APPLICATION OF A PCA MODEL APPROACH FOR MISFIRE MONITORING

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On-Board Diagnostics are a legal requirement for vehicles sold in the US and Europe their aim is to ensure that the vehicle operates within the homologated limits of the vehicle. During the calibration and development of these diagnostics there are several situations which require the analysis of large amounts of multi-dimensional data. One problem that often arises is the comparison of sets of data in order to determine whether there is a significant difference between either two sets of tests or a difference in the results as a consequence of a change in a component. In this paper we investigate this type of problem and develop a Principal Component Analysis model to help make such a decision. Data recorded from the validation work for a misfire monitor is used to develop our approach.

Keywords: Automobiles, Detection, Diagnosis, Engines.

1. INTRODUCTION

Vehicles sold throughout the world are subject to an increasingly stringent set of emission thresholds. To achieve certification, all sensors and vehicle sub-systems that may affect vehicle exhaust emissions have to be monitored by an On-Board Diagnostic (OBD) system that is part of the Engine Management System (EMS) or any other embedded controller. This requirement was first introduced in the US in 1988 for OBD1, for open and short circuit faults, and in 1994 for OBD2, for changes in sensor and actuator responses. For Europe this legislation, denoted EOBD, has been introduced for all vehicles built after January 2000. Both sets of legislation link the performance of the different diagnostics to emission thresholds. In the event of component or sub-system failure, a 'check engine' light must be illuminated as an indication to a driver that there is a problem, so corrective action can be taken to minimise the pollution caused by such a fault. As the emissions thresholds are continually reduced, more sophisticated techniques are required to be employed to meet these increasingly tightening thresholds.

The increase in the complexity of the OBD diagnostics, and also the ability to capture ever increasing amounts of data through the use of calibration tools and data loggers, has led to the need for ever more sophisticated data processing techniques to assist the calibration engineers in their work. In particular, there is current development of tools which can be used by calibration engineers to allow the visualisation of multi-dimensional data. Consequently, any such development should have the following set of requirements: applicable to a wide range of data sets and types; an ability to compare data sets which may be of different dimensions; simple and quick to use; and capable of handling large data sets, e.g. greater than 10,000 samples.

One of the popular data-driven techniques is principal component analysis (PCA). It is a well-known technique for data compression and feature extraction (Jackson and Mudholkar, 1979). It has gained considerable attention and has been successfully applied in many industrial chemical and semiconductor processes (Kourti and MacGregor, 1995; MacGregor, 2005) and recently has been applied in the automotive engine diagnostics field (Antory, 2006).

There are various other Dimension Reduction Techniques other than PCA a few are highlighted here. Kernel PCA (Schölkopf 1998) computes the principal eigenvectors of the kernel matrix, rather than those of the covariance matrix. The application of PCA in the kernel space provides Kernel PCA the property of constructing nonlinear mappings. This then overcomes the linear restriction of PCA but requires the identification of an appropriate Kernel mapping. Multidimensional scaling (MDS) (Cox and Cox 1994) maps the data from a high dimension to a low dimension by trying to maintain distances between the data points. Use is commonly made of the Sammon cost function (Sammon 1969) which measures the 'stress' or error between the high dimension and low dimensional distances. Neuroscale (Lowe and Tipping 1996) uses a Radial Basis Network to minimise the same cost Function and learn a non-linear mapping for the lower dimensional space.

The paper is organised as follows: Section 2 introduces PCA, which is followed by a discussion of the misfire monitor in Section 3. Section 4 details the implementation and analysis. Section 5 details an approach to develop reduced order PCA model and finally, Section 6 summarises and concludes the paper.

2. PRINCIPAL COMPONENT ANALYSIS

This section discusses briefly the fundamental theory of the proposed condition monitoring and diagnosis methods.

