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Fault diagnosis of automobile hydraulic brake system using statistical features and support vector machines

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ABSTRACT

Hydraulic brakes in automobiles are important components for the safety of passengers; therefore, the brakes are a good subject for condition monitoring. The condition of the brake components can be monitored by using the vibration characteristics. On-line condition monitoring by using machine learning approach is proposed in this paper as a possible solution to such problems. The vibration signals for both good as well as faulty conditions of brakes were acquired from a hydraulic brake test setup with the help of a piezoelectric transducer and a data acquisition system. Descriptive statistical features were extracted from the acquired vibration signals and the feature selection was carried out using the C4.5 decision tree algorithm. There is no specific method to find the right number of features required for classification for a given problem. Hence an extensive study is needed to find the optimum number of features. The effect of the number of features was also studied, by using the decision tree as well as Support Vector Machines (SVM). The selected features were classified using the C-SVM and Nu-SVM with different kernel functions. The results are discussed and the conclusion of the study is presented.

1. Introduction

The brake system is a safety critical component necessary for the safe operation of the vehicle. Brake failure is crucial not only for the driver and passengers but also for automobile manufacturers. In April 2007, BMW, an automobile manufacturing company recalled over 160,000 SUVs, because of a problem that could cause a potential loss of brake fluid or even the brake circuit to fail completely. Chrysler recalled 60,000 vehicles, due to an issue with potential brake failure in May 2007 [1]. There may be no sure way to prevent the possibility of a brake failure accident, but one can do their own part to prevent failure. The faults in a hydraulic brake system of an automobile are not fairly noticeable. Some warning signs that there is something wrong with brakes include a grinding or squeaking noise. If faulty brakes are used, the vehicle cannot be stopped within a reasonable distance. This causes the vehicle to veer to one side.

Fault diagnosis is an important process in the preventive maintenance of many components such as, the gear box and bearings. This can avoid serious damage if defects occur in one of the components during operation. Prevention is better than cure. Early detection of a defect, therefore, is crucial to prevent the system from malfunction that could cause damage to the entire system or an accident. It can predict the condition of the system at any time and avoid unexpected failures.

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Nomenclatures

A	$m \times n$ matrix whose elements belong to real space R
D	$m \times 1$ matrix representing class label ($+1$ and -1)
e	a vector of ones
ν	a control parameter that defines the weight of error minimization
R	real space
w	orientation parameter
γ	location parameter (location relative to origin) of separating hyper-plane

This is not only capable of identifying the failure of a machine component or system, but also predicts failure from its symptoms [2]. Therefore, a machine condition monitoring system can be effectively used as a decision support tool. Vibration and acoustic emission (AE) signals are widely used in the condition monitoring of rotating machines. By comparing the signals of a machine running in normal and faulty conditions, the detection of faults is possible. Frequency domain based spectral comparison was used dominantly for stationary signals. Due to wear and tear, the vibration signals from an automobile will be non-stationary. Data modeling using the machine learning approach can be used to solve such problems. Machine learning involves three main steps, viz, feature extraction, feature selection, and feature classification. Features can be statistical features [3], auto regressive moving average (ARMA) features [4], histogram features [4] and wavelet features [5]. In the present study statistical features were used.

There are many techniques available for feature selection. The commonly used techniques for the selection of features are the principal component analysis (PCA) [5], genetic algorithm (GA) [6,7] and decision tree (DT) [8]. The principal component analysis is a method that reduces the dimensionality of data by performing a covariance analysis between factors. As such, it is suitable for data sets in multiple dimensions, such as a large experiment. It is one of the pattern identification techniques in the data of high dimensions. It maps data from a higher dimension space to lower dimension space. In a study by Sugumaran et al., the use of a decision tree to identify the best feature selection from a given set of samples for classification was illustrated [3]. The most important feature will be placed on top of the decision tree and others will follow. Based on this, the most important features were identified. This paper makes use of the decision tree for feature selection, i.e., for the identification of good features in the order of importance and eliminating the non-contributing features. Decision trees are simple to understand and interpret. A decision tree can be represented more compactly as an influence diagram, focusing attention on the issues and relationships between events. A decision tree has value even with little hard data.

For feature classification a number of classifiers are available, namely, artificial neural network (ANN), Naïve Bayes (NB) and Bayes Net (BN), decision tree, support vector machine (SVM), proximal support vector machine (PSVM), etc.

Naïve Bayes (NB) and Bayes Net (BN) were successfully applied for the fault classification monoblok centrifugal pump [4]. NB and BN often fail to produce a good estimate of the correct class probabilities; this may not be a requirement for many applications. PSVM was also studied for the fault classification of bearings [9]. As the size of the patterns increases, the training time and also the computational complexity increases for the PSVM.

The use of vibration analysis for gear fault diagnosis and monitoring has been widely investigated and its application in industry is well established. Even visual inspection can identify the faults; industry needs an automated procedure for the identification of the faults. One commonly used technique is artificial neural network (ANN) [4]. The condition monitoring problem is treated as generalization/classification problem based on the training pattern from the samples. However, the traditional ANN approaches have limitations on the generalization of results in models that can over-fit the data [5].

