International Journal of Engineering Innovation & Research
Volume 2, Issue 4, ISSN: 2277 – 5668

Misfire Detection in an IC Engine Using Vibration Signal and Bagging Classifier

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***Abstract* – Out of all the problems in an automobile industry, misfire in an IC engine remains a difficulty which has received high attention. However, this problem prevails with deteriorating effects like drop in fuel efficiency, rise in power loss and harmful emissions containing substantial amount of unspent hydrocarbons. When misfire occurs, a discernible pattern attributed to a particular cylinder is observed. In the present study, these vibration signals have been used to extract statistical features conducive to detect misfire. Among all the extracted features, those with maximum contribution in determining classification accuracy were selected using J48 decision tree algorithm. Using these selected features with bagging classifier utilizing functional tree algorithm, the misfire and normal conditions were classified appropriately. Then, the viability of using this technique as an onboard system is discussed based on its classification accuracy and confusion matrices.**

***Keywords* – Bagging, Classification Accuracy, IC Engine, Machine Learning, Misfire.**

I. Introduction

Misfiring is a popular fault with many adverse effects. It is caused in a cylinder of an IC engine due to faulty spark plug, cracked distributor cap, engine pinging due to very high temperature, improper air-fuel mixture and inadequate compression. It can pull down the engine output to 75% of its capacity. Loss of fuel economy and pollution caused due to unspent hydrocarbons present in the exhaust gases are a few other effects of it. Therefore, it is necessary to counter this problem in order to reduce pollution and to increase the fuel efficiency. Engine misfires can be indocile to detect and diagnose. Various methods have been suggested in numerous works for detecting misfire in an IC engine. Attempts have been made by utilizing instantaneous angular velocity [1], crankshaft speed [2], cylinder deviation torque [3], instantaneous crank angle speed [4], instantaneous exhaust manifold pressure [5], acceleration signal [6]-[8] of the engine head torsional vibration signal of the crankshaft [9]-[10]. Reference [11] proposed detection of misfire in spark ignition engines by applying wavelet transform on engine block vibration signals. Bolan Liu *et al.* [12] devised a method for misfire detection of a turbocharged diesel engine via neural network. Machine learning is an eminent technique and has been an important area of research. J48 algorithm under the decision trees [13] and support vector machine [14] have been used in this field. Techniques like decision tree [15]-[16], Naïve Bayes and Bayes net [17], rough set [18], support vector machine and proximal support vector machine [19] for various fault diagnosis in centrifugal pump. Another technique except machine learning used for detecting misfire in engine is to use vibro-acoustic measurements at engine exhaust to model nonlinear methods [20]. Such systems demands good grade sensors, better data acquisition systems and high computational power. Thus, they are quite expensive. Another drawback of this technique is that it relies principally on the knowledge of an expert and does not exploits the benefits of machine learning model based on algorithms using machine features acquired from the data.

A variety of approaches have been proposed for processing the signals to give the output for a fault diagnosis system including model-based reasoning [21], optimal disturbance de-coupling [22], temporal data [23], and machine learning [24]. Machine learning is a more economic and preferable approach as the computational resources are relatively easily available, it provides good accuracy and it is reliable. Also it is possible to train the system using this approach for dynamic engine conditions. Use of engine vibration data is recommended due to its minimum requirement for instrumentation and considerable accuracy. An accelerometer is employed which is interfaced with data acquisition system to accumulate the data and statistical features are extracted from this. Later, the features are ranked and most significant features are selected keeping the classification accuracy in mind.

In this study the vibration signal is used for the misfire detection of an IC Engine. The machine learning approach has been adopted for extraction and selection of features. This paper aims at discussing the possibilities of employing bagging classifier under meta-heuristic algorithm. The classification accuracy using FT classifier is discussed and confusion matrices have been analyzed to support its use for misfire detection system.

II. Experimental Setup

2.1 Apparatus

The experimental apparatus consists of a 10 HP rated-four stroke-vertical four cylinder petrol engine with provisions made to simulate a misfire. Misfire is produced by cutting off the power supply to the spark plug of a particular cylinder. A tachometer is attached to measure and monitor the speed. Data acquisition system includes an accelerometer attached at desired position via screw and nut mechanism on the engine which measures vibration signals. This analog vibration signal from accelerometer is converted to its digital value by using a dactron FFT analyzer. Engine specifications have been mentioned in Table I.