2.1. Principal Component Analysis (PCA)

PCA reduces the dimension of the data by finding a few orthogonal linear combinations, Principal Components (PCs), of the original variables with the largest variance. Since the variance is dependent upon the scale of the variables the first step is to standardise the data so that it has a zero mean and common standard deviation. Assuming a standardised set of data the covariance matrix is given by

$$\mathbf{\Sigma} = \frac{1}{(m-1)}\mathbf{X}^T\mathbf{X} \in \Re^{n\times n} \tag{1}$$

where the data matrix, $\mathbf{X} \in \Re^{m\times n}$, in which m samples are stored as row vectors, of n ($n \ll m$). We can then use the spectral decomposition theorem to write $\mathbf{\Sigma}$ as

$$\mathbf{\Sigma} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^T \tag{2}$$

where $\mathbf{\Lambda} = diag(\lambda_1,\ldots,\lambda_n)$ is the diagonal matrix of the ordered eigenvalues $\lambda_1 \le \ldots \le \lambda_n$ and $\mathbf{U}$ is a $n\times n$ orthogonal matrix containing the eigenvectors. By transforming the data vector $\mathbf{X}$ using the following equation

$$\mathbf{Y} = \mathbf{U}^T\mathbf{X} \in \Re^{n\times m} \tag{3}$$

the data can be mapped to an orthogonal coordinate system defined by the eigenvectors. By selecting the eigenvectors with the largest eigenvalue we lose as little information in the mean-square sense. So if we denote the matrix having k eigenvectors as columns of $\mathbf{U}_k$ then, we can create a similar transform as seen in (3)

$$\mathbf{Y}_k = \mathbf{X}\mathbf{U}_k \in \Re^{m\times k} \tag{4}$$

It is the k columns of $\mathbf{Y}_k$ that are the k Principal Components (PCs) of the PCA model. This transformation enhances the ability of PCA to extract information from the original data by eliminating redundant information.

2.2. PCA for Dimension Reduction

The motivation to make use of PCA is twofold; PCA is often used as the initial starting point for a number of non-linear methods described in Section 1. In addition the size of the data being considered in Section 4 means that some of these methods are computationally prohibitive requiring the manipulation of $m\times m$ matrices.

3. MISFIRE MONITORING

The misfire monitor is a unique OBD monitor in that it does not monitor any specific component within the engine but attempts to monitor the performance of the combustion event that occurs in each cylinder. It is important to detect misfire events because they can cause severe damage not only to the engine but also to the catalytic converter. The unburned fuel mixture on the catalyst matrix itself can cause excessive heat resulting in melting and ultimately in failure. The effect of a non-functional catalytic converter will result in the release of higher than expected emissions, which should then be flagged as part of the OBD system.

The importance of detecting engine misfires has attracted many researchers, notably some works by (Williams 1996, Förster et al. 1997, Kiencke 1999, and Ilkivova 2002), to name but a few. Their research uses mathematical model representations of crank angular velocity measurements as a diagnostic tool. This type of modelling falls into a category of popular model-based methods. Recently, (Isermann 2005) gave a detailed presentation on the application side of model-based fault detection and diagnosis. Further highlights in this field were given by (Mills III 2005) at the SAE World Congress 2005, where the usefulness of automotive data for diagnostics purposes was presented. With advanced

data acquisition existing in most modern automotive vehicles today, the 'luxury' of obtaining abundant measured sensor/actuator signals can be rigorously explored for diagnostics purposes.

3.1 Misfire Validation Data

To flag a genuine misfire requires a number of misfire counts to exceed a certain threshold within a given number of engine revolutions. The misfire monitor will always record a number of 'false positives' and it is the level of these occurrences and there position in the engine operating envelope that is being investigated as part of the validation work. The data used here has been collected from the same vehicle, which has been run for approximately two weeks, with and without a change in an engine component. The aim of this study is to determine whether this change of component has any significant effect on the robustness of the existing misfire calibration.