A work was reported on condition monitoring of rotating machinery which combines wavelet transforms and auto associative neural networks to extract features from the vibration data sets in an unsupervised mode [10]. The fuzzy neural network was used to memorize the standard fault pattern pairings, between fault symptoms and faults [11–13]. The main drawback of the fuzzy and neural networks is poor capability of creating its own structure. The Winger distribution was used for analyzing the vibration signals, and an expert system was developed for vibration monitoring and diagnostics for rotating machines using the back propagation neural network (BPNN) [14]. The prominent drawback of Wigner distribution is that it produces cross-terms of large magnitudes. The principal component analysis (PCA) was used for feature selection and feature classification using the C4.5 decision tree and BPNN for the fault diagnosis of rotating machinery, such as turbines and compressors [15]. PCA models have trouble with high dimensional data or large numbers of data points, and it is not clear how to deal properly with an incomplete data set, in which some of the data points are missing.

To overcome the above drawbacks, researchers are constantly on the lookout for a classifier, which will give very high classification accuracy with a simple operation. SVM seems to be an algorithm which satisfies these requirements. Support vector machine (SVM) is used in many applications of machine learning, because of its high accuracy and good generalization capabilities [16,17]. SVM is based on the statistical learning theory. SVM classifies better than the ANN because of the principle of risk minimization. In ANN traditional empirical risk minimization (ERM) is used on training data set to minimize the error. In contrast, structural risk minimization (SRM) is used to minimize an upper bound on the expected risk, in SVM.

In the recent past, fault diagnosis of critical components using machine learning algorithm like the SVM was reported [18]. Recent work [19] reports the use of SVM for on-line condition monitoring and its comparison with the ANN. The SVM

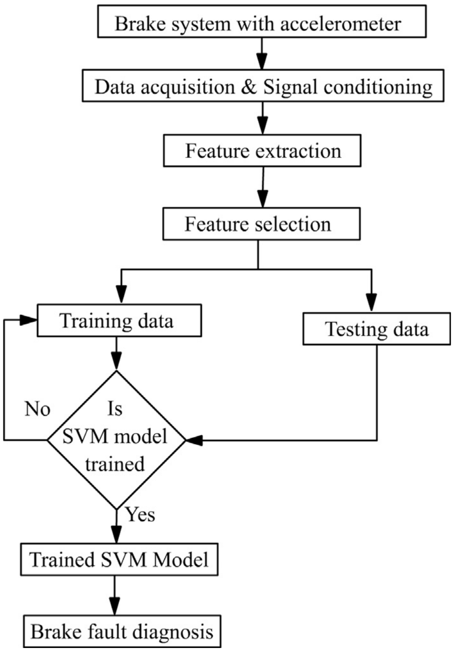

Fig. 1. Flowchart of decision tree algorithm for SVM classifier.

was successfully applied for finding faults in roller bearing, and it was proved that the classification accuracy was more than that of the ANN [2]. However, the classification of faults in hydraulic brakes using SVM has not been attempted. Hence, an attempt is made in the present study, to classify the faults in hydraulic brakes using the SVM. The flow chart of the fault diagnostic system is shown in Fig. 1.

The contributions of the present work are the following:

(1) The procedure of the fault diagnosis of the hydraulic brake system was illustrated, using the vibration signals from the brake fault simulator experimental setup, with the following simulated fault conditions: 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.
(2) From the time domain signals, a set of statistical features were extracted and the order of importance was found using the decision tree.
(3) The C4.5 algorithm was used to find out the effective number of features required for the classification.
(4) SVM was used as a classifier. For different kernel functions the SVM model was trained and the results were compared for different types of SVM. The results show the effectiveness of the extracted features from the acquired signals in the diagnosis of the brake condition.

2. Experimental studies

Referring to Fig. 1, the first two blocks are described in the following sections, namely, experimental setup and experimental procedure. Ideally, one needs to conduct the study via real vehicle on real road conditions. To simplify the study a test rig on a stationary stand was used.

2.1. Experimental setup

A commercial passenger car's (Maruti Swift) hydraulic brake system (Fig. 2) was used to fabricate the brake test rig. The test rig consists of a disc (2 of Fig. 2) and rear drum (1 of Fig. 2) brake, coupled together by a shaft. The shaft is, in turn, run by a DC motor (1HP) (7 of Fig. 2) coupled to a belt drive (3 of Fig. 2) system. The DC motor consists of an inbuilt drive. A lever is placed at the top of the motor which is connected to the accelerator pedal (9 of Fig. 2) providing variable speeds up to 2500 rpm. The brake pedal (8 of Fig. 2) is provided on the left side of the accelerator pedal. It is attached to the piston in the master cylinder (4 of Fig. 2) via a push rod. The master cylinder, the most important part of the hydraulic brake is provided with pistons to move along the bore. Since hydraulic brakes are a prominent brake system in medium motor vehicles like

