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Full length article

Brake fault diagnosis using Clonal Selection Classification Algorithm (CSCA) – A statistical learning approach

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ABSTRACT

In automobile, brake system is an essential part responsible for control of the vehicle. Any failure in the brake system impacts the vehicle's motion. It will generate frequent catastrophic effects on the vehicle cum passenger's safety. Thus the brake system plays a vital role in an automobile and hence condition monitoring of the brake system is essential. Vibration based condition monitoring using machine learning techniques are gaining momentum. This study is one such attempt to perform the condition monitoring of a hydraulic brake system through vibration analysis. In this research, the performance of a Clonal Selection Classification Algorithm (CSCA) for brake fault diagnosis has been reported. A hydraulic brake system test rig was fabricated. Under good and faulty conditions of a brake system, the vibration signals were acquired using a piezoelectric transducer. The statistical parameters were extracted from the vibration signal. The best feature set was identified for classification using attribute evaluator. The selected features were then classified using CSCA. The classification accuracy of such artificial intelligence technique has been compared with other machine learning approaches and discussed. The Clonal Selection Classification Algorithm performs better and gives the maximum classification accuracy (96%) for the fault diagnosis of a hydraulic brake system.

1. Introduction

Brakes are the most important control components in automobile. Every automobile shall be equipped with an efficient brake system which ensures the stability of the vehicle. An efficient brake system should bring the vehicle to rest within a reasonable distance. It is also desirable that the rate of retardation should be proportional to the pedal effort. The brake system must promote the highest degree of safety on the road not alone for the person driving but also for the others moving on the road. Since there are moving components involved, they are bound to get faulty due to various reasons, viz. wearing, air leak, fade, etc. When such things occur, the effectiveness of the brake system reduces resulting in accidents. It is essential that the brake system and brake components should be monitored all the time and diagnosed when faults occur. Hence maintenance of the brake system plays a vital role in terms of safety. The malfunction of the brake system can be identified through its symptoms or some warning sign; since the faults in the brake system are not fairly noticeable. A patented method was proposed for monitoring the applications of the brakes in automobiles. This device which consists of a chart recorder with traces driven by a transducer was used to measure the brake force [1]. An apparatus was developed for measuring and regulating a braking force using sensors [2]. In both the cases, the sensors have been used to measure some parameters like brake temperature, friction force and braking force etc. No such system has been proposed to measure brake pad wear, mechanical fade, reservoir leak, etc. Hence a vibration based fault diagnosis approach has been reported in the present study to monitor the condition of a brake system.

Monitoring of a brake system is not an easy job. This can be performed using intelligent techniques called fault diagnosis through machine learning. Machine fault diagnosis is a field of mechanical engineering deals with finding faults arising in machines. Many methods like vibration analysis [3], acoustic emissions [4], thermal imaging [5], etc. were used to identify the most probable faults leading to failure. Most commonly used method is vibration analysis. The vibration signals are analyzed by using methods like spectral analysis, wavelet analysis, waveform analysis, etc. Such analysis will provide the information required to make a decision about when intervention is required for maintenance. The

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results of such analysis are used for failure analysis in order to determine the original cause of the fault. This failure analysis can be done using machine learning approach. Machine learning approach consists three steps. (i) feature extraction, (ii) feature selection, and (iii) feature classification.

There are many features available in literature, namely, histogram features [6,7], statistical features [7], and wavelet features [8,9]. In the present study statistical features were used for the fault diagnosis study. The statistical features were extracted from the vibration signals which were acquired from the brake system setup, under various fault conditions. All the statistical features may not be required for classification. Hence, the most important features which contain the necessary information required for classification are to be identified. This was achieved by using feature selection. There are many techniques available for feature selection namely principal component analysis (PCA) [10], and decision tree (DT) [11]. Principal component analysis is suitable for data sets in multiple dimensions and it is not suitable for incomplete data set. In a study, the best feature sets were identified using decision tree (DT) from the given samples [11]. However, it may not be preferable due to its noise and over sensitivity property to irrelevant attributes. Hence a new technique called attribute evaluator has been used for feature selection.

Many classifier algorithms have been reported for feature classification. Algorithms like SVM and PSVM have been reported for fault diagnosis of various machine elements such as bearing, impeller of a centrifugal pump, etc [11–13]. The computational complexity of such classifiers is usually intensive, since it involves a quadratic programming. A report illustrated a fuzzy and neural network based fault diagnosis system for a centrifugal pump to classify faults at early stages [14]. The effectiveness of fuzzy classifier depends on the rules suggested by the experts or algorithms. A system was developed using artificial neural network approaches (feed forward network and binary adaptive resonance network (ART1)), for the fault classification of centrifugal pump [15]. However, training of an artificial neural network classifier is complex and time consuming one. The convergence of the training is not always guaranteed. Naïve Bayes and Bayes net algorithms were effectively used for monitoring the condition of a single point cutting tool [16]. The main drawback is that it assumes independence of features. In a study, Best First tree was used for the fault categorization [17]. It gave encouraging results when compared to decision tree. The problem with the Best first decision tree is the selection of splitting criteria to measure the impurity which requires more computation time. A classifier which will give very high classification accuracy with simple operation should be used for feature selection and feature classification. C4.5 decision tree algorithm satisfies these conditions and it has been used in many applications [18]. However, decision tree algorithm is more sensitive for irrelevant data.

