ANALYZING VERTICAL VIBRATIONS OF AUTOMOBILE WHEEL HUB TO MONITOR TYRE PRESSURE USING STATISTICAL FEATURES AND SUPPORT VECTOR MACHINE ALGORITHM

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ABSTRACT

One of the main safety measures used in automobiles are Tyre pressure monitoring systems (TPMS). These are intelligent devices fabricate to supervise the tyre pressure in automobile. The current technology use barometric sensors or vehicle speed sensors to measure the pressure directly. They mainly depend on batteries and different types of remote sensors which would increase the installation cost and complication maintenance. This paper suggests a novel technique adopting machine learning and fault diagnosis to supervise the vehicle tyre pressure indirectly. Vertical vibrations from a wheel hub are acquired using a three axis mems accelerometer sensor. After feature extraction and feature selection the selected features are classified using support vector machine algorithm. A good classification accuracy of 90% was gained.

Keywords: Tyre Pressure Monitoring System, Support Vector Machine, Machine Learning, Statistical Features, Automobile.

INTRODUCTION

Tyres are the main part of the automobiles, which can be sort as non-pneumatic and pneumatic tyres. Most of the vehicles are using pneumatic tyres for a comfortable ride; the pressurized air or nitrogen filled in the tyres. While travelling the spring action in the tyres hoses the majority of the vibrations. A radial type pneumatic tyre was selected for the current investigation as they ordinarily utilized in vehicles for good fuel economy and more comfortable ride. TPMS are small hardware equipment which supervise the vehicles tyre pressure and update the same to the vehicle operator. There are two types of TPMS are widely used, direct TPMS and indirect TPMS. Direct TPMS consists of pressure sensors to supervise the tyre pressure of a vehicle. Indirect TPMS, which rely up on some factors outside the vehicle tyre like wheel radius and vertical vibration etc. Tyre must be inflated to a specified pressure suggested by the manufacture for proper handling and good fuel economy.

The TPMS rely on integrated temperature sensors and pressure sensors (Velupillai and Güvenç 2007). The temperature is measured in order to redress the mistake produced by the barometric pressure sensor at higher temperatures. In every TPMS following components should be presented for better operation. The components are barometric sensors, wireless sensors, power source and a controller for control all the sensors (RoSPA), 2015. However, in most cases replacing the power source requires complication in maintenance. In addition, a few systems are come up with built in battery which has no provision for substitution. Indirect TPMS systems are relative in nature because after each time the tyre inflated to top value of pressure it must be reset. So for each time the TPMS should relearn the different parameters, which is quite difficult normally NIRA Dynamics, 2015. A remote tyre pressure monitoring method, in which the signal analyzer was associated with an accelerometer fixed on the tyre. The vibration frequency crests produced by the tyre while the tyre blow with a hammer would change according to the air pressure in the tyre (Howard et al., 1993). After carrying out a thorough study on different algorithms used for TPMS it is found that sensor fusion was much more better than Bayesian method (Yulan et al., 2012). Using some methods numerically compute the rolling noise of tyre and road (Dubois et al., 2013). When the tyre deflates the contact path of the tyre to the ground increases and this could increase the rolling distance and hence affects the fuel efficiency (Mohsenimanesh et al., 2005). Very low pressure in tyres will lead to the heated up and destroy itself gradually. These results in tyre wear and decrease in the fuel efficiency while driving. Persson (2005) Support vector machine classification technique was used in many problems. This kernel methodology was investigated in all possibilities of discriminating defects in quality control system in textile industry (Manimozhi and Janakiraman 2016).

EXPERIMENTAL SETUP

This work suggests a novel technique to supervise the air pressure inside a tyre by using the machine learning and fault diagnosis approaches. The vertical wheel hub vibrations are acquired from a vehicle during running condition using a tri-axial MEMS accelerometer and are classified using an algorithm in machine learning. To optimize sensitivity of the MEMS accelerometer systematic analysis has been carried out (Sri et al., 2015). The data and experimental setup used in the present study are same as one used in previous study (Anoop et al., 2016). The experimental setup, fault simulation and experimental procedure are explained in detail in previous work. In order to minimize the external electronics interference a shield wire was used to connect between the accelerometer and data acquisition device. According to Nyquist Shannon sampling theorem the sampling rate chosen for a study should be at least two times the high value of incoming frequency in order to avoid antialiasing (McLean et al., 2005). The minimum sampling rate required in the current study was calculated as 28.26 Hz and hence sampling rate was set at 66 Hz.

Feature Extraction: Total 360 samples were collected in each class. And all the features were extracted using spreadsheet software like mean median mode etc.

Feature Selection: The decision tree generated by the J48 algorithm, the detailed accuracy by class for the untrained J48 classifier and the confusion matrix resulted by the untrained J48 algorithm classifier was obtained from the previous work (Anoop et al., 2016).