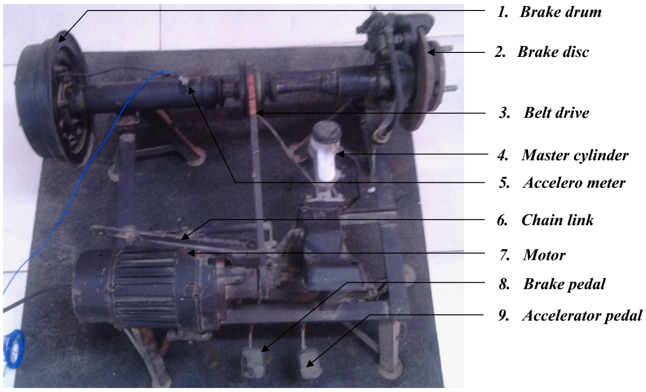

Fig. 2. Experimental setup – brake fault diagnosis. 1. brake drum, 2. brake disc, 3. belt drive, 4. master cylinder, 5. accelero meter, 6. chain link, 7. motor, 8. brake pedal, and 9. accelerator pedal.

cars, in order to experiment with the components used in real world, branded vehicles (cars) parts were considered. The dimension of the test rig is 80 cm × 80 cm × 40 cm.

A piezoelectric type accelerometer (5 of Fig. 2) was used as the transducer for acquiring vibration signals. Accelerometers are the widely used transducers in machine condition monitoring due to the following reasons: extreme ruggedness, large frequency response, large dynamic range–accelerometers can detect very small vibrations without being damaged by large vibrations; output is proportional to forces which are the cause of internal damage, and high-frequency sensitivity for detecting faults. In this case, a uni-axial accelerometer of 50 g range, 100 mV/g sensitivity, and resonant frequency around 40 Hz was used. The accelerometer was mounted near the brake drum (and brake disc) using an adhesive mounting technique. It was connected to the Data Acquisition (DAQ) system through a cable. The DAQ system is NI USB 4432 model. The card has 5 analog input channels with a sampling rate and resolution of 102.4 kilo samples per second and 24-bit respectively. The accelerometer is connected to the signal-conditioning unit, where the signal goes through the charge amplifier and an analog-to digital converter (ADC). The vibration signal in digital form is input to the computer through an USB port. It is stored directly in the computer secondary memory. The signal is then read from the memory and processed to extract different features. One end of the cable is plugged to the accelerometer and the other end to the AIO port of the DAQ system. NI – Lab VIEW was used to interface the transducer signal and the system (PC).

2.2. Experimental procedure

Initially the test rig was assumed to be in good condition (All components were brand new.). The vibration signals were measured from the hydraulic brake system working under braking condition (original speed 667 rpm, brake load 68.67 N (7 kg)). The vibration signal from the accelerometer, mounted on the brake shaft, was taken with the following settings:

(1) Sample length: the sample length was chosen arbitrarily to an extent; 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 computation time increases. To strike a balance, sample length of around 1000 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 1000 is 1024; hence it was taken as the sample length.
(2) Sampling frequency: the interval between two samples gives the sampling period (T) and inverse of this gives the sampling frequency. As per the Nyquist sampling theorem, the sampling frequency should be at least twice the highest frequency contained in the signal. By using this theorem, the sampling frequency was calculated as 24 kHz.
(3) Number of samples: minimum of 55 trials were taken for each conditions of the hydraulic braking system, and vibration signals were stored in the data files.

Data acquisition is the process of sampling signals that measure real world physical conditions into digital numeric values that can be manipulated by a computer. Data acquisition card (DAC) hardware is used here to interface between the sensor signal and a personal computer (PC).

The following faults were simulated, one at a time, while all other components remain in good condition and the corresponding vibration signals were acquired.

(1) Air in the brake fluid: the pump and hold method is used for brake bleeding; this method is altered to simulate the air in the brake fluid fault. The atmospheric air is being sucked back in through the valve on the upstroke.
(2) Brake oil spill on the disc brake (BO): using a Pasteur pipette 5 ml of DOT 3 brake oil was applied on the brake disk.

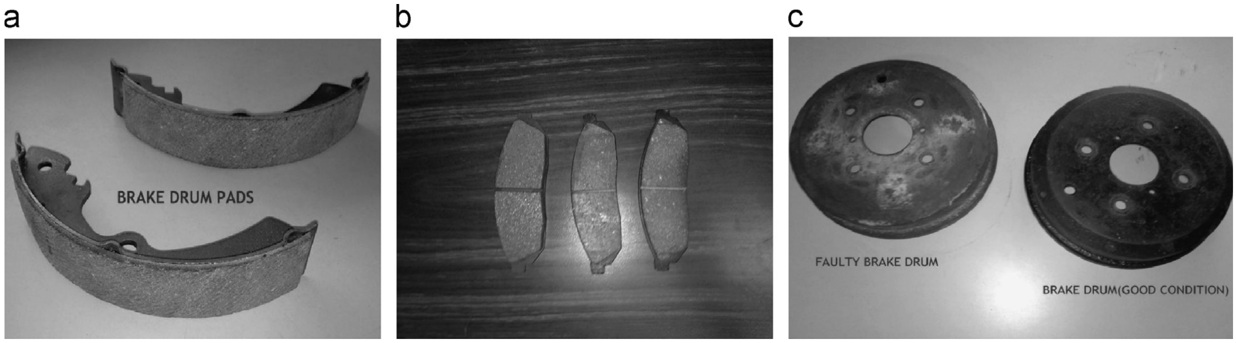

Fig. 3. (a) Drum brake pads wear condition, (b) disc brake pads wear condition, and (c) drum brake mechanical fade condition.