The immune system is a robust and powerful information process system that demonstrates features such as parallel processing, adaptation and learning via experience. Artificial Immune Systems (AIS) are machine-learning algorithms that exemplify some of the principles and attempt to take advantages of the benefits of natural immune systems for use in tackling complex problem domains [19]. The Clonal Selection Classification Algorithm (CSCA) is one such system inspired by the clonal selection theory of acquired immunity, which has shown success on broad range of engineering problem domains [20]. From the literature one can understand that many classification algorithms have been used for classifying the faults in various machine elements. In order to suggest strongly that a particular algorithm is better, a detailed study needs to be conducted. This study mainly focuses on the performance of the Clonal selection classification algorithm in the brake fault diagnosis. However, classification of faults in automobile hydraulic brake system using CSCA has not been attempted. Hence an effort has been initiated in the present study to classify the faults in the hydraulic brake using CSCA. The flow chart of the fault diagnostic system is shown in Fig. 1.

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 CSCA algorithm has been discussed in Section5. The classification accuracy of CSCA algorithm have been evaluated and discussed in Section 6. Section 7 summarizes the main findings of this paper. The Clonal Selection Classification Algorithm (CSCA) classifier with statistical features has 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 Fig. 2. The vibration signals were acquired by using a piezoelectric type accelerometer (an uni-axial type, 50 g range, 100 mV/g sensitivity and 40 kHz resonant frequency). Since accelerometer has high-frequency sensitivity for detecting faults, it can be used to detect very small amplitude vibrations without

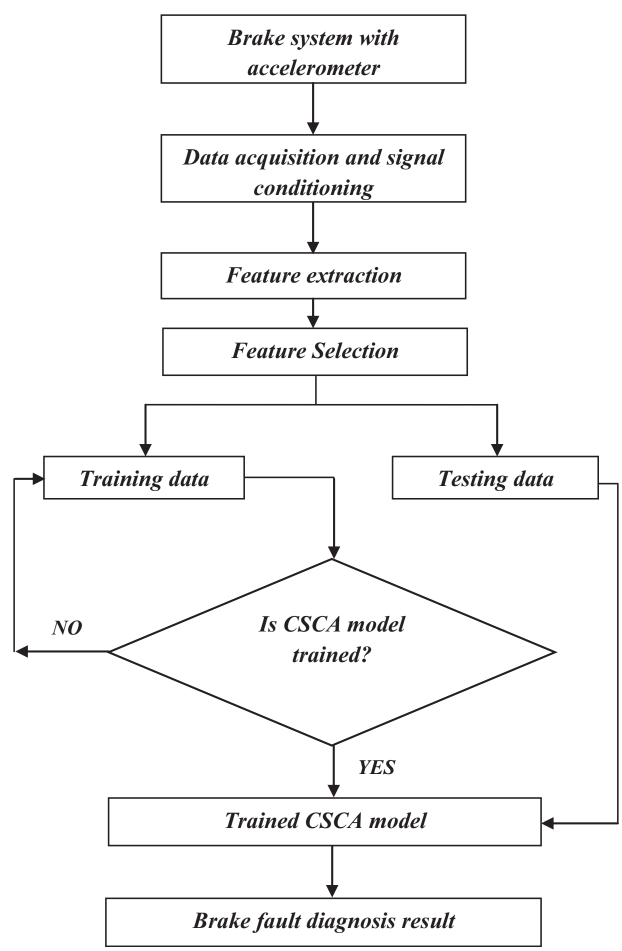

Fig. 1. Flow chart of brake fault diagnosis using CSC algorithm.

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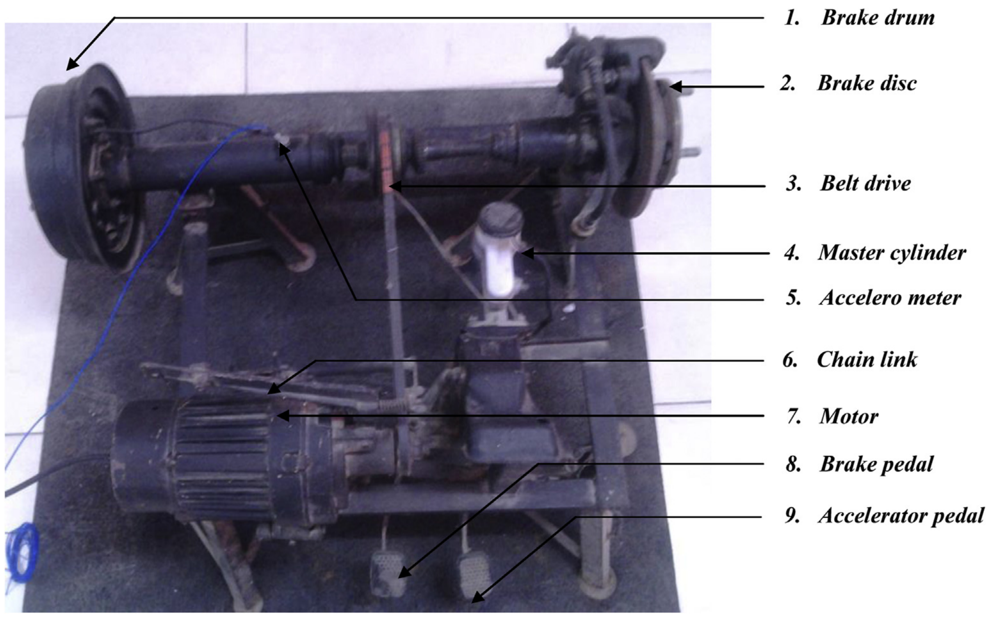

Fig. 2. Experimental setup – Brake fault diagnosis.

being damaged by large vibrations. The accelerometer was mounted near the brake drum (and/or brake disc) using a direct mounting technique as shown in Fig. 2. 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 signal passes through the charge amplifier and an analogue-to digital converter (ADC).

Initially the test rig was assumed to be in good condition. (All components were brand new). 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 [17].

