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Monitoring Automobile Tyre Pressure with Statistical Computations and J48 Decision Tree Algorithm

Hemanth Mithun Praveen, V. Sugumaran

Abstract— **Currently tyre pressure monitoring systems are used in automobiles to determine the air pressure of the tyres. These systems use pressure sensors in case of direct systems or wheel speed sensors in case of indirect systems. In this study the problem was treated as a fault diagnosis problem in which a MEMS accelerometer was used to detect vibration from the wheel hub of the vehicle. These vibration signals were extracted by selecting a suitable sampling rate. Statistical features were computed from the acquired signals and classified using the J48 Decision tree algorithms. By interpreting the signals the tyre pressure could be predicted indirectly. No major modifications were performed on the vehicle.**

Index Terms—**Decision tree, Fault diagnosis, MEMS, Statistical analysis, Tyre pressure monitoring system**

I. INTRODUCTION

Vehicle dynamics is a key area in the automobile sector which ensures vehicle stability. One of the devices which contribute to vehicle stability is the tyre. Tyres depend on pressurized air or Nitrogen to maintain proper ground contact area, in other words wheel base. Tyres when at optimum pressure not only ensure a comfortable drive but also ensure stability of the vehicle at different speeds. Alteration of tyre pressure can lead to transmission of ground vibrations (in case of over pressure) or loss in fuel economy and premature wear of tyre (in case of under inflation) and can even reduce the life of the suspension [1]. More over when a tyre is punctured the area of contact with the ground increases unevenly (with respect to the other tyres) thereby causing more friction in one point of the vehicle which can prove fatal when driving at high speeds or taking turns. Punctures are inevitable they occur on an average of 25,000 miles [2]. Punctures can also occur due to natural diffusion.

Tyre pressure monitoring systems (TPMS) are active electronic subsystems fitted on a vehicle to monitor the tyre pressure on a real time basis. They are broadly classified into two categories, based on the method of data acquisition, as direct and indirect systems. Direct systems rely on integrated barometric pressure sensors and temperature sensors [3]. These systems not only measure air pressure but also measure the temperature of the tyre. This is helpful during long drives to prevent bursting of the tyres. These systems can measure tyre pressure in static condition also [3]. However theses systems require a power source mostly an integrated battery and a transmitter of a unique ID. Replacing a battery requires separation of the tyre from the wheel more over each wheel requires a dedicated sensor this will add up cost when additional wheels are used for snow tyres. A research has been carried out to provide wireless power to the transmitter by means of induction [4] .Another research has claimed for a battery less power supply for the TPMS sensor. Energy is generated by the radio waves received [5]. Further research has proved that vibration harvesting is possible there by eliminating the need for a standalone battery [6]. Indirect tyre pressure monitoring systems acquire pressure by other means such as wheel speed from the wheel speed sensor [3]. The same sensor used by the anti-locking braking system. However they can measure the tyre condition only when the vehicle is moving [3]. Many options have been researched over the years. A research conducted in shanghai, china proposed a tyre pressure monitoring system which employs an integration of surface-micro machined piezoresistive pressure sensor and a self-testable accelerometer [5]**.** A Research in Brownlow Hill, UK proposed a tyre pressure monitoring system based on segmented capacitance rings [2].

Based on the air pressure inside the tyre every mechanical shock will have a significant impact on the vibration peaks transmitted [8]. There are multiple approaches towards processing the vibration signals obtained assuming that the system can be treated as a fault diagnosis system. Some of them include model-based reasoning [7], optimal disturbance de-coupling [10], heuristic reasoning [11], temporal data [12] etc.

This paper proposes an alternate and innovative indirect method to monitor the tyre pressure of a running automobile.

II. METHODOLOGY

The system relies on machine leaning approach which uses a MEMS accelerometer attached to the wheel hub to acquire vibration signals. Statistical data is extracted from the acquired vibration signal and appropriate conditions such as normal, puncture and idle were tagged and passed through the J48 decision tree algorithm. The classification accuracy of decision tree along with other details have been presented. Further feature selection and effects of multiple features have been studied for the most efficient classification. All notable observations have been presented.

