A Bayes learning approach for monitoring the condition of suspension system using vibration signals

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Abstract- The suspension system is an important component in an automobile, aimed to provide better comfort and good road handling characteristics during vehicle motion on uneven road conditions. Varying load conditions, prolonged operations, continuous road shocks absorption, and time-based degradation of internal components can create faults in a suspension system. Fault occurrences in the suspension system can damage the internal components that lead to malfunctioning of the system causes failure and endanger vehicle safety. Thus, condition monitoring has become an essential part of identifying fault occurrences in a suspension system. This paper is focussed on condition monitoring of suspension system using vibration signal analysis and faults are classified with the help of machine learning-based Bayesian classifiers. A test setup is fabricated to simulate the working of the suspension system under different load conditions with one good and six faulty conditions. Vibration signals are recorded and used to extract statistical features. Further J48 decision tree algorithm was utilized to identify the most significant features during feature selection process. Bayes classifiers such as NaiveBayes and BayesNet classifiers were used to find the type of fault occurrence from the selected features. The overall results of the aforementioned classifiers are compared and the best in the Bayesian classifier is suggested for real-time application.

1. INTRODUCTION

Damping of unwanted vibration remains a prime concern in automobiles. The suspension system is used to control the vibrations transmitted from road wheels to the vehicle body due to the road irregularities during vehicle motion and to maintain the contact between wheel and the road. The purpose of the sound suspension system is to provide better comfort and improve road handling characteristics. The efficient working of the suspension system is degraded by various reasons such as fatigue, wear, external damage, improper fitting, and uneven wheel pressure resulting in causes for damaging other components. Since, the suspension system is operated under heavy loads and prone to continuous vibration transmission, it is subjected to various fault occurrences. To achieve the proper functioning of the suspension system and reduce the occurrence of faults, frequent monitoring is necessary. Several condition monitoring techniques carried out in recent times vary based on the type of suspension and components used. Various literatures suggest that condition monitoring based on vibration signal analysis is predominantly used to monitor the condition of the suspension system. The suspension system consists of many parts and monitoring each component with a specific fault diagnosis method makes condition monitoring a time-consuming process [1]. McPherson suspension system is widely used in most modern front-wheel-drive cars due to its simplicity and lightweight construction [2]. The suspension system
consists of struts, lower arm, knuckles, ball joints, and tie rod. The performance of the suspension system degrades due to various reasons such as fatigue, wear, external damage, improper fitting, etc. Such factors can result in fault occurrences leading to damage to internal components and raise safety concerns. Early detection of fault can improve system reliability and safety also will minimize down time [3][4]. Condition monitoring of each component with a specific fault diagnosis technique will be a time-consuming process [5]. Hence, an efficient fault diagnosis technique is the need of the hour. The condition monitoring of the suspension system can be categorized into two types namely, the conventional method and machine learning method. In the conventional method, Using Fast Fourier Transform (FFT) the vibration signals in time domain signals are converted to the frequency domain signals and the faults can be classified by monitoring the peak frequency in a spectrum. The frequency components in the traditional FFT approach tend to change continuously due to the frequent speed variations and wear and tear of components. Such variations have made the traditional approach complex and time-consuming [6]. While the machine learning approach uses a continuous learning process and adapts to varying test conditions. The vibration signals acquired from all the test conditions are classified with the help of machine learning algorithms such as Bayesian classifiers, Decision trees, lazy classifiers, etc.

Several researches have been carried out in damper, ball joint and spring in three category based on the conventional approach which is discussed as follows. Ventura et al discussed two methods for gaining access to the condition of the shock absorber using Micro-electro-mechanical systems (MEMS) sensor. In the first method, sprung and unsprung mass acceleration measurement is used to determine the transmissibility as a function of the damping coefficient to estimate the condition of the damper. In the second method, the pressure inside the compression chamber is measured along with vehicle acceleration using sensors to monitor the condition of the damper being assessed [7][8]. Luis Carvalho et al proposed a method to determine the condition of the ball joint used in automobiles by calculating the ratio of signals acquired from both good and faulty conditions in the frequency domain [9]. Burdzik et al proposed a method to monitor the condition of suspension by means vibration signal analyzer where the signal from the exciter, wheel, and car body for the given time domain [10]. Wang et al proposed a cluster based method to identify the faults in the spring of suspension system. By acquiring accelerometer signal from 4 corner of the vehicle. The proposed method online condition monitoring using data driven approach by means probability c mean clustering to identify the fault the spring and used Fisher discrimination analysis to isolate and label the fault [11].