Each time that there has been a 'misfire event' logged by the misfire diagnostic, eight engine parameters have been logged and these are given in Table 1. Engine Speed and Intake Air Flow give an indication as to where in the operating envelope of the engine the measurements have been taken, the Intake Air Flow giving an indication of engine load. The Lambda sensor measures the proportion of oxygen in the remaining exhaust gas the EMS can then determine amount of fuel required to burn at the stoichiometric ratio (14.7:1 air:fuel by mass for gasoline) to ensure complete combustion, or Lambda equal to 1. The Spark Advance is the angle before top dead centre when the spark plug is fired by the EMS and the Throttle Position provides a measure of the throttle blade position as a percentage of available movement.

4. PROCESS MONITORING & ANALYSIS

The PCA model for the misfire validation data is built by combining both sets of data. (Data Set 1, with the original vehicle configuration contains 7358x8 data points and Data Set 2, with the component modification, has 7140x8). Due to the nature of the data it is decided to take the median of the data and then to ensure that the data is scaled so that the maximum distance from median is scaled to either -1 or 1 as appropriate. The PCA model was then developed using both sets of data, resulting in extracting the two eigenvectors associated with the highest eigenvalues for the specific models corresponding to the two data sets. Using this approach allows for a more direct comparison between the two sets of data since the same model is being used on both sets of data.

The results of the PCA Model are given in Table 2, column 2 shows the amount of variance captured by each

Table 1: Measured engine variables

Variable Number	Engine Variable
1	Intake Air Flow (g/rev)
2	Coolant Temperature (ºC)
3	Engine speed (rpm)
4	Intake Air Temperature (ºC)
5	Throttle Position (%)
6	Lambda Sensor 1
7	Lambda Sensor 2
8	Spark Advance (º)

Table 2: Variance captured by PCA

PC	Eigenvalue	Variable Captured	Total Variance Captured
Y_1	0.0865	56.8791	56.8791
Y_2	0.0220	14.4625	71.3416
Y_3	0.0183	12.044	83.3856
Y_4	0.0146	9.5756	92.9612
Y_5	0.0053	3.4592	96.4204
Y_6	0.0035	2.3194	98.7399
Y_7	0.0015	1.0147	99.7544
Y_8	0.0004	0.2456	100

of the eight principal components, column 3 shows this variance as a percentage and column 4 shows the cumulative variance extracted. Using a k of two in (4) a reduced dimension model for each of the misfire data sets was developed which captures 71% of the variance. The plots of the reduced model can be seen in Figure 1 which shows the effect of overlaying the two data sets of information onto one plot. The Blue dots indicating Data Set 1 and the Red dots Data Set 2.

There are two distinct groups of data shown in Figure 1. The cluster that contains the highest density of data is the tight grouping centred around (0.0,0.1). This contains data from a fully warm engine with high Spark Advance (50º), low throttle angle and load. The second grouping is a cloud of data centred around (-0.3,-0.1). This contains a wider variety of engine conditions but with Spark Advance less than the 50º.

The PCA model has mapped the data so that in general the data is distributed in the following manner with Spark Advance increasing along the Principal Component Axis 1 axis, Y_1 ,and Engine Speeds increasing and Engine Coolant Temperature decreasing along the Principal Component Axis Y_2 .

For misfire monitor it would be typical to see this type of data as it is indicative of 'tip in' and 'tip out' events through gear shifts and the driver taking their foot off and on the accelerator pedal. These are highly transient events and the misfire monitor has difficult correctly identifying misfires in these areas.

The two small clusters that lie away from the general data with centres at (-0.9,0.6) and (-0.9,0.4), based on previous experience, raises concerns as this typically indicates problems with the misfire calibration. Since the clusters appear in both sets of data at the same points, see Figure 3, then they do not relate to the component change or an issue with the calibration, but possibly something specific with the vehicle. When these data points were traced back it was discovered that these related to a cold start data with the coolant temperature being less than 40ºC. In addition, investigation revealed that the vehicle did not include the latest chassis specification intended for production vehicles.

5. REDUCED ORDER PCA MODEL

Using the information from the off diagonal elements of the covariance matrix it is possible to partition the data down into smaller PCA models by taking into account their interactions. This will generate a set of more accurate PCA models which will allow closer investigation of the data. Table 3 shows the off diagonal terms of the covariance matrix Σ. The largest interaction in Table 3 is the correlation between the two Lambda Sensors. This then indicates that there is little difference in the Air Fuel Ratio control bank to bank.