represents the methodology of the study

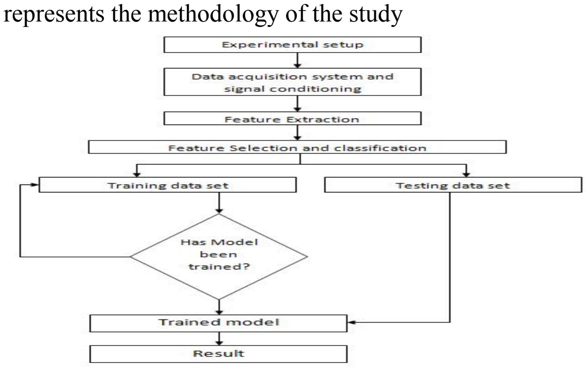

Figure 1 Methodology flowchart

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Hemanth Mithun Praveen, SMBS, VIT University, Chennai, Tamil Nadu, India
Dr. V. Sugumaran, SMBS, VIT University, Chennai, Tamil Nadu, India

III. EXPERIMENTAL SETUP

The experiment was conducted in a Maruti 800 (front wheel drive). A MEMS based accelerometer was attached to the hub of the rear right wheel by means of adhesive (refer Figure 2). The vehicle was driven between speeds of 20km/hr to 80km/hr on a regular road. The vibration signals from the accelerometer were extracted using a microcontroller a sampling rate of 66Hz. 360 Samples were taken during the test. To ensure that the experiment was unbiased to either condition; the samples were equally divided into normal, puncture and ideal. A Visual C++ program was written to acquire data and store it on a PC. In this experiment 28 psi was taken as normal, 22psi was taken as puncture, and speeds below 20 km/hr were considered as idle irrespective of their tyre pressure. The sample waveform of the tyre's vibration for the conditions of normal, puncture and idle are shown in Figure 3, 4, 5 respectively. The controller features a 10bit successive approximation ADC with a maximum sampling rate of 15 ksps. It also sets up a bidirectional connection with the PC. The sampling rate was chosen based on the nyquist-shannon theorem which states that the minimum sampling frequency must be at least twice the maximum frequency of the input signal [13]

The tyre used was 140/70 radial tyre with a max pressure rating of 44 psi.
Maximum vehicle rated speed -> 100km/hr
Maximum Wheel speed ->1840RPM
1840RPM = 30.66Hz

Therefore based on nyquist-shannon sampling theorem minimum sampling frequency must be 61.32Hz Current sampling rate set as 66Hz .

