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TPMS Data Analysis for Enhancing Intelligent Vehicle Performance

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Abstract: The main objective of the study is to analyze Tire Pressure Monitoring System (TPMS) data that contributes significantly towards the enhancement of the intelligent vehicle performance evaluation. TPMS pressure and temperature data were collected from the prototype model of the MEMS Tire Pressure Module (TPM) that was fitted on to an intelligent tire rim through its receiver. In this study, we are focusing only analytical data analysis of TPMS. In the analytical study, a novel method for data classification, goodness of fit and hypothesis testing was proposed. A classification scheme was employed to classify the temperature and pressure data based on ID at the quadrant basis operating zone of the Front Right (FR), Front Left (FL), Rear Left (RL) and Rear Right (RR) tires. Principle Component Analysis (PCA) with polynomial fitting for exploring goodness of fit of tire data was also applied. Finally, hypothesis testing using Satterthwaite statistic was carried out. Results obtained are in agreement with the null hypothesis and as such validate the usefulness of the TPMS system in maintaining and enhancing vehicle performance.

Key words: TPMS, data analysis, PCA, tire pressure and temperature, vehicle performance

INTRODUCTION

To date, a wide variety of sensor technology has been deployed for enhancing automotive safety and reliability. Likewise, for the tire Pressure Monitoring System (TPMS) which is an important research domain in the industry. Besides road safety, a TPMS can increase tire life cycle, reduce fuel consumption and improves gas mileage. Accurately inflated tires will ensure shortest braking distance, reduction in blowouts and mitigation of hydroplaning for better road handling. On the other hand, under and over inflated tires may cause abnormal tire wear, increase fuel consumption, reduce riding comfort and tire life (Jurgen, 1989, 1991, 1992). Figure 1 shows the forecasted projection of automotive units in which by the year 2010, two-third of the world automotive will be equipped with TPMS (Burgess, 2004).

The adoptions of intelligent tires with TPMS capability is inevitable as it enables drivers to be aware of a run-flat condition; the period of tire usage and driving beyond the rated speed. In addition, TPMS also provides early warning to the driver of pressure loss, tire running at low pressure, tire failure, inflating tires and location of wheels (Navet, 1998; CAN Newsletter, 2003; Bishop, 2000, 2005).

A number of TPMS and its sensor technologies have been widely investigated through experiment and data analysis which include antenna based TPMS, surface acoustic wave transponder, touch mode Radio Frequency Identification (RFID) and crystal based quartz resonator remote sensor (Kaleja *et al.*, 1999; Pohl *et al.*, 1999; Schimetta *et al.*, 2000; Wunderlich and Smith, 2000; Jakoby *et al.*, 2002; Yamamoto *et al.*, 2002). Factors such as limitation in the life cycle of the lithium battery, malfunctioning of the electromagnetic RF transceiver unit and the huge echo noise due to broadcasting pulse response through the same antenna are the major concern.

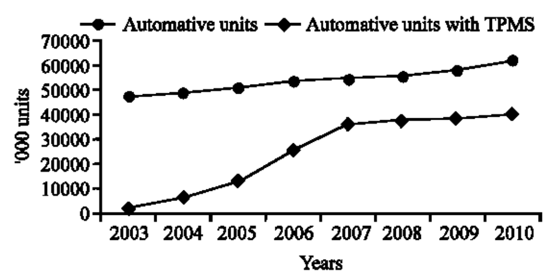

Fig. 1: Forecasted projection of automotive units with TPMS

Various types of sensors such as acoustic sensor, optical sensor, vibrating string sensor, ultra wide band technology and capacitive sensor have been analysed (Clayton and EerNisse, 1998; Milkovic, 1992; Grossmann, 1999; EerNisse, 2001; EerNisse and Wiggins, 2001; Daimler, 2005). These sensors have the potential to detect

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data of road condition that can be used to derive friction parameters, but not for force measurement (Scholl *et al*., 1991, 2003; Schimetta *et al*., 2000). The main disadvantage of these sensors is low robustness in a harsh environment during vehicle operation, not withstanding the fact that the TPMS technology is still improving and its sensor are becoming more robust. Nevertheless, the appropriate sensors for different applications of TPMS are still being investigated and analysed.

In order to meet the challenges of TPMS within the sensor limited capability factor, extensive experiments and analysis on the sensor technologies have showed that the capacitive MEMS sensor has the greatest potential for use in the development of automotive intelligent safety system (Wang *et al*., 2000; Gogoi *et al*., 2001; Gogoi and Mladenvic, 2002; Quero and Brey, 2002). Apart from its data analysis, the ability to be integrated into a complete electronics system, robustness, small size and low power consumption are some of the significant features of the MEMS sensor (Hussain *et al*., 2006). Thus, the capacitive MEMS sensor technology opens up a new perspective for an intelligent automotive safety system and perfectly fulfils the requirements on high robustness, low power consumption, other than cost benefits.