(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 (Fig. 3). These vibration signals were processed to extract the statistical features. Fig. 4(a)–(j) shows the time domain signals taken from the brake setup.

3. Feature extraction

The process of computing some measures which will represent the signal is called feature extraction. A fairly twelve set of statistical parameters were selected for the study. They are mean, standard error, sample variance, kurtosis, skewness, minimum, maximum, standard deviation, count, and mode and median. The definition of the extracted statistical features was described in a fault diagnosis approach [17]. Following the study performed by Sugumaran et al., these twelve features were extracted from vibration signals using Visual basic tool [18].

4. Feature selection

Feature selection is an important process in machine learning. The feature selection process can be used for either to improve estimators (classifiers) accuracy scores or to boost their performance on very high-dimensional data sets. With sufficient data and time, it is fine to use all the input features, including those irrelevant features, to approximate the primary function between the input and the output. There are two problems with the irrelevant features. (i) It will induce greater computational cost. (ii) The irrelevant input features may mislead the training process. Hence those input features with little effect on the output, may be ignored in order to keep the size of the approximator model small. Hence the feature selection process plays a vital role in predicting the classification accuracy. To find the best subset, Brute-force feature selection method was used to evaluate all possible combinations of the input features exhaustively. Obviously, the computational cost for exhaustive search is prohibitively high, with considerable danger of over fitting. This can be avoided through greedy methods, such as forward selection. In this paper, one such greedy selection algorithm called attribute evaluator has been used to enhance the classification accuracy of the classifier.

The best feature set using greedy based attribute evaluator has been found by estimating the leave-one-out cross validation (LOOCV) error [21]. It is computed by running the learning algorithm m times. Each time, it used a single observation from the original sample as the validation data, and the remaining observations as the training data. This is repeated until each observation is used once as the validation data. For all individual features, one attribute LOOCV error was calculated and sorted. The best individual features were added one by one, and the corresponding LOOCV error was evaluated. This procedure was repeated until all features have been evaluated. This algorithm may conclude at a

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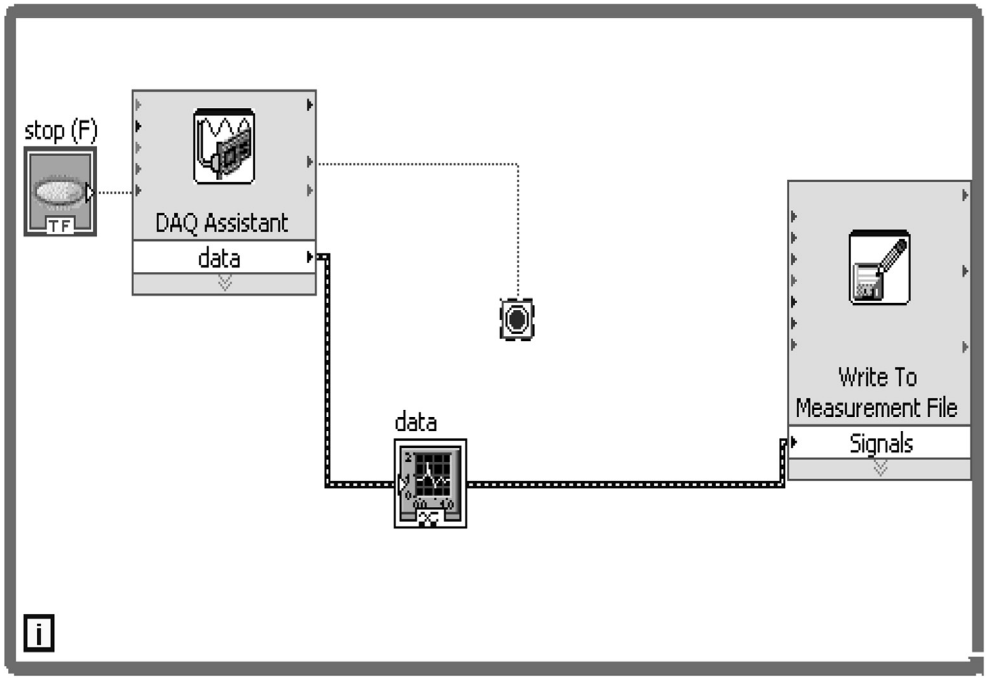

Fig. 3. LabVIEW Graphical program.

subset whose size is smaller than *m*. Hence, the greedy algorithm may end up with a better feature set.

5. Clonal Selection Classification Algorithm

In recent years, artificial immune system has been used to solve complex problem domains using the benefits of natural immune systems. In a biological process the immune system protects an organism from the potentially harmful materials (antigens) such as bacteria, viruses, etc. These antigens (pathogenic materials) are neutralized by an antibody. This immune function is performed by the B-cells (B lymphocyte cells) and T-cells (T lymphocyte cells) which are acting as a recognition cell. These cells are suited to specific antigens. Affinity is the degree of similarity between a recognition cell and a pathogenic. In an immune response, many clones are generated through hyper mutation to gain a better match with the antigen. During the hyper mutation, the mutated clones maintain the highest match (affinity) with the antigen. This process is termed as Clonal selection theory [19]. The Clonal Selection Classification Algorithm (CSCA) has been designed using this Clonal selection theory which is used to defend the organism from incursion. The goal of the algorithm is to develop a memory pool of antibodies that represents a solution to the fault diagnosis problem. This final pool of memory antibodies are provided through local and global search. In the local search more clones are produced through affinity maturation (process of an adaptive ability of an immune system). In global search, randomly generated antibodies are inserted into the population to increase the diversity.