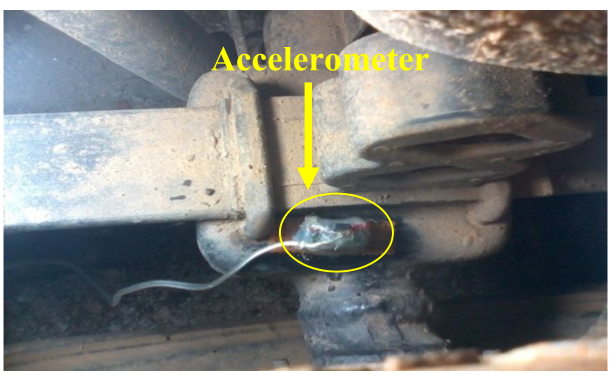

Figure 2 Accelerometer fixed on the hub

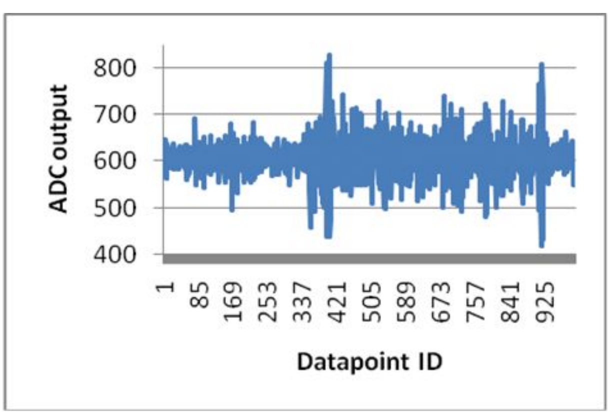

Figure 3 waveform of tyre under normal pressure

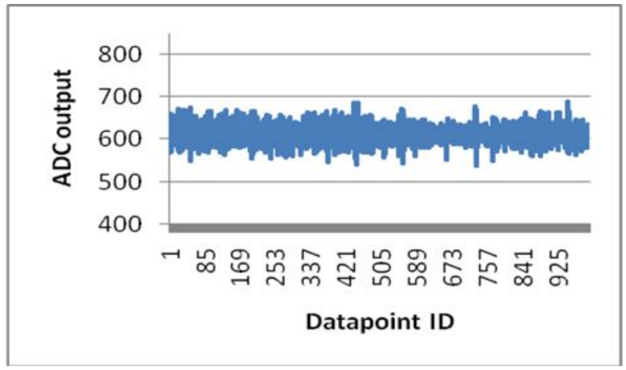

Figure 4 waveform of punctured tyre

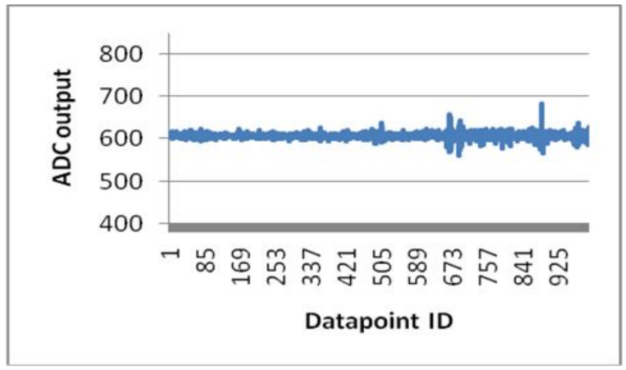

Figure 5 waveform of ideal signal

IV. FEATURE EXTRACTION

The statistical features were used to yield the required parameters from the vibration signal. The features were the designated inputs for the classifiers for diagnostic purpose. The statistical parameters acquired for this study were standard error, skewness, minimum, mean, mode, range, median and kurtosis. Each of these features were computed as per their respective equations [14].

V. FEATURE SELECTION

J48 decision tree algorithm was used to select the features as it was a statistical classifier. The features used by the tree were selected and were passed on to the next phase of the study that is classification. Remaining features were rejected. Figure 6 represents the decision tree generated by the algorithm

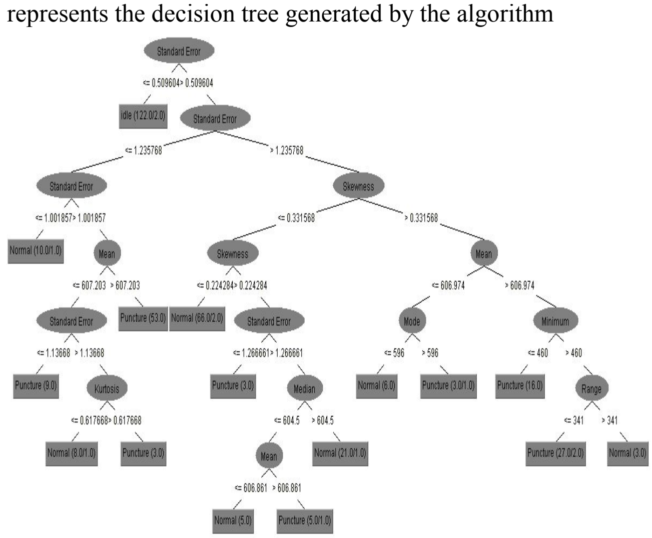

Figure 6 Decision tree generated using the J48 tree algorithm

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A. Decision tree

A schematic tree-shaped diagram used to determine a course of action or show a statistical probability. Each branch of the decision tree represents a possible decision or occurrence. The tree structure shows how one choice leads to the next. The J48 classifier was used in this study.

B. C4.5 (J48)

The J48 decision tree is a java implementation of C4.5 algorithm. The C4.5 algorithm which was introduced 1996 [16]. J48 is also known as a statistical classifier.

VI. CLASSIFIER

Decision trees are a fast and standard way to classify information. A decision tree uses a graph modeled tree to generate classification rules. A typical decision tree consists of one root, nodes, branches and leaves. Each branch in the tree is a path form the root to a leaf passing through the nodes which are the also known as classification attributes. [15]. In the current study the statistical features extracted from the vibration signals were considered as the inputs to the classification algorithm and the corresponding decision tree was obtained. The class labels and the nodes were represented as leaves in the decision tree; they were associated with the classes which were being classified. All the branches of the tree represent all the cumulative decisions that lead to the leaves. The decision tree initiates the classification from the root and continues to move deeper through nodes until a pure leaf node is identified. Appropriate estimation criteria at each decision node can be used to select the most useful feature for classification.