Table 1: Specifications of the engine

Make	Hindustan Motors
No. of cylinders/stroke	Four cylinders/four stroke
Fuel	Gasoline(Petrol)
Rated power	7.35 kW
Rated speed (alternator)	1500 rpm
Engine stroke length	73.02 mm
Engine bore diameter	88.9 mm
Cooling type	Water cooled

The experimental apparatus used for acquiring the training data is shown in Fig.1.

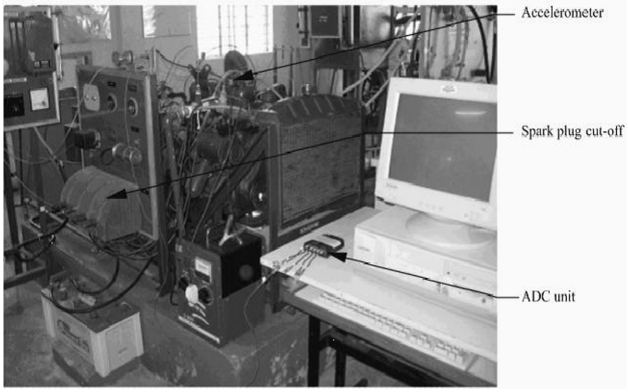

Fig.1. Experimental Setup

The basic flow diagram of the whole process is shown in Fig.2.

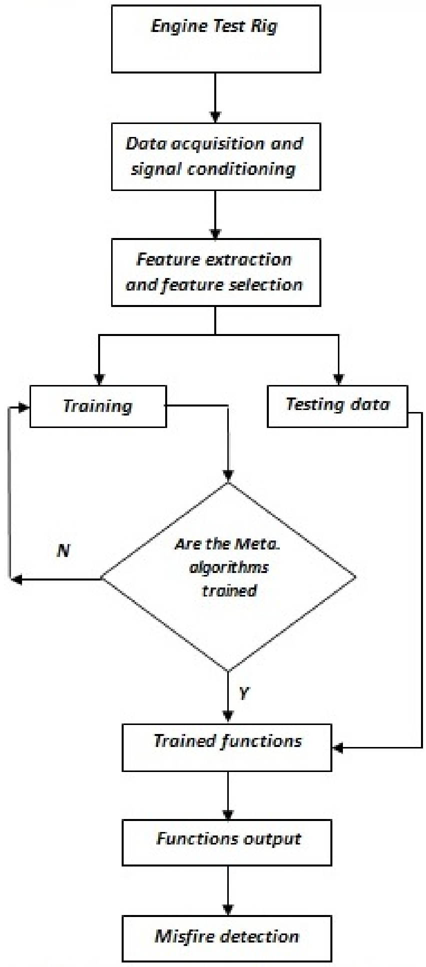

Fig.2. Flow diagram for Engine Misfire Detection

2.2 Experimental Procedure

The engine was started at no load by means of electrical cranking and is allowed to warm for 5 minutes. The engine was then allowed to stabilize. After the engine got stabilized, analyzer was switched on and data was collected at 1500 rpm, with a sampling frequency of 24 kHz and a sampling length of 8192. At these conditions, the vibration signals were recorded for five cases i.e. no misfire and misfire in cylinder one, two, three or four. All the events were simulated at 1500 rpm. Fig.3 and Fig.4 show the vibration signal waveform for misfire in cylinder 1 and normal condition respectively.