The main objective of the Clonal selection classifier algorithm is to maximize the classification accuracy. In order to maximize the classification accuracy, the diverse population with high fitness antibodies is essential instead of a single antibody solution. This is obtained by revealing the antibody to a set of antigens. However, a single exposure to all antigens is a practical problem with the large data sets. Hence a batch training methodology was adopted to break the training set in to partitions as batches. The partition set acts as a system which is permitted to the pathogen sets for multiple exposures after which the system acclimatize the fitness of an antibody. This batch training process is adopted in the Clonal Selection Classification Algorithm. Each data set in a class act as antigens. Antibody with highest fitness score is used to train the partition set. The affinity (distance measure) is used to classify the data set belongs to unknown class. Overview of the Clonal selection Classification algorithm is shown in Fig. 5 [20].

The following parameters are used in CSCA algorithm:

Initial population size (S): Defines the number of antigens with which to seed the antibody population ($S = 88$ in the present study);

Total generations (G): The number of generations used to train the system. ($G = 5$).

Clonal selection factor (α): Used to either increase or decrease the number of clones produced each generation ($\alpha = 1$).

Minimum fitness threshold (ε): Used to prune the antibody population size.

Algorithmic procedure of a CSCA:

Step 1: Antibody (G) is exposed with randomly selected antigens (S).

Step 2: Entire populations are selected and exposed to antigen set and fitness score is calculated for each antibody.

Step 3: The clones are generated and mutated for the selected set.

Step 4: The generated clones and the selected antigens are inserted to the population.

Step 5: The antibodies with less fitness score ($<\varepsilon$) are removed (pruned) from the selected set.

Step 6: Modified fitness score is calculated after pruning.

Step 7: Raw data is exposed to antibody population. With the highest affinity, the antigens are applied to classify the data.

6. Results and discussion

From the test setup, the vibration signals were taken under different simulated fault conditions. Information contained in the vibration signal was extracted using a number of statistical

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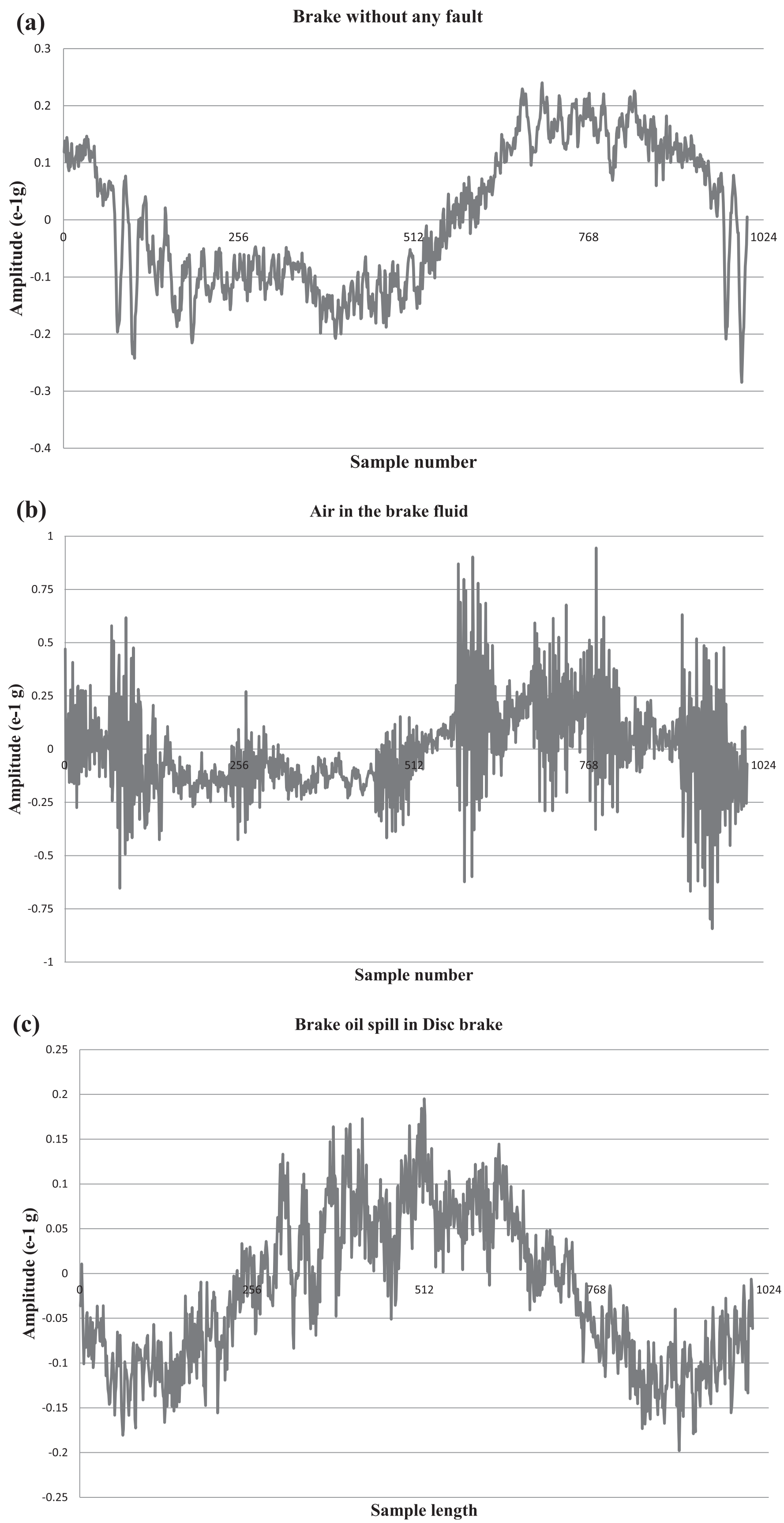

Fig. 4. (a) Vibration signal – Brake without any fault. (b) Vibration signal – Air in the brake fluid. (c) Vibration signal – Brake oil spill. (d) Vibration signal – Disc brake pad wear (even) – inner. (e) Vibration signal – Disc brake pad wear (even) – inner & outer. (f) Vibration signal – Disc brake pad wear (uneven) – inner. (g) Vibration signal – Disc brake pad wear (uneven) – inner & outer. (h) Vibration signal – Drum brake mechanical fade. (i) Vibration signal – Drum brake pad wear. (j) Vibration signal – Reservoir leak.