VII. RESULTS AND DISCUSSION

The classifier scored a classification accuracy of 91.11 %. It classified 328/360 instances correctly. The confusion matrix is shown below in TABLE 1. Figure 7 shows the decision tree generated by the algorithm.

The decision attributes are provided below

```
Standard Error <= 0.509604: idle (122.0/2.0)
Standard Error > 0.509604
|  Standard Error <= 1.235768
|  |  Standard Error <= 1.001857: Normal (10.0/1.0)
|  |  Standard Error > 1.001857
|  |  |  Mean <= 607.203
|  |  |  |  Standard Error <= 1.13668: Puncture (9.0)
|  |  |  |  Standard Error > 1.13668
|  |  |  |  |  Kurtosis <= 0.080168: Normal (5.0)
|  |  |  |  |  Kurtosis > 0.080168: Puncture (6.0/2.0)
|  |  |  Mean > 607.203: Puncture (53.0)
|  Standard Error > 1.235768
|  |  Skewness <= 0.331568
|  |  |  Skewness <= 0.224284: Normal (66.0/2.0)
|  |  |  Skewness > 0.224284
|  |  |  |  Maximum <= 770
|  |  |  |  |  Kurtosis <= 0.220199: Normal (18.0/3.0)
|  |  |  |  |  Kurtosis > 0.220199: Puncture (5.0)
|  |  |  |  Maximum > 770: Normal (11.0)
|  |  Skewness > 0.331568
|  |  |  Mean <= 606.974: Normal (9.0/2.0)
|  |  |  Mean > 606.974: Puncture (46.0/5.0)
```

Number of Leaves : 12
Size of the tree : 23

TABLE 1
Confusion matrix for J48 tree

Classified as	Normal	puncture	idle
Normal	103	0	17
Puncture	0	120	0
Idle	13	2	105

TABLE 2 shows the stratified cross-validation details. TABLE 3 shows the detailed accuracy by class

TABLE 2
cross-validation for j48

Correctly Classified Instances	328/360
Kappa statistic	0.8667
Root mean squared error	0.234
Root relative squared error	18.97 %
Incorrectly Classified Instances	32/360
Mean absolute error	0.0844
Relative absolute error	18.97 %
Total Number of Instances	360

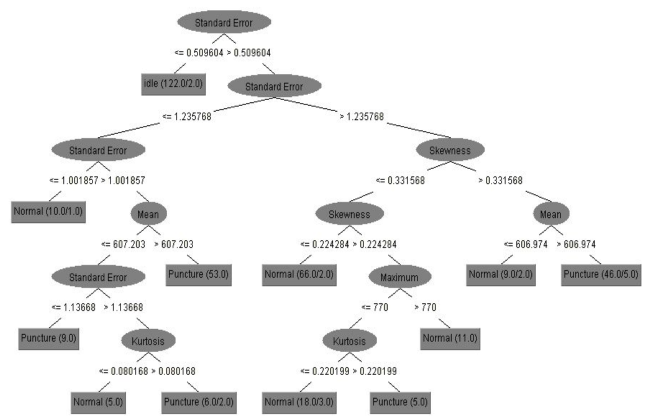

Figure 7 Decision tree generated using the J48 tree algorithm

TABLE 3
Detailed accuracy by class for J48 tree

TP	FP	PR	R	F	RO	C
0.858	0.054	0.888	0.858	0.873	0.934	N
1	0.008	0.984	1	0.992	0.993	P
0.875	0.071	0.861	0.875	0.868	0.91	I
0.911	0.044	0.911	0.911	0.911	0.946	W

TP -> TP Rate
FP -> FP Rate
PR ->Precision

R -> Recall
F -> F Measure
RO -> ROC area
C -> Condition
N -> Normal
P -> Puncture
I -> Idle
W -> Weight average (Not a class)

The classifier depends on four variables which are minimum number of objects, confidence factor, random seed, and number of folds. The variation of these parameters vs the algorithms classification accuracy are plotted in figure [8 - 11] respectively

