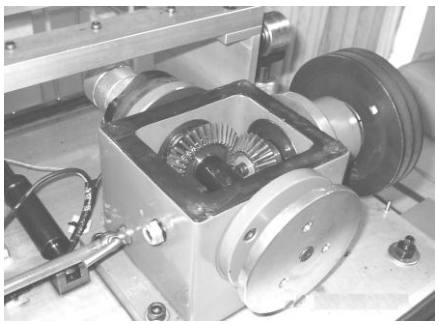

Fig.3 Inner view of gear box

II. EXPERIMENTAL STUDIES

Fig. 2 shows the fault simulator with sensor and Fig 3 show the inner details of the bevel gear box. A variable speed DC motor (0.5 hp) with speed up to 3000 rpm is the basic drive. A short shaft of 30mm diameter is attached to the shaft of the motor through a flexible coupling; this is to minimize effects of misalignment and transmission of vibration from motor. The shaft is supported at its ends through two roller bearings. From this shaft the motion is transmitted to the bevel gear box by means of a belt drive. The gear box is of dimension 150mm X 170mm X 120mm and the full lubrication level is 110mm and half lubrication level is 60 mm. SAE 40 oil was used as a lubricant. An electromagnetic spring loaded disc brake was used to load the gear wheel. A torque level of 8 N-m was applied at the full load condition. The various defects are created in the pinion wheels and the mating gear wheel is not disturbed. With the sensor mounted on top of the gear box vibrations signals are obtained for various conditions. The selected area is made flat and smooth to ensure effective coupling. A piezoelectric accelerometer (Dytran model) is mounted on the flat surface using direct adhesive mounting technique. The accelerometer is connected to the signal-conditioning unit (DACTRAN FFT analyzer), where the signal goes through the charge amplifier and an Analogue-to-Digital Converter (ADC). The vibration signal in digital form is fed to the computer through a USB port. The software RT Pro-series that accompanies the signal conditioning unit is used for recording the signals directly in the computer's secondary memory. The signal is then read from the memory and replayed and processed to extract different features.

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A. Experimental procedure

In the present study, four pinion wheels whose details are as mentioned in Table.1 were used. One was a new wheel and was assumed to be free from defects. In the other three pinion wheels, defects were created using EDM in order to keep the size of the defect under control. The details of the various defects are depicted in Table.2 and its views are shown in Fig.4

Table 1 Detail Of Faults Under Investigation

Gears	Fault Description	Dimension (mm)
G1	Good	--
G2	Gear Tooth Breakage (GTB)	8
G3	Gear with Crack at root (GTC)	0.8 x 0.5 x 20
G4	Gear with Face Wear	0.5

Table 2 Gear Wheel And Pinion Details

Parameters	Gear Wheel	Pinion Wheel
No. of teeth	35	25
Module	2.5	2.5
Normal pressure angle	20^0	20^0
Shaft angle	90^0	90^0
Top clearance	0.5 mm	0.5 mm
Addendum	2.5 mm	2.5 mm
Whole depth	5.5 mm	5.5 mm
Chordal tooth thickness	$3.93^{-0.150}$ mm	$3.92^{-0.110}$ mm
Chordal tooth height	2.53 mm	2.55 mm
Material	EN8	EN8

The size of the defects is a little bigger than one can encounter in the practical situation; however, it is in-line with work reported in literature [12]. The vibration signal from the piezoelectric pickup mounted on the test bearing was taken, after allowing initial running of the gear box for some time.

The sampling frequency was 12 000 Hz and sample length was 8192 for all speeds and all conditions. The sample length was chosen arbitrarily; however, the following points were considered. Statistical measures are more meaningful, when the number of samples is more. On the other hand, as the number of samples increases the computational time increases. To strike a balance, sample length of around 10000 was chosen. In some feature extraction techniques, which will be used with the same data, the number of samples is to be 2^n. The nearest 2^n to 10,000 is 8192 and hence, it was taken as sample length. Many trials were taken at the set speed and vibration signal was stored in the data. The raw vibration signals acquired for various experimental conditions form the gear box using FFT are shown in Fig 5.