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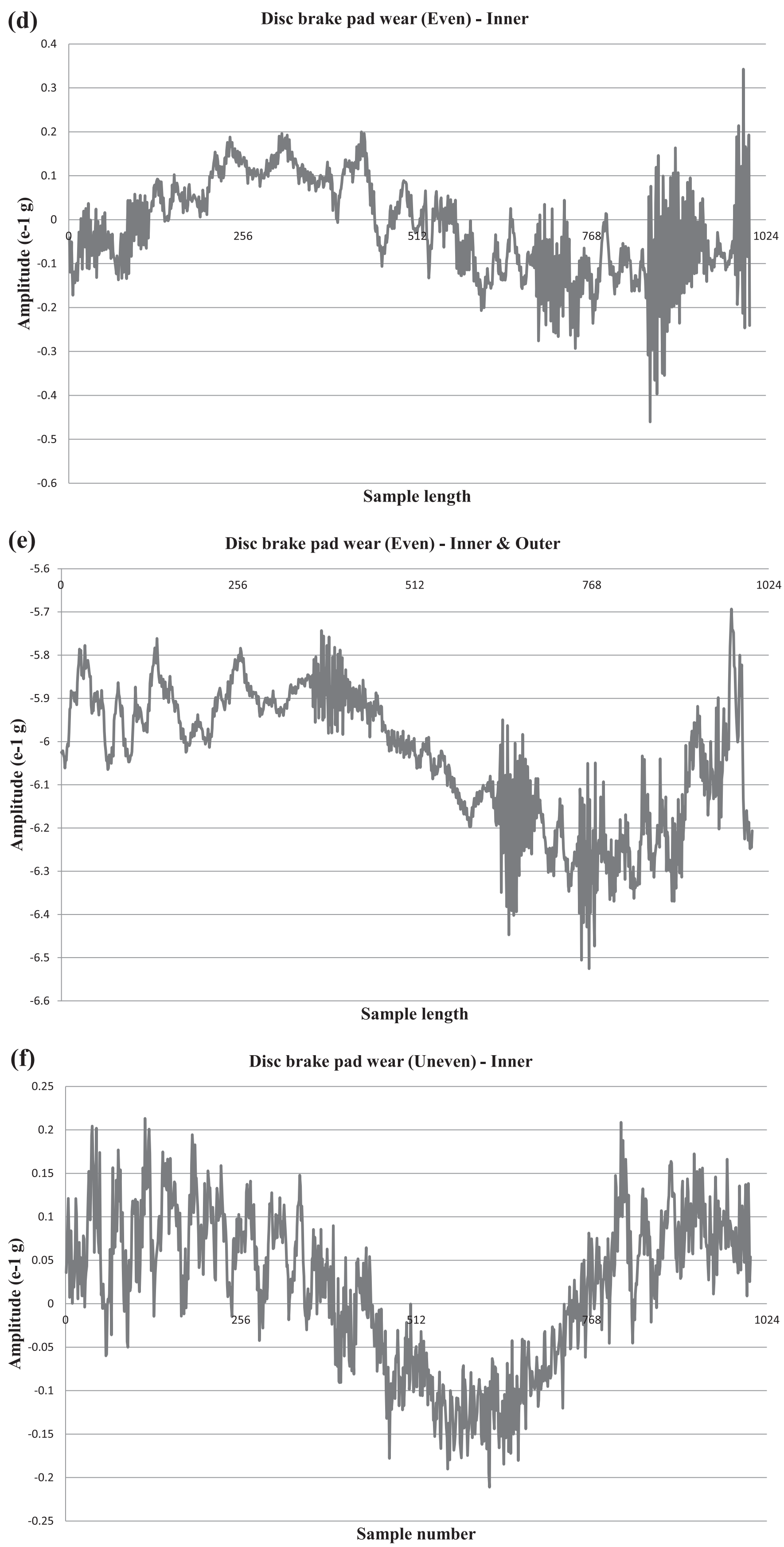
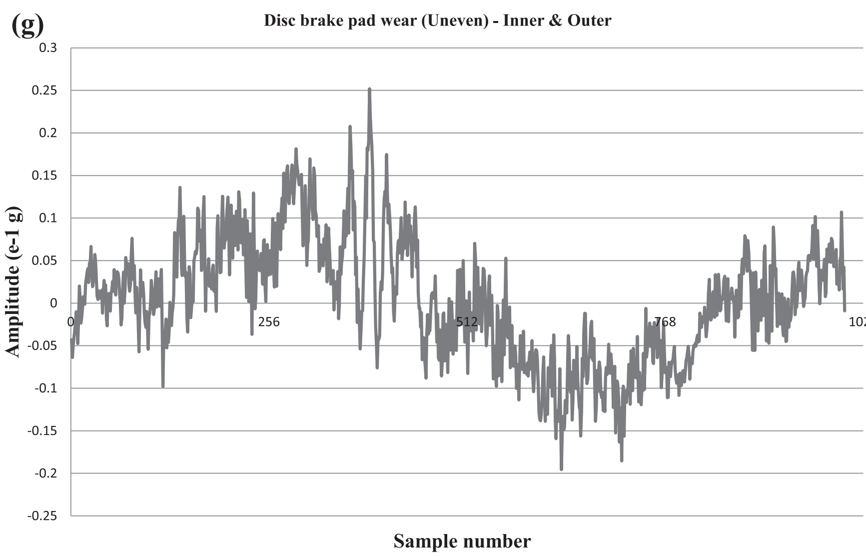
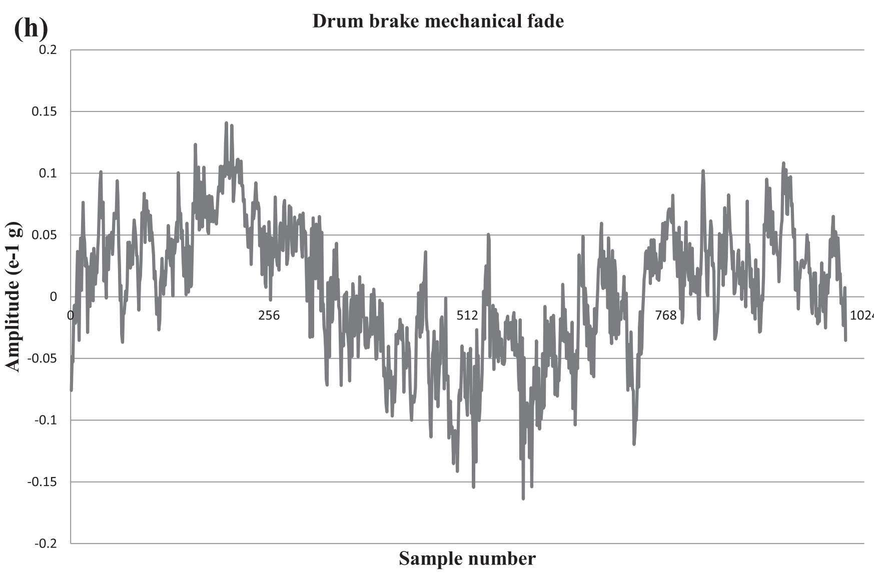
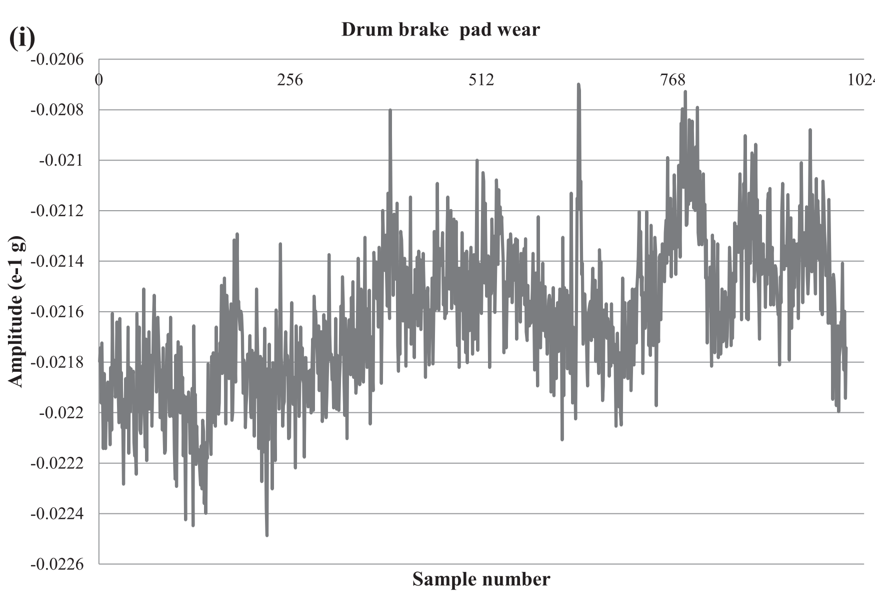