Hence, the objective of this research is to report on the analytical data analysis through automatic and discrete monitoring of an automobile tire pressure and temperature using Principle Component Analysis (PCA). A set of receiver output signal from so-called intelligent tire were collected for analysis that evaluate the performance of vehicle on safety and reliable TPMS. The paper also provides an overview of the method of data analysis, its principle components, goodness of fit, hypothesis testing and analytical results.

TPMS DATA ANALYSIS

Data analysis is one of the major statistical issues that can contribute significantly towards the enhancement of a reliable TPMS. The analysis of tire data is based on raw data collected on a real time vehicle operation. There were 200 observations in the data set. The data set comprises three variables namely tire ID, pressure and temperature. In the data set, 0, 1, 2 and 3 are the ID of tires FR, FL, RL and RR. The collected data were analysed using Matlab Statistic Toolbox. Before analysing the data, variables were created, labeled and categorised using Matlab coding. This study is a premier work on TPMS using raw data of a real time vehicle. This section discusses the methods of analysis used in this study that include the principle component analysis, data fitting and hypotheses testing.

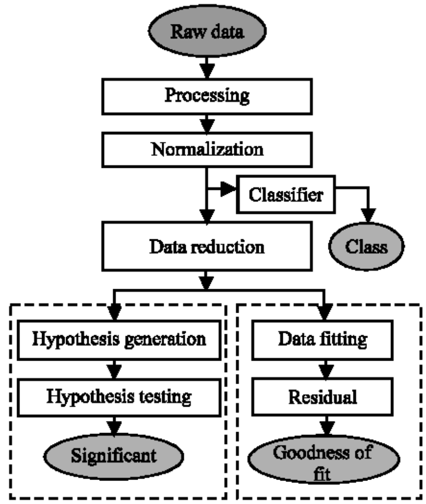

Fig. 2: Analysis method of raw TPMS data

The method for analyzing the TPMS data is shown in Fig. 2. This analysis was designed with the model techniques described below. Firstly, the raw data of all variables were processed and then normalized. The normalized data is then classified according to the tire ID as in FR, FL, RL and RR. The normalized data was reduced and simplified by replacing a group of variables with a single new variable using the principle Component Analysis (PCA). Hypothesis generation and testing was applied in order to determine the statistical significance of difference between and amongst the variables. Finally, this study analyzed the principle components with the polynomial fitting to find the best fits of the sample observations that minimizes the sum of square residuals.

Principle component analysis: Principle Component Analysis (PCA) is a quantitatively rigorous method to reduce the dimensionality of large set of variables to a small set that still contains most of the information in the large set whilst achieving simplification. PCA simplifies the problems by replacing a group of variables with a new set of variables. This generation of new set of variables is called Principle Component (PC). The PC characteristic is a linear combination of the original variables which are orthogonal to each other. PCA can also be used to find signals in noisy data.

To describe the structure of a principal components analysis, a multivariate data X, with n rows and m columns was assumed. The m elements of each row are scores or measurements on a subject such as tire ID, pressure and temperature. Data X was standardized, so that each column mean is 0 and each column variance is 1. Each column is a vector variable z_i, i = 1,. . . , m. The main idea of PCA is to derive a linear function y for each of the vector variables z_i. This linear function is referred to a component of z. The computation of a single element for the jth y vector,

$$y = v'z \tag{1}$$

where, v' is a column vector of V and V is a m×m coefficient matrix that carries the m-element variable z into the derived n-element variable y. The dimension of z is 1 x m, the dimension of v' is m x 1. The scalar algebra for the component score for the ith individual of y_j, j = 1,. ..m is as:

$$y_{ij} = v'z_{1i}+v'z_{2i}+....v'_p z_i \tag{2}$$

This becomes in matrix notation for the entire y as,

$$Y = V'Z \tag{3}$$

Equation 3 represents an orthogonal transformation, where Y is the transformed variable, Z is the original standardised variable and V is the premultiplier to go from z to y. Transformed vector Y consists of elements that are uncorrelated provided that V such that matrix D_y is a diagonal matrix and all off-diagonal elements of D_y must be zero.