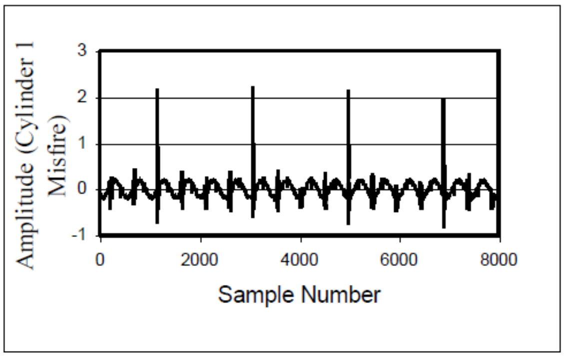

Fig.3. Vibration signal for misfire condition in cylinder 1

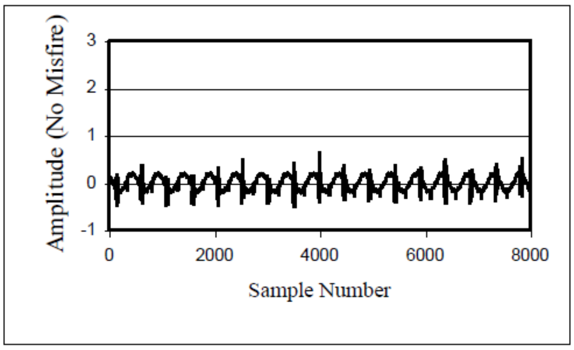

Fig.4. Vibration signal for normal condition

International Journal of Engineering Innovation & Research
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III. Feature Extraction and Feature Selection

Feature extraction is process of computing various parameters, mainly the statistical features for a signal which provides all the required information about the signal. Descriptive statistics for a particular signal gives a wide range of parameters namely mean, standard error, median, mode, standard deviation, sample variance, kurtosis, skewness, range, minimum, maximum, sum and count. Descriptive statistics tool in Microsoft Excel 2003 were used to perform this operation.

However, only a few selected features are required for classification. To remove irrelevant features, statistical feature selection is done. The relevant features were selected using J48 decision tree algorithm and the effect of the number of features on classification accuracy was recorded. Feature selection was done in such a way that only extracted statistical features which together contribute highest to the classification accuracy with a particular function remain. Sugumaran *et al.* [13] have proposed an algorithm for feature selection. By applying the proposed algorithm, following features were selected in descending order according to their contribution to the classification accuracy, sample variance, standard error, kurtosis, minimum, mean, standard deviation, skewness and range.

IV. Classifier

4.1 J48 Algorithm

A lot of variety for pruning is offered by this algorithm. Pruning reduces the size of the tree thus producing lesser and simpler results. It also reduces computational time by decreasing the size of the tree. The basic algorithm is that it continues classifying until each leaf is pure. However, this technique has a drawback; affirming maximum accuracy on the training data via this method can lead to overfitting, i.e. the classifier may create highly selective and stringent rules for training data. Thus an overfit model is not adaptive on new data and hence it is inefficient. Pruning is employed to rectify the overfitting of the experimental data [13].

4.2 Bagging Classifier

Bagging classifier is a type of meta-heuristic classifier which is also known as Bootstrap aggregating classifier. Bagging classifier is based on the idea of data re-sampling. It leads to creation of various subsets. Each subset is utilized in creating one classifier. Thus, a particular classifier is acquired using every subset. This aggregation of particular classifiers for different subsets leads to production of a compound classifier is created. This compound classifier is often more accurate than the particular classifiers.

Kristína Machová *et al.* [25] have elaborated on bagging methods using decision trees as a role of base classifier. Here functional tree (FT) classifier was used as a base classifier.

V. Results and Discussion

In the present study, misfire detection using machine learning has been discussed. J48 algorithm and bagging classifier using FT decision tree have been used to determine classification accuracy and confusion matrix. These are then utilized to discuss about the possibilities of using bagging classifier for an on board system. Various statistical features have been extracted from the data and out of them many relevant features such as, standard deviation, sample variance, standard error, minimum, mean, kurtosis, skewness and range were selected. The results are discussed for the same.

5.1 Effects of number of features

Out of a large number of features, features having most relevant contribution to classification accuracy were selected based on J48 tree algorithm and variation of classification accuracy with change in number of features is recorded. Table 2 shows the variation of classification accuracy with number of statistical features.

According to Table II, classification accuracy is maximum (90.4%) when 12 features are used. For bagging classifier using functional trees, the classification accuracy can be generalized to increase with increase in number of features. However, a classification accuracy of 87.4% was achieved using seven features. Although using 7 features reduces classification accuracy by 3% it is suggested to use seven features because choosing more number of features increases the computational time, complexity and cost of the system. A microprocessor would require more time to compute the result using twelve or thirteen features than it would need for seven features. Using seven features also obviates the need of a high end microprocessor, thus, reducing the onboard cost of the system. Therefore, it would be a better choice to choose seven features to make it suitable for real time application.