(3) Drum brake pad wear (DRPW): The drum brake pad under study was made of asbestos and of a thickness of 7.50 mm. Brakes are designed to wear out. If the pads wear too far, the metal backing on the brake pad comes in contact with the brake rotor. In such condition vibration and noise will occur due to the metal to metal contact. To simulate this faulty condition, the thickness of both the brake pads (left and right) was reduced from 7.50 mm to 5.70 mm by using cylindrical grinding machine (silicon carbide wheel) (Fig. 3(a)).
(4) Disc brake pad wear (even) – inner (DPWI): the disc brake pad wear under study was made of asbestos and of a thickness of (at good condition) 16.50 mm. Inner pad wear usually occurs when the piston cannot retract properly. If the pads wear too far, the metal clamping on the brake pad comes in contact with the brake rotor. Hence the rotor gets damaged. To simulate this faulty condition, the thickness of inner brake pad was reduced from 16.50 mm to 12.40 mm by using the surface grinding machine (silicon carbide wheel)
(5) Disc brake pad wear (even) – inner and outer (DPWIO): disc brake pad wear under study was made of asbestos and of a thickness of 16.50 mm. When brakes are applied, pressure will pull pads against the rotors. When the brakes are released, there is no actual pressure to move the pads away from the rotors. When the slides start to stick, the pressure will pull the pads against the rotors, and then they would be riding against the rotor. Sometimes the brake calliper is not released properly. In such cases, inner brake pad will wear out more than the outer pad. This can also cause excessive brake dust. To simulate this condition the thickness of inner brake pad was reduced from 16.50 mm to 11.60 mm, and that of the outer brake pad was reduced from 16.50 mm to 12.40 mm, by using the surface grinding machine (silicon carbide wheel) (Fig. 3(b)).
(6) Disc brake pad wear (uneven) (UDPWI) – inner: the disc brake pad wear under study was made of asbestos, and of a thickness of 16.50 mm. If the disc brake pad wear uneven from top to bottom, then there will be a stick in slide pin. By using the shaper machine inner brake pad was machined with a downward gradient (0.6°) 15.12 mm (big radii) – 14.72 mm (small radii).
(7) Disc brake pad wear (uneven) – inner and outer (UDPWIO): the disc brake pad wear under study was made of asbestos, and of a thickness of 16.50 mm. If the inner pad is thinner than the outer, then the inner pad wear will be more. And this can be caused by a sticking calliper or dirt in the lines causing the calliper not to fully release on it. If the disc brake pad wear is uneven from top to bottom, then there will be a stick in slide pin. The inner brake pad was machined with a downward gradient (1.6°) 14.76 mm (big radii) – 14.12 mm (small radii) and the outer one was machined with a downward gradient (0.6°) 15.12 mm (big radii) – 14.72 mm (small radii) by using a shaper machine.
(8) Reservoir leak (RL): the brake fluid reservoir under study has 250 ml capacity. The air tight seal of the reservoir is opened, using a pipette 50 ml of DOT 3 brake fluid was siphoned out of the reservoir and the seal was left open.
(9) Drum brake mechanical fade (DRMF): brake fade is the reduction in stopping power that can occur, after repeated or sustained application of the brakes, especially in high load or in high speed conditions. The drum brake under study is made of cast iron and has a volumetric coefficient of expansion 33.3×10^{-6} m^3 per °C. An already used brake drum was used to simulate this condition (Fig. 3(c)).

Fig. 4(a)–(j) shows the time domain signals taken from the brake setup. Once the faults were simulated, the vibration signals were recorded and feature extraction and feature selection were carried out using these vibration signals.

3. Feature extraction and feature selection

The process of computing some measures which will represent the signal is called feature extraction. A fairly wide set of statistical parameters were selected as the basis of the study. They are mean, standard error, sample variance, kurtosis, skewness, minimum, maximum, standard deviation, count, and mode and median. These features were extracted from the vibration signals. The definition and process of extracting statistical features were described for bearing fault diagnosis by Sugumaran et al. [9]. Following the footsteps of Sugumaran et al., the effect of number of features and feature selection were