Fig.4a Bevel gear in good condition

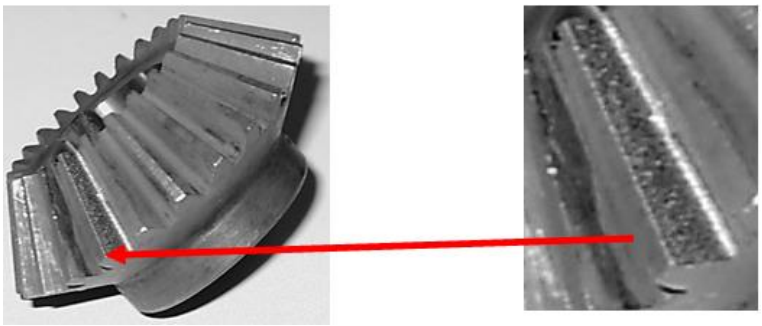

Fig.4b Bevel gear with face wear

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Fig. 4c Bevel gear with tooth breakage

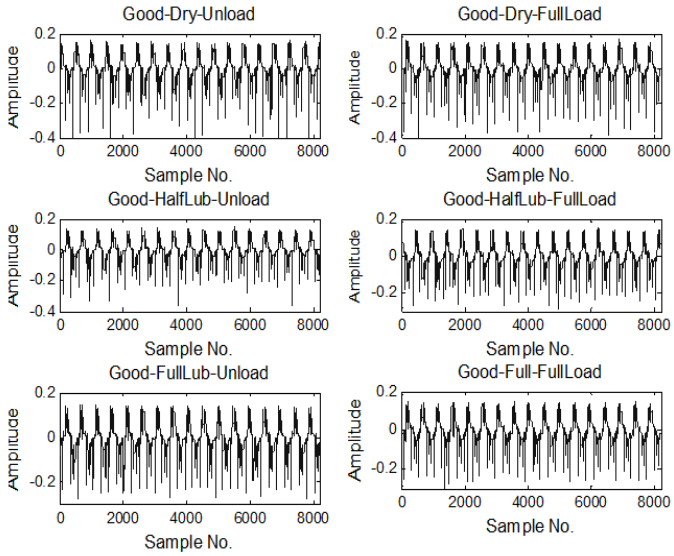

Fig. 5 Bevel gear with tooth breakage

III. FEATURE EXTRACTION

A. Hilbert transform

Hilbert transform is a time-domain convolution that maps one real-valued time-history into another. It is defined by [13] $H[x(t)] = \frac{1}{\pi}\int_{-\infty}^{\infty}\frac{x(t)}{t-\tau}\,d\tau$ (1) where t is time, $x(t)$ is a time domain signal, and $H[x(t)]$ is the Hilbert transform of $x(t)$. Because Hilbert transform is a frequency-independent 90° phase shifter, the non-stationary characteristics of the modulating signal are not affected by this method at all. Amplitude and phase modulation functions, $a_m(t)$ and $b_m(t)$, respectively, can be extracted by Hilbert transform. Demodulation is accomplished by forming a complex-valued time-domain signal called the analytic signal, $A[x(t)]$, which is defined as

$$A[x(t)] = x(t) + iH[x(t)] = a(t)e^{i\emptyset(t)}, i = \sqrt{-1} \quad (2)$$

The resulting complex time-domain signal can be converted from the real/imaginary format to the magnitude/phase format given below $a(t) = \sqrt{x^2(t) + H^2[x(t)]}$ (3)

$$\emptyset(t) = arctan\frac{H[x(t)]}{x(t)} \quad (4)$$

Hilbert transform produces a complex time series. The envelope is the magnitude of this complex time series and represents an estimate of the modulation present in the signal due to sidebands [14]. It reveals modulation in signals caused by a faulty gear. In addition, it removes carrier signals and this will decrease the influence of irrelevant information for the purpose of gearbox fault detection and be helpful for identification of the fault in the time–frequency plot via visual inspection. The Hilbert transform is applied to the vibrations signal of the gear box and Fig 6(a) to Fig 6(b) shows the Hilbert transform plots for different conditions of the gear box under study.