Feature Classification – Support Vector Machines: Jegadeeshwaran and Sugumaran (2015) proposed that generally, in classifying low dimensional non-linear problems, most of the classifiers face a lot of difficulties in classification. Support Vector Machine (SVM) is a new method in statistical learning theory. SVM is a supervised learning algorithm in which the features are provided for the learning machine with associated labels. The all features selected can be act as the different dimensions of the created hyper plane. Support vector machine algorithm creates a hyper plane which divides the whole hyper space in to different classes. For better classification the SVM algorithm tried to get large difference between each class. SVM uses ‘predictors’ and ‘target(s)’. The predictors are used to build the SVM model and the target is the final condition to be achieved. SVM consists of two kernel functions which are used to formulate the classification. The kernel functions are listed as C-SVC and nu – SVC. SVM having four functions other than the two kernel functions. These functions are classified as Linear, Sigmoid, Polynomial and Radial Basis Function (RBF).

RESULTS AND DISCUSSION

A total of two kernels with four functions each were tested. All eight results were compared. The variations of classification accuracy with both the kernels were shown in table 1. Total 8 results were generated in table 1. The highest classification accuracy obtained is 90% with the combination of C-SVC kernel with the RBF. The processing time for the highest classification accuracy was 17 seconds.

For good real time application of the classifier system the processing duration should be minimum. The different processing duration of each kernel in combination with SVM functions are explained in table 2.

Table 1.Classification accuracy of different kernels

Classification %	Linear	Polynomial	RBF	Sigmoid
C-SVC	86.67	84.17	90.00	86.94
nu-SVC	86.67	87.22	81.61	80.00

Table 2.Comparison of processing time for different kernels

Classification time	Linear	Polynomial	RBF	Sigmoid
C-SVC	2m 14s	9h 37m 49s	17s	3m 12s
nu-SVC	1s	13m 33s	5s	1m 11s

SVC Classification Parameters (RBF): Many combinations are tested during the study using the kernels and functions. Highest classification accuracy is resulted in combinations with c-SVC and RBF. The SVM parameter for the same combinations is shown in table 3. For improving the classification accuracy the algorithm need to be trained. The training dataset is explained in table 4. Table 5 represents the testing or validation data set. The confusion matrix for the training dataset and testing or validation data set are shown in Table 6 and Table 7 respectively.

Table 3.SVM parameters

Parameter	Value/ Action
Type of SVM model	C-SVC
SVM kernel function	Radial Basis Function (RBF)
Search criterion	Minimize total error
Number of points evaluated during search	137
Minimum error found by search	0.086
Epsilon	0.001
Gamma	4.516
C	1094.228
Number of support vectors used by the model	83

Table 4.Training data result

Category	Actual		Misclassified		Percent	Cost
	Count	Weight	Count	Weight		
NORMAL	120	120	3	3	2.500	0.025
PUNCTURE	120	120	6	6	5.000	0.050
IDLE	120	120	0	0	0.000	0.000
Total	360	360	9	9	2.500	0.025

Overall accuracy = 97.50%

Table 5.Testing/Validation data result

Category	Actual		Misclassified		Percent	Cost
	Count	Weight	Count	Weight		
NORMAL	120	120	18	18	15.000	0.150
PUNCTURE	120	120	18	18	15.000	0.150
IDLE	120	120	0	0	0.000	0.000
Total	360	360	36	36	10.000	0.100

Overall accuracy = 90.00%

Table 6.Training data confusion matrix

Classified as	Normal	Puncture	Idle
Normal	117	3	0
Puncture	6	114	0
Idle	0	0	120

Table 7.Testing/Validation data confusion matrix

Classified as	Normal	Puncture	Idle
Normal	102	16	2
Puncture	17	102	1
Idle	0	0	120

The resulted SVM model used a total of 83 support vectors (Table 3). The processing time duration for building a model was found to be 17 seconds. During training the algorithm achieved a classification accuracy of 97.5% (Table 4). However, after validation it result a maximum classification accuracy of 90 % (Table 5). From Table 7 it can be noted as total samples are 120 each for three classes. Out of the 120 samples the algorithm correctly classified 102 samples are normal, 102 samples are puncture and 120 samples as idle.

CONCLUSION

A novel method for supervise the tyre pressure of vehicles which uses machine learning and fault diagnosis approach has been suggested. The statistical features were acquired and the selection of prominent features was carried out using the J48 Algorithm. Support vector machine algorithms were used to classify the selected features. A total of two kernels with four functions each were used. All eight results were compared. A highest classifycation accuracy of 90.00% was result when the C-SVC kernel was used with the radial basis function. The validation was done by the classifier and all values have been tabulated. From the above result one can confidently say that the C-SVC kernel with the RBF function can be used for tyre pressure monitoring system.

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