Goodness of fit: Whenever a model is fitted to the data, the main objective is to know how well the model fits. PCA with polynomial fitting ensures that the sample regression that best 'fits' the sample observations in the sense that it minimizes the sum of the squared residuals. There are two measurements of goodness of fit that is numerical and graphical. Numerical measurement uses goodness of fit statistics whilst graphical representation uses residual. The parametric models for numerical method to evaluate the goodness of fits are the Sum of Square Error (SSE), coefficient of multiple correlation, R^2, adjusted R^2 and Root Mean Square Error (RMSE).

SSE measures the ith data of n data point which is the square of total deviation of the response values y_i from the fit to the response values y_i bar multiplied with weighted regression w_i. A value closer to 0 indicates a better fit.

$$SSE = \sum_{i=1}^{n} w_i (y_i - \hat{y}_i)^2 \tag{4}$$

The measurement of goodness of fit is the coefficient of the multiple correlation R^2, defined as correlation between the response values and the predicted response values or the ratio of the sum of Square of the Regression (SSR) and the Total Sum of Squares (SST). Since R^2 is a proportion, it must be between 0 and 1, so that this gives some standard by which it can be judged whether the fit is good or bad. The higher the value of the R^2, the greater is the explanatory power of the estimated regression model.

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \tag{5}$$

The adjusted-R^2 uses the R^2 defined above and adjusted based on the residual degrees of freedom. The residual degrees of freedom is defined as the number of response values n minus the number of fitted coefficients m estimated from the response values. The adjusted R^2 statistic is generally the best indicator of the fit quality when there are additional coefficients to the model. With a value closer to 1 indicating a better fit.

$$\text{Adjusted } R^2 = 1 - \frac{SSE(n-1)}{SST(n-m)} \tag{6}$$

The statistic RMSE is also the fit standard error and the standard error of the regression, where a RMSE value closer to 0 indicates a better fit. For the graphical measure, residual is defined as the difference between the response data, y and the fit to the response data y at each predictor value. The residuals approximate random errors if the model fits the data correctly. Therefore, if these residuals appear to behave randomly, it suggests that the model fits the data well. However, if the residuals form a systematic pattern, it is a clear sign that the model fits the data poorly.

$$r = y - \hat{y} \tag{7}$$

Hypotheses testing: A review on TPMS showed that it provides warning to the driver of pressure and temperature loss, tire running at low pressure, tire failure and inflation of tires (Jurgen, 1989). Generally it is assumed that the adoption of TPMS can improve safety and reliability in operation as well as increase tire life and reduce fuel consumption. In the absence of a TPMS, undetected abnormalities in tire pressure and temperature may cause severe accident, increase in fuel consumption as well as reduction in riding comfort and tire life (Burgess, 2004). To statistically prove TPMS effectiveness, we have simulated an abnormal tire condition in one of the tires. We hypothesized such that when the tire is in good condition, the TPMS data made of pressure and temperature readings are normally distributed and have equal mean. Alternatively, the hypothesis is that when the tire is in bad condition, the TPMS data made of pressure and temperature readings are not normally distributed with equal mean. We will use this to test the effectiveness of TPMS in enhancing vehicle performance. The monitored TPMS tire pressure and temperatures are the same in all tires affect the reliability in real-time vehicle operation.

In testing the hypothesis, if the significant level alpha is 0.05 and the result, h is 1, the null hypothesis is rejected at the significant level 0.05. However, if h is 0, then the null hypothesis is accepted. The statistics significance of each of the coefficients is obtained using ANOVA test. The Satterthwaite's test significance is the p-value associated with the t-statistic defined as:

$$T = \frac{\bar{x} - m}{s/\sqrt{n}} \tag{8}$$

where, x is a sample of normal distribution, n is the number of observations in x sample, s is the sample standard deviation and under the null hypothesis, mean of x is equal to m.

ANALYTICAL RESULTS AND DISCUSSION

The analytical data is carried out by mounting the TPM tire module on the tire rim that transmit the tire signal to the receiver module. Then, the receiver signals are carried out using Agilent 54622D Mixed-Signal Oscilloscope. The data is available by changing threshold value of the sensor in MCU. The collected data helps in the evaluation of the testing process and performance of the TPMS of the vehicle.

Classification of tire data: A classification scheme was employed to classify each tire condition. Figure 3 shows the pressure and temperature data and the classification results for each tire. The four tires are denoted by their ID of FR, FL, RL and RR which belong to the 1st, 2nd, 3rd and 4th quadrant, respectively. The FL tire has been classified as having an abnormal condition in which one of the data is seen outside the normal operating zone of the 2nd quadrant. The normal operating zone for each quadrant is within the dashed marked area of the quadrant. On the contrary, the other tires with ID of FR, RL and RR are all operating at normal condition having all data situated within the normal operating zone of the 1st, 3rd and 4th quadrants, respectively. In sum, this implies that the proposed classification scheme has correctly classified the tire condition as operating either normally or abnormally based on the acquired TPMS data.