In the engineering applications, we always like to directly use some existing software packages to compute the Hilbert transform. A built-in function named 'hilbert' in Matlab, an extensively used scientific and engineering software tool, is designed for the computation. For a vector v of finite data, the action of 'hilbert' on v produces a complex vector Hilbert (v) of the same dimension, whose imaginary is the Hilbert transform of v. The principle of computing the Hilbert transform of v by 'hilbert' in Matlab is to calculate the fast Fourier transform (FFT) Fv of v firstly, multiply Fv by the sign multiplicator $-i\,sgn(\cdot)$, and apply the inverse fast Fourier transform (IFFT) to get the discrete Hilbert transform of v. In the sequel, we call the method for the computation of the Hilbert transform with 'hilbert' in matlab the m*atlab method*, or MM for short. Using mat lab the Hilbert transform coefficients of the gear box vibration signal is extracted and the corresponding statistical features are extracted and fed as input for J 48 algorithm for identifying the best features.

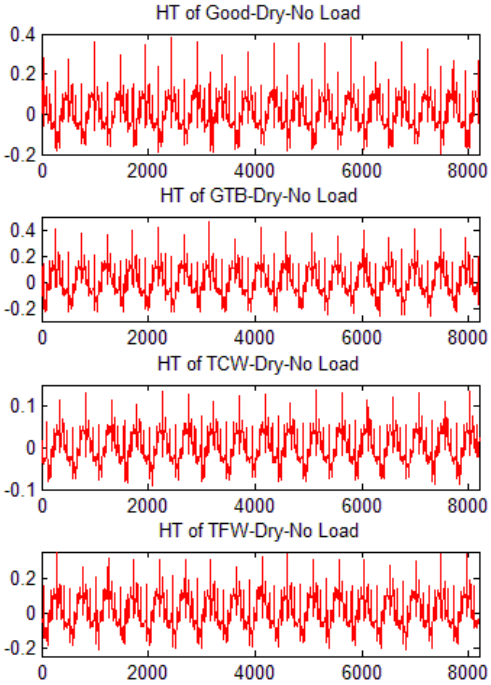

Fig.6 Bevel gear with tooth breakage

B. Using J 48 (WEKA) algorithm in the present work

A standard tree induced with c5.0 (or possibly ID3 or c4.5) consists of a number of branches, one root, a number of nodes and a number of leaves. One branch is a chain of nodes from root to a leaf; and each node involves one attribute. The occurrence of an attribute in a tree provides the information about the importance of the associated attribute as explained in [15]. A Decision Tree is a tree based knowledge representation methodology used to represent classification rules. J48 algorithm (A WEKA implementation of c4.5 Algorithm) is a widely used one to construct Decision Trees as explained in [16].

The decision tree algorithm has been applied to the problem under discussion. Input to the algorithm is set of statistical features of the Hilbert transform coefficients. It is clear that the top node is the best node for classification. The other features in the nodes of decision tree appear in descending order of importance. It is to be stressed here that only features that contribute to the classification appear in the decision tree and others do not. Features, which have less discriminating capability, can be consciously discarded by deciding on the threshold. This concept is made use for selecting good features