From the literature survey, the following observations were made.

- Most of the research findings based on data driven method talks about the detection of a single fault such as faults in damper, spring and ball joints.
- Model based method of fault identification is not suitable for suspension system due to the dynamic nature of the suspension system.
- The fault detection in semi and active suspension systems are used to design fault tolerance system to maintain uninterrupted working of the suspension system
- Machine learning approach is widely used in active suspension system

Based on the observations made a novel technique is proposed for the condition monitoring of the suspension system based on the Machine learning approach. The following technical contributions are presented as follow:

1. Vibration-based condition monitoring is performed with help of a machine learning algorithm.
2. Multiples fault occurrences in a component can be identified.
3. The proposed method will pay way to online condition monitoring of suspension system.
4. Classification is carried out with the help of BayesNet and Naive Bayes algorithms.
This article is constructed with the following sections: Experimental setup and procedure along with a brief introduction of faults considered are explained in Section 2. Feature extraction and selection processes are described in Section 3, a brief description of the Bayesian classifier is discussed in section 4. Section 5 projects the derived results and the necessary discussion. The conclusion of the present study is given in Section 6.

2. EXPERIMENTAL STUDIES

The experimental setup is designed to simulate the working of suspension system in the uniform road profile at a constant speed. The fault condition component is replaced for each fault study and their signals are acquired from accelerometer placed in the lower arm. The measured signals are sent to analog to digital converter to collect data for recording. The features were extracted from the data acquired for fault classification. The basic work flow of the study is given figure 1.

2.1 McPherson suspension system

![Flow chart of suspension system fault diagnosis system.](image-url)
The McPherson suspension system is used in the present study due to its lightweight and simplicity. The strut, lower arm, knuckle, driveshaft and tie rod constitute the McPherson suspension system. The present study equips a commercially available Hyundai i10 suspension system. Other components like idle roller, pulley, and frame are fabricated such that the drive from constant speed AC motor of 1400 rpm is transmitted to the drive shaft through belt and pulley arrangement. The driveshaft is connected to the wheel by knuckle bearing through which the power from the motor is transmitted to the road wheel. For increasing the sprung mass, the idle roller is raised with the help of a hydraulic jack and supporting column. A lock nut is attached to the hydraulic jack to prevent any further movement. The increase in height induces load variations in the suspension system which has been measured using a pressure gauge attached to the hydraulic jack. The overall setup is illustrated in Figure 2.

![Figure 2 Experimental setup](image)

2.2 Data acquisition system

A piezoelectric type accelerometer is attached to the lower arm as shown in Figure 2 with help of general purpose adhesive. The drive from the motor is transmitted to the wheel via belt drive and the drive shaft so that final speed of 1200 rpm is maintained. The vibration signals from the accelerometer are acquired by the Data Acquisition system (DAQ) where the signal conditioning is carried out. The signals are amplified and filtered from unwanted noises during signal conditioning. These signals are acquired at a sample length of 10,000 at the rate of 20 kHz from a sensor of 10.26 mV/g sensitivity are recorded. The first 100 trials from the acquired signals are taken into consideration for feature extraction. The above process is repeated for different faults under 3 load conditions namely, no load, 200 psi, and 400 psi pressure.