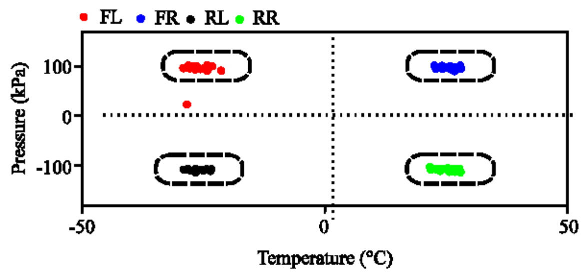

Fig. 3: Pressure and temperature data classification

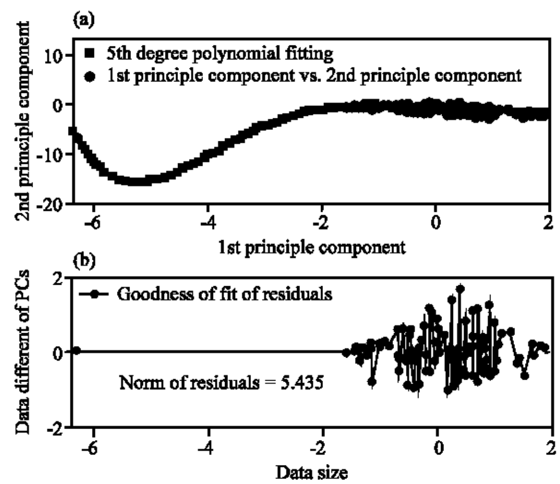

Fig. 4: Principle component analysis and goodness fit

Goodness of fit: The goodness of fit statistic for the model was tested with all the variables. Figure 4 shows the goodness of fit of the principle component analysis with polynomial fitting. The fitting result of parametric model of SSE is 0.1358 with 95% confidence bounds, which is close to 0 and indicates that the data fits well. The value of the multiple correlations R^2 coefficient is 0.8452, whilst the adjusted R^2 value is 0.8267. Both reveal about 85% and 83% match in the outcome which indicates a good fit. In addition, the RMSE value of 0.161, which is close to 0, also implies that the data fits well. In Fig. 4b, residuals of the polynomial fit appear to be randomly scattered around zero, which again indicates the model perfectly fits the data under study.

Hypotheses testing: To test the hypothesis, Analysis of Variance (ANOVA) is performed. At 0.05 significance level?, three results accept the null hypothesis i.e., h = 0 which means FR, RL and RR tires pressure and temperature are normally distributed with equal means and these signify good tire condition. However, the result for tire FL showed otherwise. The hypothesis test suggests that the pressure and temperature data in tire FL are not normally distributed with an equal mean and therefore the null is rejected. This result in turn implies that tire FL is in bad condition which agrees with the simulation. The probability value ($\tilde{p}-\text{value}$) associated to the test of the FR, RL and RR tires further confirm our result with p-value of 0.8442, 0.7667 and 0.2619, respectively. The p-values for tire FR, RL, RR convincingly exceed 0.05 that strongly suggest the acceptance of null hypothesis. On the other hand, the p-value for the FL tire that is faulty, is only 0.0085, which is less than 0.05 and therefore we rejected the null hypothesis. In short, we have statistically proven that TPMS can play an important role to enhance tire safety, performance and maintain reliable operation of the vehicle.

CONCLUSION

In this research, a novel frame work for tire pressure and temperature data analysis has been presented. The implemented TPMS is explored for its data analysis. Analytical analysis has been done. The Agilent 54622D Mixed-Signal Oscilloscope is used for collect the data from the mounted TPM through the receiver of the TPMS. A novel analytical method is proposed for data classification, ascertaining goodness of fit and its hypothesis testing. The classification is assessed based on ID and it was found that the FR, FL, RL and RR tires correctly classified their individual data at the operating zone of 1st, 2nd, 3rd and 4th quadrant, respectively. The goodness of fit of the PCA with polynomial fitting was proven to satisfy the parametric model SSE, R^2, adjusted-R^2 and RMSE results. ANOVA test using Satterthwaite statistic was used to test the null hypothesis by calculating its p-level. Results obtained are in agreement with the null hypothesis and as such theoretically proves the TPMS effectiveness in monitoring tire condition thus improving vehicle performance.

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