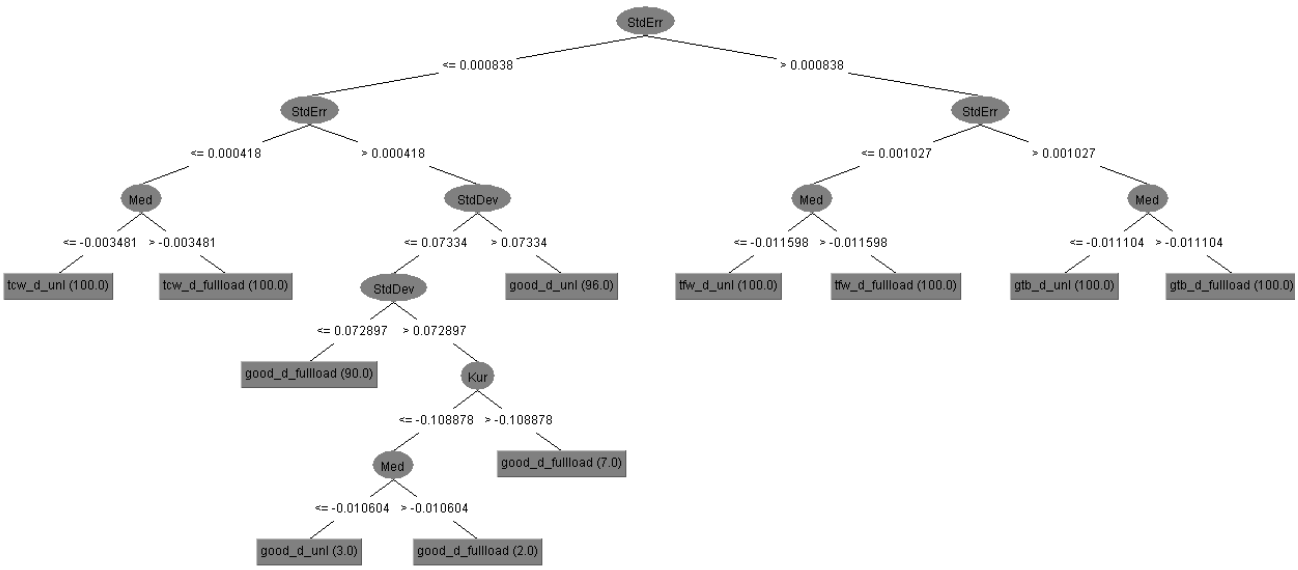

Fig. 7a. Good-dry-no load Vs GTB, GTC, TFW-dry-no load.

The algorithm identifies the good features for the purpose of classification from the given training data set, and thus reduces the domain knowledge required to select good features for pattern classification problem. The decision trees shown in Fig 7(a) to Fig (7b) are output for various lubrication and loading conditions of different faults compared with good conditions of the pinion gear wheel.

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Based on above trees its clear that of all the statistical features, standard error, median, standard deviation and sample variance play a dominant role in feature classification using Hilbert transform coefficients. These four predominant features are fed as an input to SVM for further classification.

IV. PROXIMAL SUPPORT VECTOR MACHINE (PSVM)

PSVM is a modified version of Support Vector Machine (SVM). The SVM is a new generation learning system based on statistical learning theory. SVM belongs to the class of supervised learning algorithms in which the learning machine is given a set of features (or inputs) with the associated labels (or output values). Each of these features can be looked upon as a dimension of a hyper-plane. SVMs construct a hyper-plane that separates the data into two classes (this can be extended to multi-class problems). While doing so, SVM algorithm tries to achieve maximum separation between the classes (See Fig. 10) separating the classes with a large margin minimizes a bound on the expected generalization error.By 'minimum generalization error', we mean that when a new set of features (that is data points with unknown class values) arrive for classification, the chance of making an error in the prediction (of the class to which it belongs) based on the learned classifier (hyper-plane) should be minimum. Intuitively, such a classifier is one, which achieves maximum separation-margin between the classes. The above process of maximizing separation leads to two hyper-planes parallel to the separating plane, on either side of it. These two can have one or more points on them. The planes are known as 'bounding planes' and the distance between them is called as 'margin'. By SVM 'learning', we mean, finding a hyper-plane, which maximizes the margin. The points lying beyond the bounding planes are called support vectors. As for as data points belonging to A- are concerned P1, P2, P3, P4, and P5 are support vectors (See Fig. 9), but P6, P7 are not support vectors. Similar thing hold good for class A+. These points play a crucial role in the theory and hence the name support vector machines. Here by 'machine', we mean an algorithm