The faults considered in the study for condition monitoring of the suspension system are tie rod Ball joint worn out, loweram ball joint, lower arm bush worn out, strut mount failure, strut external damage, strut worn out and wheel low pressure. The faults discussed in the study and their brief introductions of all the faults considered with the reason for failure and symptoms with typical image are discussed in Table 1.
Table 1 Description of various faults in a suspension system

| S.No | Fault Condition         | Components affected | Reason for failure                                      | Symptoms                                      |
|------|-------------------------|---------------------|--------------------------------------------------------|------------------------------------------------|
| 1    | Strut external damage   | Strut               | Physical damage                                        | Dent                                          |
| 2    | Strut mount failure     | Strut mount         | Fatigue, sudden road shocks                            | Visible crack                                  |
| 3    | Lower arm bush worn-out | Lower arm           | Varying loads, harsh driving conditions, degradation over time | Cracking noise, loss in directional control     |
| Component          | Issue                                                                 |
|-------------------|----------------------------------------------------------------------|
| Strut worn-out     | Difference in vehicle height, bouncy ride, once-side steering pull   |
| Ball joint worn-out| Lubrication loss, steering vibration, uneven tyre wear               |
| Lower arm          | Wheel wobbling, steering vibration, uneven tyre wear                 |
| Tie rod            | Wheel wobbling, steering vibration, uneven tyre wear                 |
| Tyre               | The difference in vehicle height, hard steering                      |
| Check valve failure| Puncture                                                            |

| Issue                          |
|-------------------------------|
| Lubrication loss, heavy loads |
| Driving in uneven road, heavy loads |
| Check valve failure, puncture |

| (Lubrication loss, heavy loads) | (Driving in uneven road, heavy loads) | (Check valve failure, puncture) |
|---------------------------------|--------------------------------------|-------------------------------|
| (Lubrication)                   | (Driving)                            | (Check)                       |
| (Loss)                          | (Road)                               | (Valve)                       |
| (Heavy)                         | (负荷)                               | (Failure)                     |
| ( Loads)                        | (道路)                               | (漏斗)                         |

| Strut worn-out | Ball joint worn-out | Lower arm | Tie rod | Tyre | Check valve failure |
|----------------|---------------------|-----------|---------|------|---------------------|
| Difference in vehicle height | Bouncy ride | Once-side steering pull | Lubrication loss | Steering vibration | Uneven tyre wear | Puncture |
3. EXTRACTION OF FEATURE AND FEATURE SELECTION

Feature extraction is the process of extracting useful parameters from a raw signal which can establish the information required to characterize the signal. The fault in the system has its own vibration pattern which can be detected using statistical parameters of vibration signals. This has been proved by many researchers reported in the literature [12][13][14][15]. Thus a statistical feature will be the best method of features extraction with less complexity and less processing time. Statistical features extract various parameters through descriptive statistics [16]. Table 2 presents the parameters and their brief definitions which are extracted using descriptive statistics.

| Parameters     | Description                                                                                      |
|----------------|-------------------------------------------------------------------------------------------------|
| Mean           | The ratio between sum of the data and the total number of values in a dataset                   |
| Standard error | Error during the distribution of statistic sampling                                              |
| Median         | Median is the intermediate value in a dataset that differentiates the lower and higher values.   |
| Range          | Difference between the maximum value to the minimum value                                       |
| Sample variance| The distribution measure of a given dataset                                                      |
| Skewness       | Asymmetry in the distribution of statistical data                                                |
| Kurtosis       | The spread of data around the mean.                                                             |
| Standard deviation | The variation of data set point with the mean value                              |
| Mode           | The value which occurs repeatedly in a data set                                                 |
| Maximum        | The maximum value possessed in the data set                                                      |
| Sum            | The total sum of all the data set=(x1+x2+x3……xn)                                               |
| Minimum        | The least value possessed in the data set                                                       |

Out of these descriptive features, only some features will contribute positively to classification. Adding more number of features will increase computation time and complexity. To reduce computation time and increase classification accuracy, unwanted features are removed and the most significant features are determined. The J48 decision tree algorithm, a clone of C4.5 algorithm, is used in the process for feature selection. For its superior classification performance, it was utilized to select important features in the feature selection process [17][18][19]. In the decision tree, features are ranked from top to bottom with increasing significance. Figure 3 shows the decision tree of selected features for the no-load condition using J48 algorithm.
Figure 3 Decision tree representing the most significant feature from top to bottom