Fig. 4. (*continued*).







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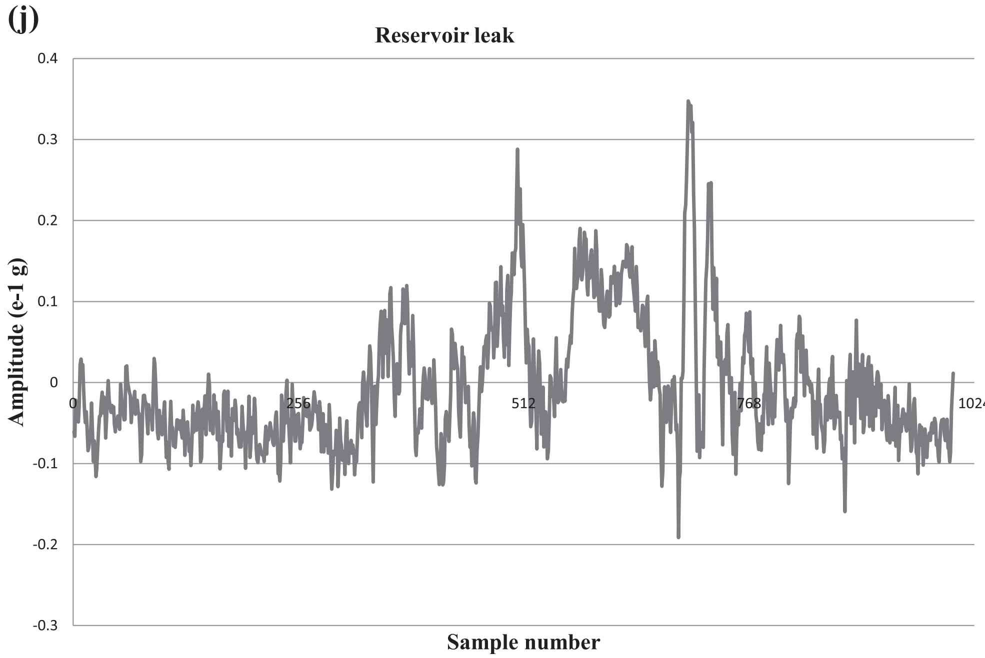