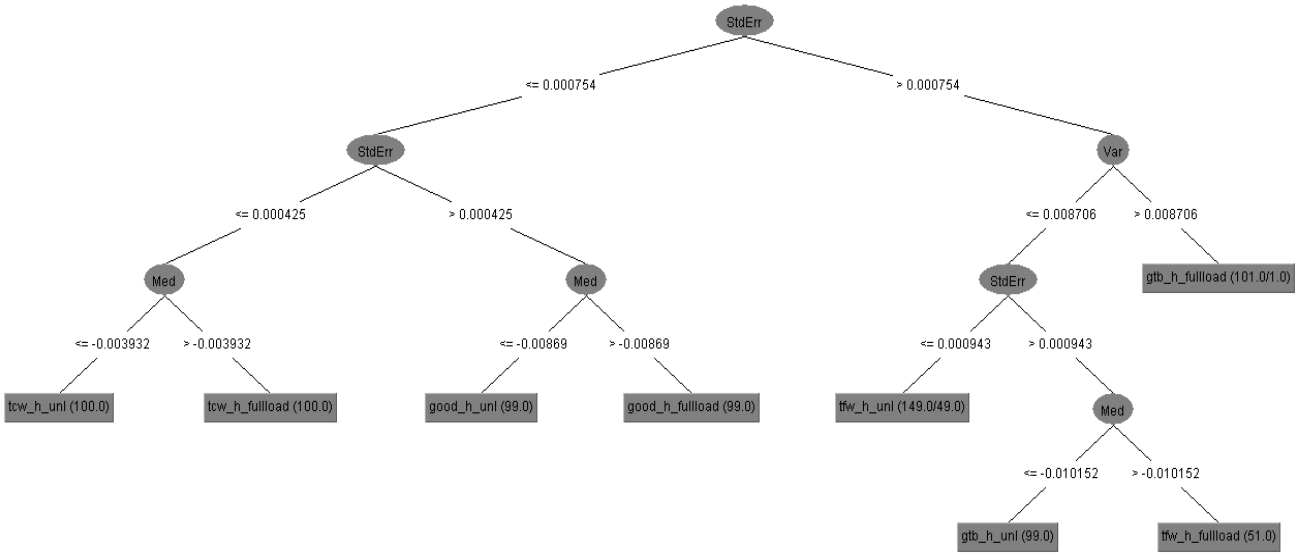
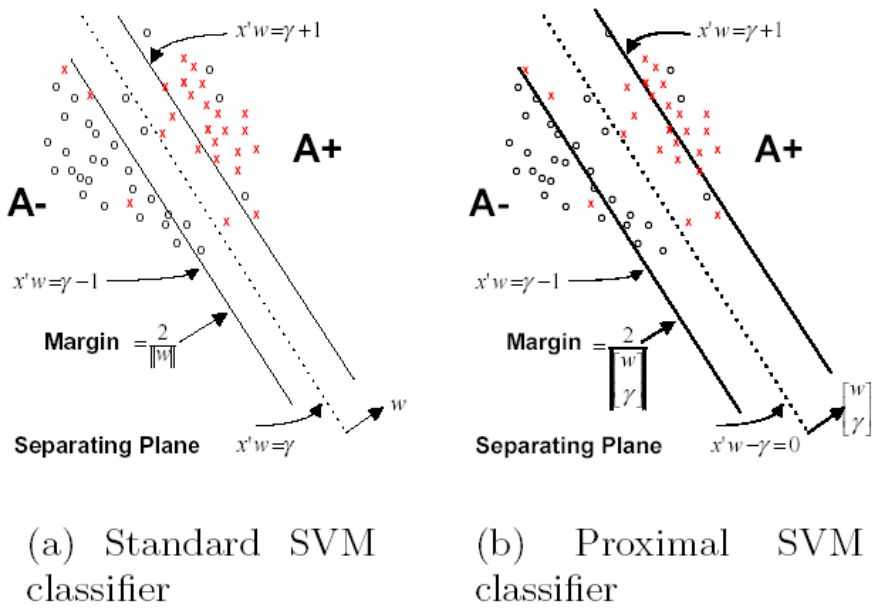


Fig. 7b Good-dry -full load Vs GTB, GTC, TFW-dry -full load



(a) Standard SVM classifier (b) Proximal SVM classifier

Fig. 8 Proximal support vector classification

Referring to Fig. 10, y represents deviation (scaled by $1/\|\mathbf{w}\|$) of the point from the plane passing through the centroid of the data cluster (A+ or A –) to which the point belongs. Hence, there is no non-negativity constraint on **y**.