4. CLASSIFIERS DESCRIPTIONS

4.1. Bayes classifier:

A Bayes rule-based classification algorithm is the Naïve Bayes algorithm, which assumes that the attributes $X_1...X_n$, given $Y$, all are constitutionally distinct from one another. The advantage of such a statement has been that the interpretation of $P(X|Y)$ are significantly simplified and the issue of measuring it from the effects of testing. For eg, consider the condition if $X = X_1, X_2$

$$P(X|Y) = P(X_1, X_2 | Y) = P(X_1 | X_2, Y)P(X_2 | Y) = P(X_1 | Y)P(X_2 | Y) \cdots \cdots (1)$$

Most commonly, when $X$ comprises $n$ attributes which are $Y$-independent constitutionally,

$$P(X_1 \ldots X_n | Y) = \prod_{i=1}^{n} P(X_i | Y) \cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots (2)$$

Note that since $Y$ as well as $X_i$ is Boolean variables, the description of $P(X_i = x_i | Y = y_j)$ required $i, j, k$ or needs $2n$ parameters. If we do not allow a conditional assumption of independence, this is a drastic decrease relative to the $2(2^n - 1)$ the requisite parameters for characterizing $P(X|Y)$.

Now let's extract the Naïve Bayes classifier usually assumes that $Y$ is any single-value vector and that $X_1...X_n$ attributes are any particular attributes or attributes of real value. We aim to train the classifier to emit the distribution of probability over potential values of $Y$, which we ask to classify for each new $X$ case. The representation for probability that $Y$ will take on its prospective $k^{th}$ value, according to Bayes law, is

$$P(Y = y_k | X_1 \ldots X_n) = \frac{P(Y = y_k)P(X_1 \ldots X_n | Y = y_k)}{\sum_j P(Y = y_j)P(X_1 \ldots X_n | Y = y_j)} \cdots \cdots \cdots \cdots (3)$$
Where, the sum of all potential $y_j$ of $Y$ values are taken over. Now, provided that the $X_i$ is conditionally independent of $Y$, we can rewrite Eq (3) as

$$P(Y = y_k | X_1 \ldots X_n) = \frac{P(Y = y_k) \prod_i P(X_i | Y = y_k)}{\sum_j P(Y = y_j) \prod_i P(X_i | Y = y_j)} \quad \text{......................... (4)}$$

Above Eq (4) is the basic equation for the classification of the Naïve Bayes. This equation illustrates well how determine the likelihood the $Y$ will have on any specified value based on observed $X_{\text{new}}$ attribute values and provided the estimated distributions of $P(Y)$ and $P(X_i | Y)$ from training results, given a new instance of $X_{\text{new}} = (X_1 \ldots X_n)$. The classification law of Naïve Bayes for obtaining the critical value of $Y$ based on one’s interest is given in Eq(5)

$$Y \leftarrow \arg\max_{y_k} \frac{P(Y = y_k) \prod_i P(X_i | Y = y_k)}{\sum_j P(Y = y_j) \prod_i P(X_i | Y = y_j)} \quad \text{......................... (5)}$$

Simplifying to follows (since $y_k$ doesn't rely on a denominator)

$$Y \leftarrow \arg\max_{y_k} \prod_i P(X_i | Y = y_k) \quad \text{......................... (6)}$$

The Bayes Net consists of a collection of variables among variables forming a directed acyclic graph $G= (V, E)$, $V = (A_1, A_2 \ldots A_n)$ and a collection of guided edges, $E$, where a cumulative distribution of variables is described by a conditional distribution to every parent variable. A node $A_i \in V$ is a random variable and the conditional dependency between $A_i$ and $A_j$ is a directional edge from $A_i$ to $A_j$, $(A_i, A_j)$. Each vector in a Bayesian network is independent from its non-descendants, provided the value of its parents will be in $G$. To correctly infer subsequent distribution, such $G$-encoded independence decreases the amount of parameters needed to describe a joint distribution. The joint distribution $P (V)$ in the Bayesian network over for each vector a conditional distribution has a parametric form which can be learned by calculating the maximum probability. All the conditional distributions defined in the Bayes Net are the product of $P(V)$ is

$$P(A_1, A_2 \ldots A_N) = \prod_{i=1}^{N} P(A_i | Pa_i) \quad \text{......................... (7)}$$

When the conditional distribution of $A_i$ is $P(A_i | Pa_i)$, provided that $Pa_i$ represents that parent collection of $A_i$. For each vector, a conditional distribution does have a parametric structure that must be obtained by calculating the possible probability.