Fig. 4. (*continued*).

features. Twelve statistical features namely, mean, standard error, median, standard deviation, variance, kurtosis, skewness, and range, minimum, maximum, sum and count were extracted from the vibration signals. The effect of features on classification accuracy was found using the attribute evaluator. The attribute evaluator evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. Subsets of features that are highly correlated with the class while having low inter-correlation are preferred. In the attribute evaluator, the best first search method was used. It searches the space of attribute subsets by Greedy hill climbing augmented with a backtracking facility. Best first may start with the empty set of attributes and search forward, or start with the full set of attributes and search backward, or start at any point and search in both directions (by considering all possible single attribute additions and deletions at a given point). The following search conditions were selected for attribute evaluation.

Search method	Best first
Start set	No attributes
Search direction	Forward
Total number of subsets evaluated	86
Merit of best subset found	0.918

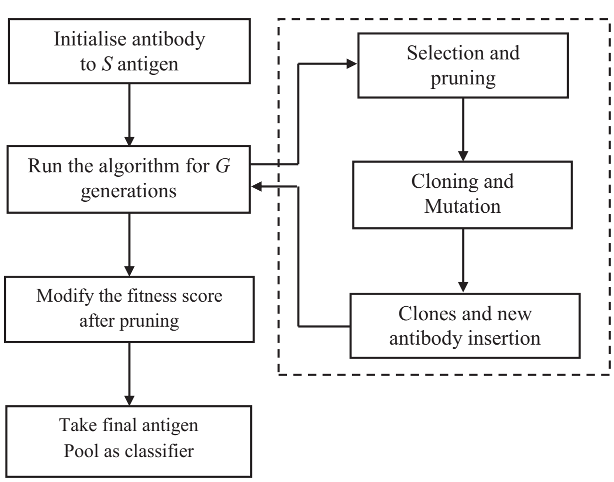

Fig. 5. Overview of the CSCA technique.

In the attribute subset evaluator, twelve nominal classes were used for search. At the end of the Greedy search, nine attributes were selected for classification. The selected attributes are, namely, minimum, standard error, sample variance, kurtosis, skewness, mean, median, standard deviation and maximum. The selected nine features were classified by using CSCA. Table 1 shows the parameter used for the classification using CSCA.

The first feature (minimum) in the attribute evaluator was selected for classification. The first feature alone was classified using CSCA and the classification accuracy was noted down. Then the first feature was clubbed with the second feature in the in the attribute evaluator. The clubbed two features were classified using CSCA and the accuracy was noted again. Referring to Table 2 the accuracy is increasing. The third feature located in the in the attribute evaluator was also clubbed with the previous one and the accuracy value was noted down. This procedure was repeated for all selected attributes. Remaining three statistical features were also clubbed with the other feature sets and the corresponding classification accuracy was also noted down. It has been noted that, after a certain number of combinations (say 9), the classification accuracy fell down. Table 2 shows the classification accuracy for the selected number of features. Referring Table 2, when the number of features is equal to nine, the classifier gives the maximum classification accuracy. The top nine features were selected by using supervised attribute subset evaluator. The classification and misclassification details are generally presented in the form of a

Table 1
Parameters for CSCA.

Generations completed	5
Antibodies pruned per generation	441.6 (218.376)
Antibodies without error per generation	59.8 (15.536)
Population size per generation	630.4 (12.737)
Antibody fitness per generation	2.599 (3.583)
Antibody class switches per generation	10 (7.071)
Selection set size per generation	10.2 (2.638)
Training accuracy per generation	93.818 (1.534)
Inserted antibodies per generation	10.2 (2.638)
Cloned antibodies per generation	550.2 (1.166)
Data reduction percentage	84%
Total antibodies	88
Total training instances	550

Table 2
Effect of number of features on the classification accuracy.

No. of features	Classification accuracy of CSCA (%)
1	48.18
2	48.36
3	61.27
4	91.27
5	93.82
6	93.45
7	93.09
8	92.91
9	**96.00**
10	95.27
11	29.45
12	30.55

square matrix called as Confusion matrix. Confusion matrix for training data set is shown in Table 3. The general procedure for reading and understanding the confusion matrix is as follows.

From the confusion matrix, one can understand that 55 samples in each class were considered for each condition of the brake system. All the diagonal elements of the confusion matrix represent the number of correctly classified data points and the non diagonal elements represent the incorrectly classified data points. In this fashion, the classification accuracies were found and compared. First row in the confusion matrix represents, the number of data sets corresponding to "GOOD" condition. The first element (the diagonal element) in the first column represents, how many data sets are correctly classified as "GOOD" condition. In the first row, 55 data sets belongs to "GOOD" condition, all are correctly classified as "GOOD" condition. Hence non diagonal elements are zero. It means that there is no misclassification among them. Similarly second row, second element in the confusion matrix, represents Air in reservoir ("AE") condition. The second element in the second column indicates, how many data sets belongs to ("AE") condition, is correctly classified as "AE" condition. The non diagonal elements represent, how many data sets belongs to "AE" condition are misclassified as other fault condition. In this fashion, all the 55 data sets belong to "AE" condition were correctly classified as AE condition. Like in GOOD condition, non diagonal elements in second row are zero. Hence in this class also, there is no misclassification. In the fourth row, fourth column elements represent, the data set belongs to disc brake pad wear – Inner (DPWI) condition. The diagonal element represents the correctly classified elements. In this way, among 55 data points, only 53 data points were correctly classified. One data point is misclassified as BO condition, and another data point is misclassified as disc brake pad wear uneven – inner ("UDPWI") condition.