Table II: Classification accuracy v/s no. of features

No. of features	Classification Accuracy (%)
1	73.4
2	73.4
3	73.6
4	76.4
5	76.6
6	84.4
7	87.4
8	87.2
9	87.2
10	87.6
11	90.4
12	90.4

5.2 Classification using J48 Algorithm

In this section, results obtained using J48 algorithm will be discussed. Important observations are drawn from the obtained confusion matrix. Table III shows the confusion matrix for J48 algorithm.

Table III: Confusion matrix for J48 algorithm

TEST	C1	C2	C3	C4	Normal
C1 Misfire	81	0	10	9	0
C2 Misfire	0	99	0	0	1
C3 Misfire	7	0	53	40	0
C4 Misfire	6	0	23	71	0
Normal	1	0	0	0	99

From Table III, it can be observed that 99 % of the misfire conditions were properly classified which is appreciable. Hence, J48 decision tree is capable of identifying the faulty signal and good signals. However, at many instances, the normal condition was misclassified as a faulty condition and at one instance misfire was classified as normal condition which is not desirable. This algorithm demonstrates an overall classification accuracy of 80.6% when optimized for minimum number of objects equal to 3.

5.3 Classification using Bagging Classifier

With 452 correctly classified instances out of 500 instances, the bagging classifier provides a classification accuracy of 90.4%. Table IV shows confusion matrix for bagging classifier. This system demonstrates 100 % accuracy in differentiating a misfire condition from a normal condition.

Table IV: Confusion matrix for bagging classifier using functional trees

TEST	C1	C2	C3	C4	Normal
C1 Misfire	97	0	1	2	0
C2 Misfire	0	100	0	0	0
C3 Misfire	5	0	76	19	0
C4 Misfire	2	0	19	79	0
Normal	0	0	0	0	100

As observed from Table IV, 97 misfires out of 100 instances were correctly classified for cylinder 1, 100/100 instances were correctly classified for cylinder 2 whereas 76/100 instances were correctly classified for cylinder 3 and 79/100 instances were correctly classified for cylinder 4. This data supports this classifier as a good approach for implementation on an onboard system. Fig. 5 shows the variation of classification accuracy with number of iterations. The maximum accuracy of 90.4% was achieved with 30 iterations. Going for iterations more than 30 makes the calculations cumbersome and also doesn't yield a better result.

It was found that bagging classifier using functional tree algorithm has better classification accuracy than J48 algorithm for present system. Therefore, it is suitable for misfire detection of an IC engine using 7 features and it exhibits a good classification accuracy of 87.4%.

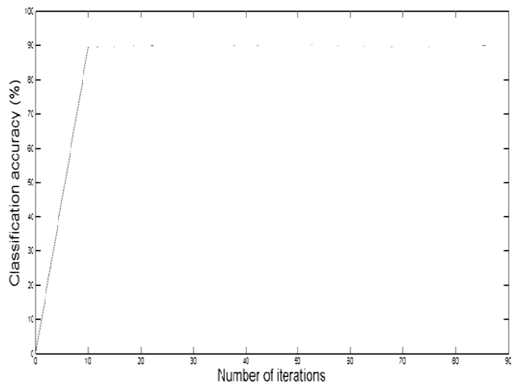

Fig.5. Variation of classification accuracy with number of iterations

VI. Conclusion

Detection of misfire in IC engines is extremely important to avoid fuel wastage, reduce the amount of hydrocarbon emissions and to save money. A new method using bagging classifier making use of functional tree algorithm was suggested as a possible solution for misfire detection. Use of vibration signals from engine block ensures great accuracy and lesser cost. The setup used is robust, requires less effort and is not too sophisticated. It can be inferred that the bagging classifier using functional tree algorithm is better than J48 algorithm for misfire detection in an IC engine. It is quite evident from the confusion matrices that bagging classifier provides high overall classification accuracy with perfect accuracy in distinguishing between fault and normal conditions.

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