5. RESULT AND DISCUSSION

5.1. Effect of features in classification

The extracted features were used to distinguish between good and faulty conditions from the vibration signals. During the process, a few of the statistical features may be less significant in the classification of faults which can be removed. The significance of the extracted features were observed in
the tree by depth-first technique which is use to find the rank of features in classifying the class efficiently [10]. It was visualised that the significance of features in the process of classification is in the sequence of decreasing order i.e. Sum, Mean, Sample Variance, Skewness, Kurtosis, and Median. Further addition of features reduces the accuracy and increases the computation time. The features selected were utilized to establish a model that provides the best possible classification accuracy for a practical application which required less computational power. The Figure 4 represent the effect of number of features in J48 classifier performance in no load condition and in Table 3 compared the variation in classification accuracy before and after feature selection process.

Figure 4 Effect of features in classification

Table 3 Effect of features in classification accuracy using J48 algorithm

| J48 Classifier- with minimum number of obj 2 | Accuracy in % |
|---------------------------------------------|---------------|
| Using all the statistical features | Using selected statistical features |
| No-load | 93.125 | 94 |
| Load at 200psi | 92.25 | 92.375 |
| Load at 400 psi | 91 | 91.375 |

5.2. Performance evaluation of classifiers to varying load

In the present study, Bayesian algorithms namely, Naive Bayes and BayesNet were used to classify faults from the selected features. During this process, the default parameters were kept uniform for both BayesNet and Naive Bayes classifiers. The resulting classification accuracy shows that the BayesNet classifier outperformed the Naive Bayes classifier by classifying the maximum number of instances correctly. Table 4 represents the comparison of Bayesian classifiers for different load conditions. The comparative plot of the classifier is shown in Figure 5.
Table 4 Comparison of classifier performance to varying load

| Condition | No Load | 200 Psi | 400Psi |
|-----------|---------|---------|--------|
| Classifiers | BayesNet Naive Bayes | BayesNet Naive Bayes | BayesNet Naive Bayes |
| Time- sec | 0.06 | 0.01 | 0.02 | 0 | 0.01 | 0 |
| Accuracy % | 88.5 | 86.25 | 88.5 | 86.37 | 88.25 | 87.5 |

Figure 5 Performance of the classifier to varying load condition

Table 5 overall performance of Bayesian classifiers

| Classifier | Overall Accuracy % | Time to build model (sec) |
|------------|---------------------|---------------------------|
| BayesNet   | 88.41               | 0.03                      |
| Naive Bayes | 86.70             | 0.003                     |
5.3. Classification using BayesNet

The performance of the BayesNet classifier at no load condition is represented in the form of the confusion matrix in Table 5. In the confusion matrix ‘a’ denotes Good condition and alphabet ‘b’ to ‘h’ represent Lower arm ball joint fault (labjf), lower arm bush worn-out (labwo), strut external damage (sted), strut mount fault (stmf), strut worn-out (stwo), tie rod ball joint worn-out (trbjf), and wheel low pressure (wlp) respectively. During classification process, the parameter is set to the default value, and verified with 10 fold cross-validation, and found that BayesNet classifier classify fault conditions with 88.5% accuracy i.e. out of 800 instances the 708 instances were correctly classified rest 92 instances were misclassified., in the case of Naive Bayes classifier with no load condition classifier has accuracy of 86.25%.

The accuracy of 88.5% was attained by following classification by a BayesNet classifier in no load condition. The table 6 shows the confusion matrix bayes net classifier in no load condition, the diagonal element in the confusion matrix below denotes the correctly classified instance, other element in the matrix denotes misclassified fault instances.

|   | a | b | c | d | e | f | g | h |
|---|---|---|---|---|---|---|---|---|
| a | 99 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| b | 0 | 77 | 19 | 0 | 0 | 1 | 0 | 3 |
| c | 0 | 7 | 83 | 4 | 0 | 0 | 0 | 1 |
| d | 0 | 0 | 11 | 72 | 3 | 0 | 14 | 0 |
| e | 0 | 1 | 8 | 1 | 90 | 0 | 0 | 0 |
| f | 0 | 3 | 1 | 0 | 0 | 96 | 0 | 0 |
| g | 0 | 0 | 4 | 1 | 0 | 95 | 0 | 0 |
| h | 1 | 0 | 3 | 0 | 0 | 0 | 96 | 0 |