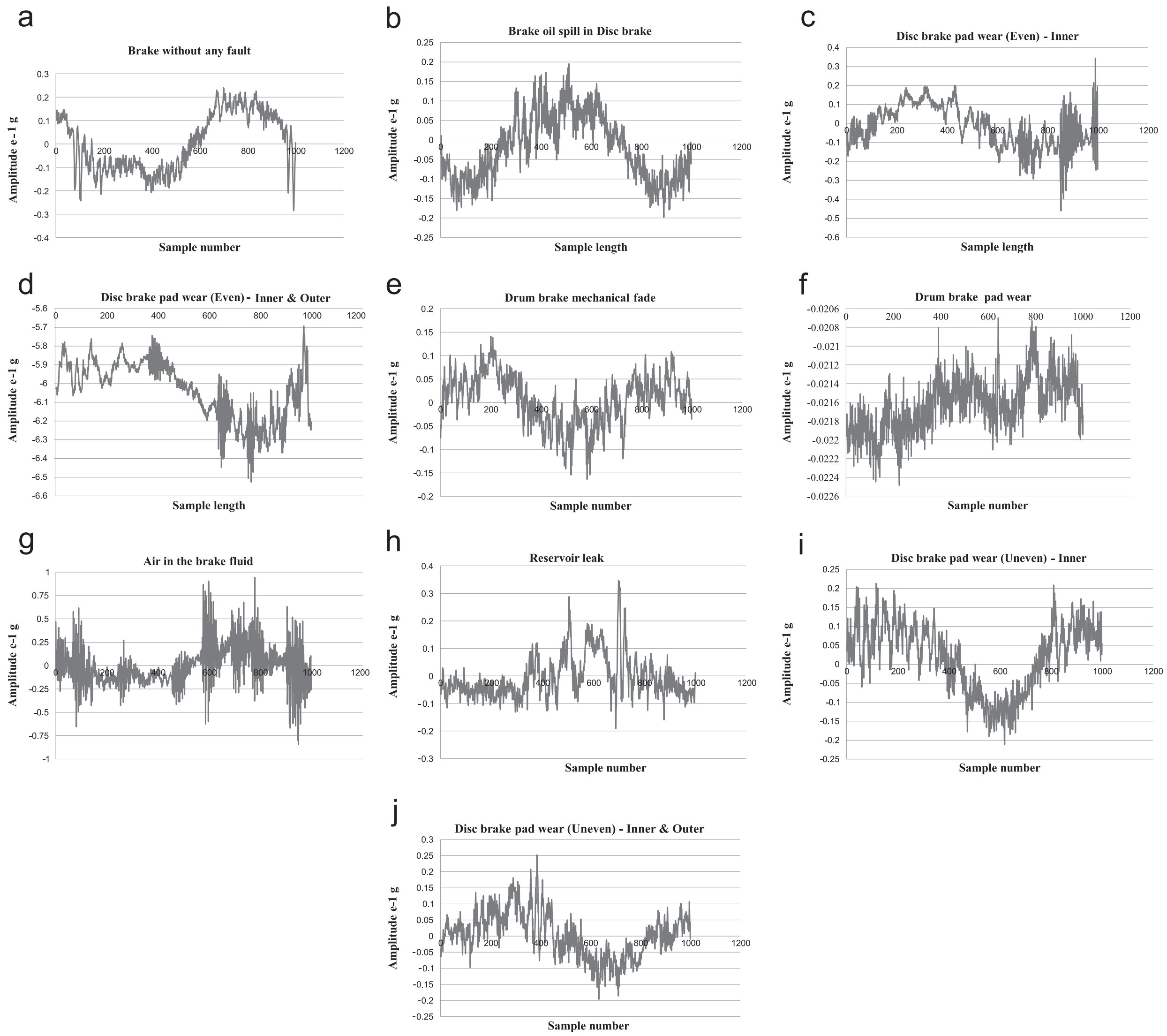

Fig. 4. (a) Vibration signal – brake without any fault, (b) vibration signal – brake oil spill, (c) vibration signal – disc brake pad wear (even) – inner, (d) vibration signal – disc brake pad wear (even) – inner & outer, (e) vibration signal – drum brake mechanical fade, (f) vibration signal – drum brake pad wear, (g) vibration signal – air in the brake fluid, (h) vibration signal – reservoir leak, (i) vibration signal – disc brake pad wear (uneven) – inner, and (j) vibration signal – disc brake pad wear (uneven) – inner & outer.

carried out. In the present study the selected good features namely minimum, standard error, sample variance, kurtosis and skewness are classified by using different types of the SVM model.

4. Classification using support vector machines (SVM)

Referring to Fig. 1. Classification is the next immediate step after feature selection. As mentioned earlier, the SVM is used as a classifier in the present study. The support vector machine (SVM) is a new generation learning system, based on the statistical learning theory. In classifying low dimensional non-linear problems, often the classifier faces a lot of difficulty in classification. This problem is tackled by the SVM. The idea is to map the original pattern space into the high dimensional feature space through some non-linear mapping functions, and then construct the optimal separating hyper-plane in the feature space. Thus, the non-linear problem in low dimensional space corresponds to the linear problem in the high dimensional space.