A. Application of PSVM for problem at hand and results

The efficiency of classification using PSVM was found to be around 95%.The feature vectors corresponding to good gear were compared with those of the faulty gears at different loading and lubrication levels, by taking each fault at a time.For each condition feature vectors consisting of 100 feature value sets were collected from the experiment at 2000 rpm. 70 samples in each class were used for training and 30 samples are reserved for testing PSVM. Training was done and the values of 'w' (Weights), 'g' (Gamma) and efficiency obtained for statistical features of Hilbert coefficients using PSVM are tabulated in table 3A,3B and 3C respectively.

Table 3a PSVM Results For Statistical Featurres Of Hilbert Transform

SNo*	Nu	W	G	%	SNo*	Nu	W	G	%
1	0.1	-0.0011	2.709	96	4	-0.55	0.0151	-0.0509	32
		-0.0053					0.0389		
		0.2067					-0.096		
		0.5357					-2.8081		
	-0.55	-0.0054	7.82	97		-0.1	0.0009	0.0036	41
		-0.0257					0.0066		
		0.999					-0.0158		
		2.6152					-0.4703		
	-0.5	-0.0058	7.415	98		0.1	-0.0007	-0.017	91.5
		-0.0275					-0.0065		
		1.0658					0.0119		
		2.8042					0.4546		
2	-0.55	0.004	9.400	97	5	-0.1	-0.002	-0.3965	20
		0.0249					-0.0095		
		0.9361					-0.0212		
		-2.8311					1.2507		
	-0.1	-0.0022	-4.458	0		0.1	0.0016	0.2928	97
		-0.013					0.008		
		-0.4191					0.0152		
		1.4922					-1.0367		
	0.1	0.0009	1.696	98		0.2	0.003	0.5129	96
		0.0052					0.0147		
		0.1796					0.024		
		-0.5934					-1.9117		
3	-0.1	0.0024	-5.677	97	6	-0.1	0.0007	-1.4589	22.5
		0.0089					0.0032		
		-0.6125					-0.154		
		-1.0344					-0.5604		
	-0.5	-0.0055	8.350	98		0.1	-0.0006	0.9364	90
		-0.0119					-0.0036		
		0.9269					0.1311		
		1.6925					0.299		
	-0.55	-0.0033	7.910	98		0.2	-0.001	1.6806	96.5
		-0.0124					-0.0048		
		0.879					0.2305		
		1.4136					0.5551		

Table 3b PSVM Results For Statistical Featurres Of Hilbert Transform

S.No*	Nu	W	G	%	S.No	Nu	W	G	%
7	0.1	-0.0012	0.835	80	10	0.2	-0.0016	-0.7277	77.5
		-0.0063					-0.0107		
		0.1074					-0.0874		
		0.2307					0.2779		

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	0.15	-0.0017	1.177	87		0.5	-0.0041	-1.4014	80
		-0.0092					-0.0266		
		0.1493					-0.1606		
		0.3351					0.6525		
	0.17	-0.0019	1.302	95		0.6	-0.0049	-1.561	95.5
		-0.0103					-0.0318		
		0.1647					-0.1772		
		0.3752					0.7704		
8	-0.1	-0.0009	-0.612	20	11	0.2	0.0019	-1.3327	93.5
		-0.0042					0.0073		
		-0.0513					-0.1922		
		0.7685					-1.4833		
	0.05	0.0004	0.246	95		0.3	0.0027	-1.7426	96
		0.0019					0.0101		
		0.0231					-0.2512		
		-0.2941					-2.0828		
	0.1	0.0008	0.460	95		0.4	0.0033	-2.0527	95.5
		0.0037					0.0126		
		0.0407					-0.2972		
		-0.7655					-2.6164		
9	-0.3	-0.0192	30.82	6.5	12	0.1	-0.001	0.5804	82
		-0.0726					-0.0055		
		3.906					0.0933		
		7.9826					0.3571		
	0.1	-0.0012	1.458	96		0.3	-0.0028	1.3742	88.5
		-0.0055					-0.0152		
		0.2019					0.2136		
		0.4111					1.0138		
	0.5	-0.0019	2.260	97		0.35	-0.0032	1.5126	96
		-0.0091					-0.0175		
		0.3062					0.2361		
		0.6847					1.1689		