The trend of superior performances of BayesNet classifiers is followed in other loading conditions. Bayes net classifier has a classification accuracy of 88.5% and 88.25%, Naive Bayes has 86.37% and 87.5% classification accuracy for 200 psi and 400 psi load conditions respectively, the classifier classifies the fault conditions with 88.25% accuracy. The confusion matrix of BayesNet classifier at 200 psi and 400 psi load is given in Table 6 and Table 7 respectively. From the confusion matrix we can understand that the fault signal low arm ball joint fault (b = labjf) and strut external damage (d = sted) has maximum misclassification comparing all the load condition, the signal pattern for the particular faults is been interfere by the external noise causing misclassification since signal taken in dynamic situations, also there is chance for misclassification is due to the algorithm due to limitation in number of data set taken for the particular studies, is not sufficient to establish the relationship between independent variables. From this one can understand that there is a need for study to reduce misclassification further.
Table 7 Confusion matrix of BayesNet classifier at 200 psi load

| a | b | c | d | e | f | g | h | classified as |
|---|---|---|---|---|---|---|---|----------------|
| 91 | 3 | 2 | 2 | 1 | 0 | 1 | 0 | a = good |
| 12 | 75 | 0 | 1 | 9 | 0 | 0 | 3 | b = labjf |
| 0 | 0 | 93 | 0 | 1 | 0 | 0 | 6 | c = labwo |
| 4 | 0 | 0 | 76 | 7 | 12 | 1 | 0 | d = sted |
| 0 | 6 | 0 | 3 | 90 | 0 | 1 | 0 | e = stmf |
| 0 | 0 | 0 | 4 | 0 | 96 | 0 | 0 | f = stwo |
| 1 | 1 | 0 | 0 | 2 | 0 | 96 | 0 | g = trbjf |
| 5 | 1 | 1 | 1 | 1 | 0 | 0 | 91 | h = wlp |

Table 8 Confusion matrix of BayesNet classifier at 400 psi load

| a | b | c | d | e | f | g | h | classified as |
|---|---|---|---|---|---|---|---|----------------|
| 83 | 0 | 0 | 3 | 0 | 10 | 4 | 0 | a = good |
| 0 | 92 | 2 | 0 | 0 | 0 | 0 | 6 | b = labjf |
| 0 | 2 | 97 | 0 | 0 | 0 | 0 | 1 | c = labwo |
| 0 | 3 | 1 | 78 | 9 | 0 | 5 | 4 | d = sted |
| 2 | 0 | 0 | 2 | 94 | 0 | 2 | 0 | e = stmf |
| 12 | 0 | 0 | 0 | 0 | 88 | 0 | 0 | f = stwo |
| 0 | 0 | 0 | 1 | 5 | 0 | 94 | 0 | g = trbjf |
| 0 | 13 | 0 | 7 | 0 | 0 | 0 | 80 | h = wlp |

6. CONCLUSION

This article describes an approach based on Bayes classifier that identifies the variations in vibration signals pattern for different suspension fault conditions. The statistical features from vibration signals were extracted and further feature selection was carried out using J48 algorithm. Classification was performed on selected features with the help of two Bayesian based machine learning classifiers. A 10-fold cross-validation was adopted to verify the BayesNet and Naive Bayes classifiers. The performances between the classifiers are evaluated and it is observed that the BayesNet classifier displayed maximum over all classification accuracy of 88.4%, under all loading conditions when compared with Naive Bayes.
classifier having 86.70%. The faults lower arm ball joint fault and external strut damage are the reason for the low accuracy so there is further need of study on misclassification. We can conclude that the BayesNet classifier will be more suitable for identifying other five faults in the suspension system effectively with given number of data set. Thereby increase the reliability, comfort of the vehicle and reduce the downtime of the suspension system.

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