Using the information in Table 3 it was decided to split the data to give two PCA models PCA1 and PCA2. In this case all of the variables, apart from Intake Air Temperature, have a strong correlation with the Spark Advance so this variable will be included in both of these new models.

PCA1: consists of the following variables Intake Air Flow, Coolant Temperature, Engine Speed, Intake Air Temperature and Spark Advance. Generating a PCA model using this reduced set of variables model for the first 2 Principal Components has captured 82% of the variance, see Table 4.

Figure 2 shows the comparison between the two data sets data for the reduced model PCA1. This plot is similar to that Figure 1 it shows the same 3 sets of clusters. However, since PCA1 has been constructed from a reduced set of data the clusters are more clearly defined. The cluster of concern relating to the detection of misfires during cold start is now located at (-0.9,0.65). One noticeable difference between the two sets of Data

is that for clusters at centred at (-0.3,-0.1) and (0.0,0.1) have Data Set 1 values less than Data Set 2. This is because the ambient temperature under which Data Set 1 was collected was lower than that for Data Set 2.

Table 5 shows how the Principal Components ($\mathbf{Y}_1$ and $\mathbf{Y}_2$) map to the data $\mathbf{X}$ for PCA1. These coefficients show that for x axis, $\mathbf{Y}_1$, mainly consist of mainly Spark Advance and y axis, $\mathbf{Y}_2$, is a more complex combination of all of the variables as we have seen previously in Figure 1..

PCA2: consists of Intake Air Flow, Throttle Position Sensor, Lambda Sensor 1, Lambda Sensor 2, Spark Advance. Intake Air Flow has been included in PCA2 since it has a relationship with the two Lambda Sensors. Throttle Sensor has also been included in this model to ensure that all of the original data is represented in at least one of the models even though it does not have a strong relationship with any of the variables. Generating a model using this reduced set of data results in PCA2 have capturing 94% of the variance for the first two Principal Components.

Table 7 shows how the Principal Components ($\mathbf{Y}_1$ and $\mathbf{Y}_2$) map to the data $\mathbf{X}$ for PCA2. This shows that the Figure 3 is mainly of Spark Advance ($\mathbf{Y}_1$) plotted against the two Lambda Sensors ($\mathbf{Y}_2$). Investigation of the data show that values where $\mathbf{Y}_1 < -0.7$ have a Spark Advance of 0 or less. This condition is typically run at cold start conditions to help heat up the catalysts and at conditions when Torque needs to be taken out of the engine quickly.

6. CONCLUSION

Even though PCA fits a linear model to the data it has allowed the visualisation of the Misfire Validation Data. By making use of the information contained within the covariance matrix has allowed for detailed reduced order PCA models of the original data to be developed.

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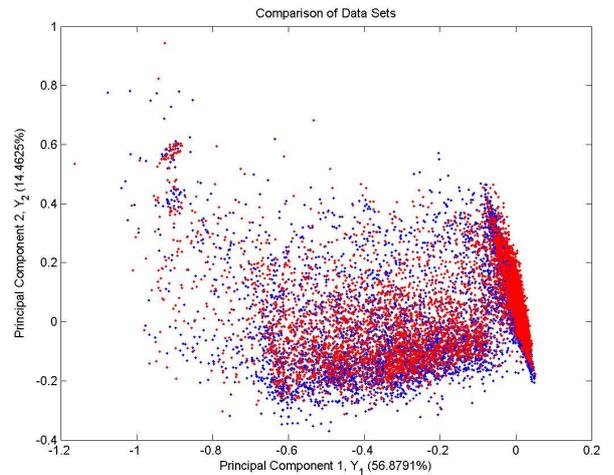
Figure 1: Comparison of PCA
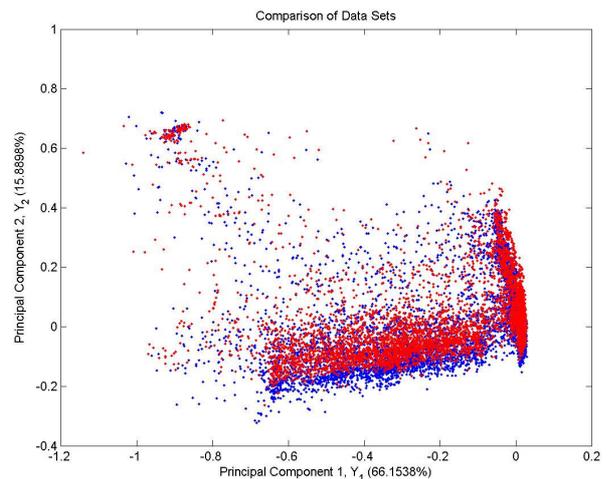