The SVM comes under the category of supervised learning algorithms in which the learning machine is given a set of features 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 hyper-space into two classes (this can be extended to multi-class problems).While doing so, the SVM algorithm tries to achieve the maximum separation between the classes (Fig. 6) [18]. The

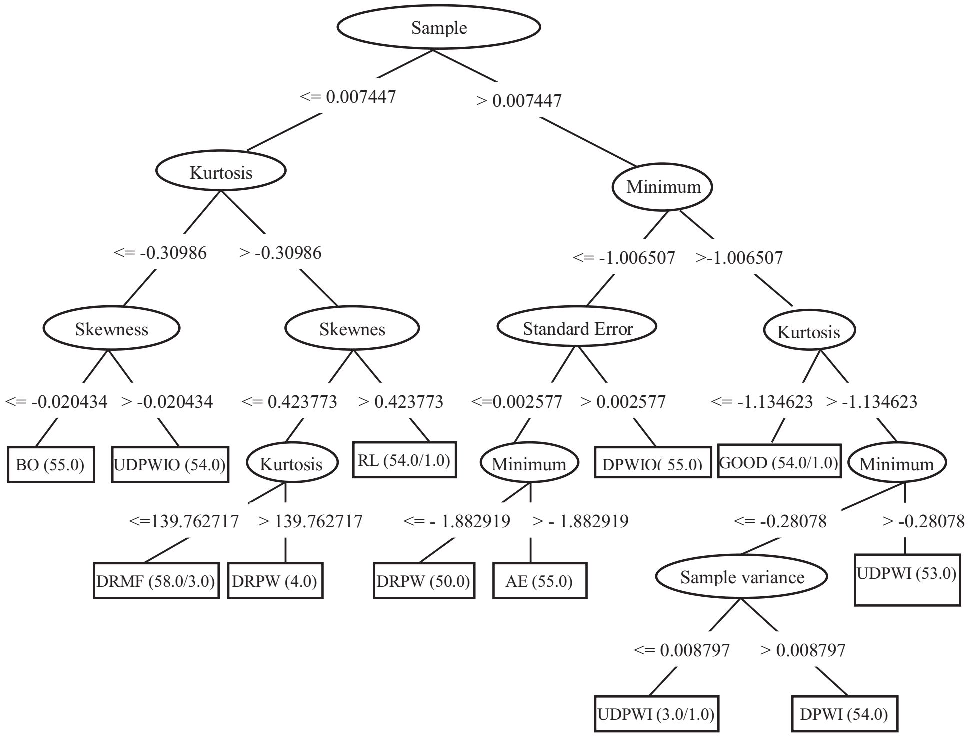

Fig. 5. Decision tree.

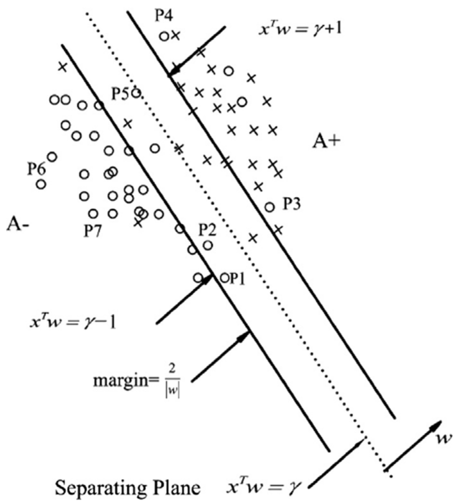

Fig. 6. Standard SVM classifier.

expected generalization error is minimized by separating the classes with a large margin. Minimum generalization error means, when a new set of features arrive for classification, the chance of making an error in the prediction 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 the 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 the 'margin'.

By SVM, 'learning' mean, finding a hyper-plane, which maximizes the margin and minimizes the misclassification error. The points lying beyond the bounding planes are called support vectors. The data points $P1$, $P2$, $P3$, $P4$, and $P5$ belonging to $A-$ are support vectors (Fig. 6), but $P6$, $P7$ are not. Same facts hold good for class $A+$. These points play a crucial role in the theory and hence the name support vector machines (SVMs).

Here, by 'machine', means an algorithm. The notations used by Fung have been followed. In the formulation, 'A' is a $m \times n$ matrix whose elements belong to real space, 'D' is a $m \times 1$ matrix representing the class label ($+1$ and -1), 'e' is a vector of ones and 'v' is a control parameter that defines the weight of error minimization and bounding plane separation in the objective function. 'R' is real space 'w' is the orientation parameter and 'γ' is the location parameter (location relative to origin) of separating hyper-plane.

In SVM, the objective function is

$$\min_{(w,\gamma,y)}(\gamma e^T y + (1/2)W^T W), \quad (w,\gamma,y) \in R^{n+1+m\ldots} \tag{1}$$

$$\text{Subject to } D\,(Aw - e\gamma) + y \geq \mathrm{e} \quad \text{where } y \geq 0. \tag{2}$$

where,

$$A \in R^{n+1+m}, \quad D \in \{-1,+1\}^{m\times 1}, \quad e = 1^{m\times 1} \tag{3}$$

If the training features are separated without errors by an optimal hyper-plane, the expected error rate on a test sample is bounded by the ratio of the expectation of the support vectors to the number of training vectors. The smaller the size of the support vector set, more general the above result will be. Further, the generalization is independent of the dimension of the problem. In case such a hyper-plane is not possible, the next best is to minimize the number of misclassifications whilst maximizing the margin with respect to the correctly classified features. Originally, support vector machines were designed for binary classification [20,21]. Currently there are several methods that have been proposed for multi-class classification, such as "one-against-one", "one-against-all", and directed acyclic graph (DAG) [22–24]. In the present study one against all classification was carried out.