Table 3c Different Condition Of Comparision

1	Good-dry-No Load Vs GTB-dry-No-Load	10	Good-Half-Full Load Vs GTB-Half-Full Load
2	Good-dry-No Load Vs GTC-dry-No Load	11	Good Half-Full Load Vs GTC-Half-Full Load
3	Good-dry-No Load Vs TFW-dry-No Load	12	Good Half-Full Load Vs TFW-Half-Full Load
4	Good-dry-Full Load Vs GTB-dry-Full Load	13	Good-Full-No Load Vs GTB-Full-No Load
5	Good-dry-Full Load Vs GTC-dry-Full Load	14	Good-Full-No Load Vs GTC-Full-No Load
6	Good-dry-Full Load Vs TFW-dry-Full Load	15	Good-Full-No Load Vs TFW-Full-No Load
7	Good-Half-No Load Vs GTB-Half-No Load	16	Good-Full-Full Load Vs GTB-Full-Full Load
8	Good-Half -No Load Vs GTC-Half-No Load	17	Good-Full-Full Load Vs GTC-Full-Full Load
9	Good-Half -No Load Vs TFW-Half -No Load	18	Good-Full-Full Load Vs TFW-Full-Full Load

Table 3d PSVM Results For Statistical Featurres Of Hilbert Transform

S.No*	Nu	W	G	%	SNo	Nu	W	G	%
13	-0.55	0.0074	0.06	7.5	16	0.01	-0.0001	0.0245	90
		0.0463					-0.0007		
		-0.1052					0.0049		
		-4.4774					0.0614		
	0.2	-0.0021	-0.0271	96.5		0.02	-0.0002	0.0488	95
		-0.0133					-0.0014		
		0.026					0.0094		
		1.2515					0.1224		
	0.07	-0.0008	-0.0092	96		0.03	-0.0004	0.073	100

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		-0.0048					-0.0021		
		0.0085					0.0139		
		0.4563					0.183		
14	0.3	0.0034	-0.9302	91	17	0.1	0.0012	-0.4424	67.5
		0.0128					0.0047		
		-0.1414					-0.0662		
		-1.6839					-0.7439		
	0.4	0.0044	-1.1684	93.5		0.15	0.0018	-0.6178	87.5
		0.0166					0.0069		
		-0.1773					-0.0711		
		-2.1749					-0.7438		
	0.5	0.0053	-1.3786	95		0.16	0.0019	-0.6499	95
		0.0201					0.0073		
		-0.2095					-0.0956		
		-2.6373					-1.0023		
15	0.1	-0.001	0.6836	75	18	0.09	-0.0008	0.4674	92.5
		-0.005					-0.0042		
		0.105					0.0713		
		0.5005					0.421		
	0.2	-0.0018	1.2619	90		0.1	-0.0009	0.5169	97.5
		-0.0095					-0.0047		
		0.1905					0.0786		
		0.9449					0.4661		
	0.3	-0.0026	1.7558	95		0.13	-0.0011	0.6625	100
		-0.0135					-0.006		
		0.264					0.1		
		1.344					0.5999		

V. DISCUSSION

1) The use of Hilbert transform and extraction of statistical features from Hilbert coefficients was found to be very efficient for classification using PSVM.
2) Decision tree is a good tool in selecting the best features among the extracted feature vectors. standard error, sample variance, standard deviation and median value were found to be the most contributing features.
3) In PSVM, the parameters w (Weight) and γ (Gamma) define the separating plane. These can be used for testing a new set of data and classifying the faults accordingly. The efficiency for various conditions using PSVM for Hilbert coefficients are shown in table 3.
3) From table 3 the classification capability of PSVM is almost complete in all cases of gear box. It is able to identify the different faults, loading conditions and lubrication conditions correctly.
4) The high efficiency obtained in classification may be due to removal of carrier signals which will decrease the influence of irrelevant information in the transformed data.

VI. CONCLUSION

Fault diagnosis of Gear box is one of the core research areas in the field of condition monitoring of rotating machines. The method developed using Hilbert coefficients carry out the fault diagnosis of the gear box efficiently.

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