Figure 2: Comparison of PCA1
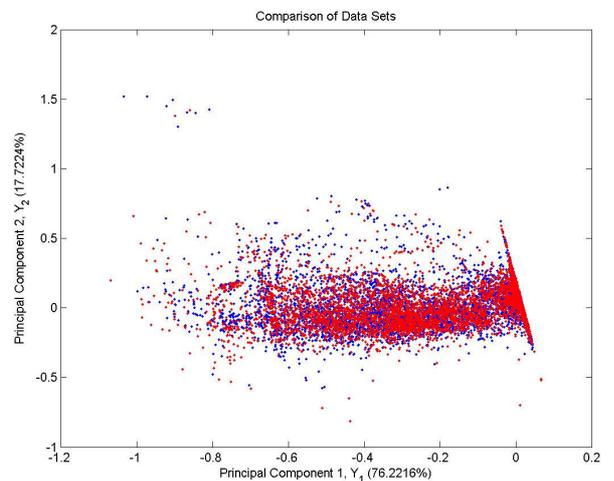

Figure 3: Comparison of PCA2

Table 3: Upper Diagonal of the Covariance Matrix (Σ)

	Coolant Temperature	Engine Speed	Intake Air Temperature	Throttle Position	Lambda Sensor 1	Lambda Sensor 2	Spark Advance
Intake Air Flow	0.4648	0.0545	0.1669	0.1695	0.1998	0.2252	0.5892
Coolant Temperature		0.1703	0.1985	0.1017	0.1771	0.1453	1.1593
Engine Speed			0.2673	0.1454	0.1785	0.1201	0.4225
Intake Air Temperature				0.0026	0.0954	0.1324	0.1252
Throttle Position					0.1484	0.1442	0.3339
Lambda Sensor 1						0.8892	0.4527
Lambda Sensor 2							0.3605

Table 4: Variance captured by PCA1

PC	Eigenvalue	Variable Captured	Total Variance Captured
Y_1	0.0857	66.1538	66.1538
Y_2	0.0206	15.8898	82.0436
Y_3	0.0145	11.2294	93.2731
Y_4	0.0054	4.1476	97.4206
Y_5	0.0033	2.5794	100

Table 5: Coefficients for PCA1 Model

	U_1	U_2
Intake Air Flow	-0.081773	0.23344
Coolant Temperature	0.17803	-0.8068
Engine Speed	-0.047177	-0.24492
Intake Air Temperature	-0.022567	0.45543
Spark Advance	0.97923	0.16487

Table 6: Variance captured by PCA2

PC	Eigenvalue	Variable Captured	Total Variance Captured
Y_1	0.0840	76.2216	76.2216
Y_2	0.0195	17.7224	93.9440
Y_3	0.0043	3.9436	97.8876
Y_4	0.0016	1.4622	99.3498
Y_5	0.0007	0.6502	100

Table 7: Coefficients for PCA2 Model

	U_1	U_2
Intake Air Flow	-0.078283	0.16808
Throttle Position	-0.044075	0.10704
Lambda Sensor 1	-0.070984	0.66432
Lambda Sensor 2	-0.060932	0.71205
Spark Advance	0.99155	0.10934