A kernel function is an integral part of the SVM and contributes in obtaining an optimized and accurate classifier [25]. A kernel function serves as a separating function, a hyper-surface which optimally separates the input data into two classes involving minimal support vectors. The support vectors are data points in input space lying on the kernel function hyper-surface. There is no formal way to decide, which kernel function is suited to a class of classifier problems [26]. The most commonly used kernels are radial basis function (RBF), polynomial, linear, multilayer perceptron and sigmoid. These kernel functions were used in this study.

5. Results and discussion

The fault diagnosis of the hydraulic brake system was taken up. The machine learning approach was used with the statistical features and SVM combination. The results are discussed below.

5.1. Statistical features using C-SVM

(1) Twelve statistical features that discriminate the fault conditions were mean, standard error, median, standard deviation, variance, kurtosis, skewness, range, minimum, maximum and sum, count. The decision tree gives an orderly representation of the features showing their relative importance in classification. The same has been formed with the test data. From the decision tree, only five features that contributed to the classification are selected for training and testing. They are (1) minimum value (2) standard error, (3) sample variance, (4) kurtosis, and (5) skewness.

(2) The effect of number of features on classification accuracy is given in Table 1. It shows that when the number of features are 5, 6 and 7 in each class, the classifier gives good accuracy. Out of them to select the right number of features, the strategy can be to select the one which gives less computational time (or) one that gives the maximum classification accuracy. This has to be decided based on the application and the available computational resources. In the present study, minimal computation time strategy was used because the onboard processors on vehicles have limited computational resources.

(3) The C-SVM is trained using linear, RBF, sigmoid and polynomial kernels. Kernels are compared with the help of accuracy while they are used for classification. For different kernel functions, the classification accuracy of C-SVM for statistical features is presented in Table 2. Among all other kernel functions, the RBF for C-SVM gives the best classification accuracy (98.72%).

(4) The parameter values used for the RBF function to maximize the classification accuracy:

Epsilon = 0.001
C = 50,000
Gamma = 0.0815

(5) The confusion matrix for the particular RBF function is also presented in Table 3.

5.2. Statistical features using Nu-SVM

(1) As discussed in Section 5.1, from the decision tree, the top five features that are contributed to classification are selected for training and testing. The classification accuracy of Nu-SVM for the statistical features is presented in Table 4.

(2) Among the considered kernel functions, RBF kernel with Nu-SVM gives better classification accuracy (97.749%).

(3) Parameter values used for RBF function to maximize the classification accuracy:

Epsilon = 0.001
Gamma = 21.2308
Nu = 0.10532

Table 1
Effect of number of features on classification accuracy.

No. of features	Classification accuracy		
	C4.5 Decision tree	**C-SVM**	**Nu-SVM**
1	48.00	51.63	42.90
2	80.90	86.18	86.90
3	90.72	85.81	85.81
4	95.81	97.09	86.54
5	**97.45**	**98.72**	**98.36**
6	97.27	98.62	98.54
7	96.90	98.90	98.54
8	96.90	98.62	98.54
9	96.90	98.90	98.00
10	97.09	98.36	96.36
11	97.09	98.36	98.54
12	97.09	98.36	98.54

Table 2
Classification accuracy of statistical features using C-SVM.

Sl. no.	Type of Kernel function	No. of support vectors used by the model	Classification Accuracy
1	Linear	162	98.54
2	**RBF**	**160**	**98.72**
3	Sigmoid	154	98.72
4	Polynomial degree 1	78	98.36
5	Polynomial degree 2	60	98.72
6	Polynomial degree 3	56	98.72
7	Polynomial degree 4	56	98.72

Table 3
Confusion matrix for C – SVM – RBF Kernel function.

Category	*AE*	*BO*	*DPWI*	*DPWIO*	*DRMF*	*DRPW*	*GOOD*	*RL*	*UDPWI*	*UDPWIO*
GOOD	55	0	0	0	0	0	0	0	0	0
BO	0	55	0	0	0	0	0	0	0	0
DPWI	0	0	55	0	0	0	0	0	0	0
DPWIO	1	0	0	54	0	0	0	0	0	0
DRMF	0	0	0	0	53	0	0	1	0	1
DRPW	0	0	0	0	0	54	0	1	0	0
AE	0	0	0	0	0	0	55	0	0	0
RL	0	0	0	0	1	0	0	54	0	0
UDPWI	0	0	1	0	0	0	0	0	54	0
UDPWIO	0	0	0	0	0	0	0	0	1	54

GOOD: brake without any fault; BO: brake oil spill; DPWI: disc brake pad wear – inner; DPWIO: disc brake pad wear inner & outer; DRMF: drum brake mechanical fade; DRPW: drum brake pad wear; AE: air in brake fluid; RL: reservoir leak; UDPWI: uneven disc pad wear (inner) UDPWIO: uneven disc pad wear (inner & outer).