Figure 8 Minimum number of objects vs classification accuracy

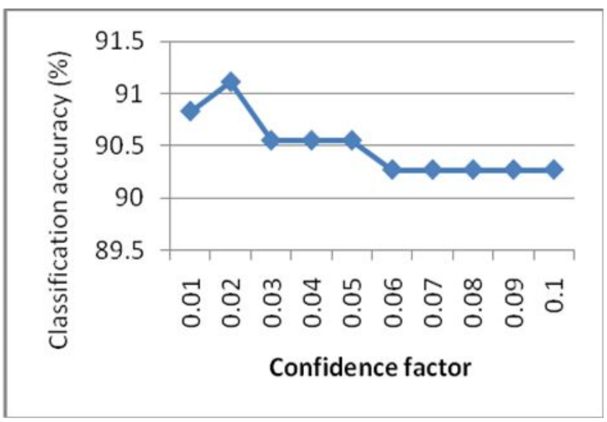

Figure 9 Confidence factor vs classification accuracy

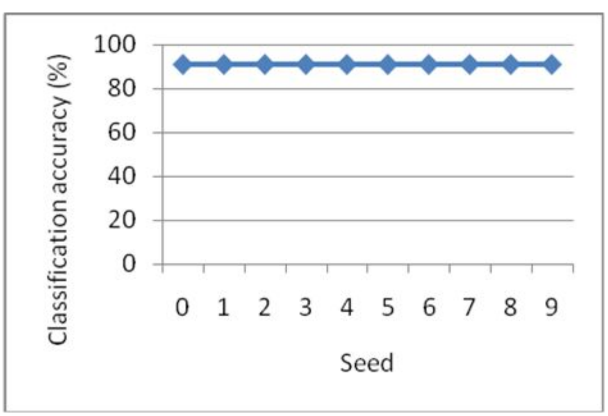

Figure 10 Random seed vs classification accuracy

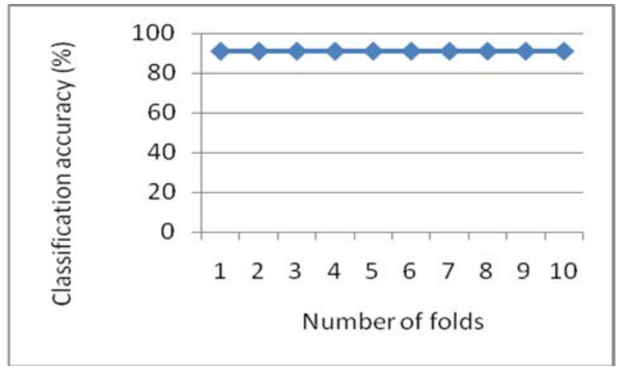

Figure 11 Number of folds vs classification accuracy

The value of objects for trained algorithm are shown in TABLE 4

TABLE 4
Values for objects of the trained J48 tree

Sl. no	Objects	Value
1	Confidence factor	0.25
2	Minimum number of objects	5
3	Number of folds	3
4	seed	1

CONCLUSION

A new indirect system was proposed for estimation of automobile tyre pressure. As vehicles are becoming bigger and faster monitoring tyre pressure becomes crucial as the vehicle stability depends on the pressure of air in the tyre. The proposed system employs a commonly available MEMS accelerometer and a low power micro control unit to acquire the signal. The maximum classification accuracy of 91.11% was attained when J48 decision tree was used. This paper reports a study conducted in which the J48 decision tree was used to classify the vibration signal from the wheel hub after the required statistical features were computed.

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Hemanth Mithun Praveen was born in Trivandrum, Kerala, in 1991. He completed his B.E in mechanical engineering from Noorul Islam university, Thuckalay, kanyakumari district, Tamil nadu in the year 2013. At present he is pursuing his M.S by research at VIT University, Chennai, Tamil Nadu, India. His research is in the field of fault diagnosis.

Dr. V. Sugumaran received the B.E. degree in Mechanical Engineering from the Amrita Institute of Technology & Science, 1998 and the M.Tech in Production Engineering, from The National Institute of Engineering, 2003. Ph.D. degree in Fault Diagnosis, from Amrita School of Engineering, Amrita University, Coimbtore, Tamil Nadu, India, in 2008.

From 2000 to 2009, he was an Associate Professor, with the Amrita School of Engineering, Coimbatore, Tamil Nadu. From 2009 t0 2011, he was working with SRM University, Chennai, Tamil Nadu. Since 2011, he has been an Associate Professor with the School of Mechanical and Building Sciences, VIT University, Chennai, Tamil Nadu, India. He is the author of two books, more than 85 international journal publications. He has also filed three patents. His research interests include Condition Monitoring & Fault Diagnosis, Machine learning / Data mining in manufacturing and Mechanical Engineering. He presented papers in 43 International / National Conferences. He is also acting as a Reviewer for many international journals and editor for four international journals.