The classification accuracies were found and the following results were obtained.

Total number of instances	550
Correctly classified instances	528 (96%)
Incorrectly classified instances	22 (4%)
Kappa statistic	0.9556
Mean absolute error	0.008
Root mean squared error	0.0894
Relative absolute error	4.444%
Root relative squared error	29.8111%

In the present case, none of the fault conditions has been misclassified as "GOOD" condition and none of the "GOOD" condition has also been misclassified as other fault conditions. Hence the fault detection accuracy is 100%. However there were some misclassification amongst the other fault conditions and hence classification accuracy for CSCA was found to be 96%.

6.1. Detailed accuracy by class

Table 4 shows the detailed accuracy by class for CSCA. For an Ideal classifier, the true positive rate (TP rate) must be 1, whereas the false positive rate (FP rate) should be 0. TP (True positive) rate is the proportion of the conditional class that was correctly identified as belonging to that particular conditional class. FP (false positive) is the proportion of the misclassified cases that were incorrectly classified as positive.

Referring, Table 4, the weighted verge of the TP rate is close to one (0.96) and the FP rate is very close to 0. The small deviation is due to some misclassification among the different fault conditions. Hence the overall classification accuracy was calculated as 96% which is equivalent to the TP rate. Similarly, the precision, recall and F-measure value is also close to 1, which is an expected value of an ideal classifier. An F-measure is the harmonic mean of precision and recall, and a larger F-Measure value indicates a higher

Table 3
Confusion matrix for CSCA with statistical features.

Category	GOOD	AE	BO	DPWI	DPWIO	UDPWI	UDPWIO	DRMF	DRPW	RL
GOOD	55	0	0	0	0	0	0	0	0	0
AE	0	55	0	0	0	0	0	0	0	0
BO	0	0	53	1	0	1	0	0	0	0
DPWI	0	0	1	53	0	1	0	0	0	0
DPWIO	0	1	0	0	52	0	0	0	2	0
UDPWI	0	0	3	2	0	50	0	0	0	0
UDPWIO	0	0	0	2	0	0	53	0	0	0
DRMF	0	0	0	0	0	0	0	51	0	4
DRPW	0	0	0	0	0	0	0	0	55	0
RL	0	0	0	0	0	0	0	4	0	51

GOOD: Brake without any fault; AE: Air in brake fluid; BO: Brake oil spill; DPWI: Disc brake pad wear – inner; DPWIO: Disc brake pad wear inner & outer; UDPWI: Uneven disc pad wear (inner) UDPWIO: Uneven disc pad wear (inner & outer); DRMF: Drum brake mechanical fade; DRPW: Drum brake pad wear; RL: Reservoir leak.

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Table 4
Detailed accuracy by class – CSCA algorithm.

TP Rate	FP rate	Precision	Recall	F-measure	ROC area	Class
1	0	1	1	1	1	GOOD
1	0.002	0.982	1	0.991	0.999	AE
0.964	0.008	0.93	0.964	0.946	0.978	BO
0.964	0.01	0.914	0.964	0.938	0.977	DPWI
0.945	0	1	0.945	0.972	0.973	DPWIO
0.909	0.004	0.962	0.909	0.935	0.953	UDPWI
0.964	0	1	0.964	0.981	0.982	UDPWIO
0.927	0.008	0.927	0.927	0.927	0.96	DRMF
1	0.004	0.965	1	0.982	0.998	DRPW
0.927	0.008	0.927	0.927	0.927	0.96	RL
0.96	0.004	0.961	0.96	0.96	0.978	Wt. avg

GOOD: Brake without any fault; AE: Air in brake fluid; BO: Brake oil spill; DPWI: Disc brake pad wear – inner; DPWIO: Disc brake pad wear inner & outer; UDPWI: Uneven disc pad wear (inner) UDPWIO: Uneven disc pad wear (inner & outer); DRMF: Drum brake mechanical fade; DRPW: Drum brake pad wear; RL: Reservoir leak.

Table 5
Overall classification accuracy – a comparative study.

S.No.	Name of the classifier	Classification accuracy
1	**CSCA**	**96%**
2	RBF network	95.27%
3	Fuzzy	95.09%
4	JRIB	94.18%
5	Simple logistics	93.09%

classification quality. F-measure depends on precision and recall. Hence for all the three cases, the average value is close to 1 (0.96). The above encouraging results have been obtained through the 10-fold cross validation. The overall classification accuracy of the Clonal selection classification algorithm was found to be 96%.

6.2. Comparative study

Table 5 shows the overall classification accuracy of the different machine learning algorithms such as Radial Basis Function network (RBF), Fuzzy Inference Engine, JRIB and simple logistics. It indicates that the Clonal Selection Classification Algorithm (CSCA) classifier gives the maximum classification accuracy for the problem concerned.

7. Conclusion

This paper deals with vibration based fault diagnosis of automobile hydraulic brake system using an artificial intelligence technique called CSC algorithm. Nine classical fault conditions were simulated in a brake system. The simulated fault conditions were tested and for each fault condition, the vibration signals were acquired using a piezo-electric transducer. Twelve set of statistical features were extracted from the vibration signal using feature extraction techniques. Feature selection was then carried out using attribute evaluator. The selected features were classified using Clonal selection classification algorithm. Out of 550 data sets, 96% of data sets have been correctly classified. The 4% mis-classification is due to the insufficient information contained in the vibration signal. Hence the results of the CSC algorithm are encouraging one. From the study, one can confidently say that CSC algorithms were found to be good contender and it can be used for practical applications of fault diagnosis of the hydraulic brake system. It creates a hope for a better practical model for the brake fault diagnosis study, which would save many lives from the accidents.

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