Table 4
Classification accuracy of statistical features using Nu-SVM.

Sl. no.	Type of kernel function	No. of support vectors used by the model	Classification accuracy
1	Linear	509	96.90
2	**RBF**	200	**98.36**
3	Sigmoid	520	87.81
4	Polynomial degree 1	167	97.45
5	Polynomial degree 2	86	97.27
6	Polynomial degree 3	55	98.54
7	Polynomial degree 4	171	98.36

Table 5
Confusion matrix for Nu – SVM – RBF kernel function.

Category	*AE*	*BO*	*DPWI*	*DPWIO*	*DRMF*	*DRPW*	*GOOD*	*RL*	*UDPWI*	*UDPWIO*
GOOD	55	0	0	0	0	0	0	0	0	0
BO	0	55	0	0	0	0	0	0	0	0
DPWI	0	0	55	0	0	0	0	0	0	0
DPWIO	1	0	0	54	0	0	0	0	0	0
DRMF	0	0	0	0	52	0	0	1	0	2
DRPW	0	0	0	1	0	53	0	1	0	0
AE	0	0	0	0	0	0	55	0	0	0
RL	0	0	0	0	1	0	0	54	0	0
UDPWI	0	0	1	0	0	0	0	0	54	0
UDPWIO	0	0	0	0	0	0	0	0	1	54

GOOD: brake without any fault; BO: brake oil spill; DPWI: disc brake pad wear – inner; DPWIO: disc brake pad wear inner & outer; DRMF: drum brake mechanical fade; DRPW: drum brake pad wear; AE: air in brake fluid; RL: reservoir leak; UDPWI: uneven disc pad wear (inner) UDPWIO: uneven disc pad wear (inner & outer).

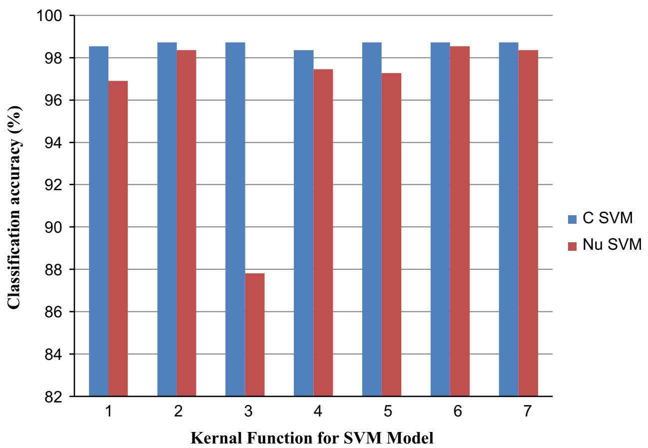

Fig. 7. Comparison of C-VSM with Nu SVM. 1. Linear kernel ; 2. RBF Kernal; 3. Sigmoid kernel; 4. Polynomial degree 1; 5. Polynomial degree 2; 6. Polynomial degree 3; 7. Polynomial degree 4.

(4) It is evident that from Table 4, RBF kernel in Nu-SVM gives maximum classification accuracy. 98.36% of faults are correctly classified in this Nu-SVM model.
(5) From the confusion matrix (Table 5), one can understand that a minimum of 55 data samples were considered for each condition of the brake system. The number of correctly classified data points is represented in the diagonal elements of the confusion matrix, and the incorrectly classified data points are represented in the non-diagonal elements of the confusion matrix. In this fashion, the classification accuracies were found and compared for various types of the SVM model for different families of statistical features.
(6) The effect of number of features was studied for both C-SVM and Nu-SVM and are tabulated (Table 1). Referring to Fig. 7, the effectiveness of the SVM can be found.

6. Conclusion

From the results presented in Section 5, the following conclusions are drawn: the fault diagnosis of the hydraulic brake system can be performed, using the vibration signals and machine learning techniques. Only the most frequently occurring faults were considered. Under static condition of the test rig, the simulated faults were tested in our laboratory. Using the C4.5 decision tree algorithm and the SVM classifier algorithm, the classification accuracy was found for different numbers of statistical features. If a small misclassification is tolerable, then the top (good) five statistical features, namely, minimum, standard error, sample variance, kurtosis, skewness are sufficient. For more accurate fault diagnosis, seven good statistical features, namely, minimum, standard error, sample variance, kurtosis, skewness, standard deviation, mean are required. If the top five features are selected, the RBF kernel of the C-SVM classification model seem to be better, compared to other kernel functions which were taken for the study of the statistical features. Comparing the results of the SVM based on the kernel functions, radial basis function (RBF) has more classification accuracy in both types of SVM, and can be suggested for practical applications. However, one should note that there are more statistical features available, which are not considered in the present study. Due to the encouraging results, future study on brake fault diagnosis is possible on real vehicles under real road conditions.

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