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SMART DIAGNOSTIC SYSTEM FOR AUTOMOTIVE MULTISTAGE MECHANICAL TRANSMISSIONSUSING MULTI-CLASS SUPPORT VECTOR MACHINE

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ABSTRACT

The need for semi-autonomous or autonomousoperations, communication delay, short contact periods as wellas the need for survival in harsh environments poses uniquechallenges to mechanical transmission systems. Predictive health monitoring (PHM) systems are currently gaining in popularity due to their effectiveness in providing robust information about the system condition and reducing maintenance costs. However, PHM systems require reliable monitoring techniques, such as vibration, acoustic emission, and oil debris analysis. These techniques have shown the need to apply intelligent algorithms in order to benefit from the advantage of each technique in classifying faults and predicting the onset of failure. This paper presents a PHM system for monitoring different gear faults using vibration analysis and support vector machine (SVM) algorithms. Experiments were conducted on a multi-stage gearbox under three conditions, normal, external excitation and high temperature. The model is verified through additional experimental observations.

KEYWORDS

Mechanical transmission, condition based maintenance, vibration analysis, health monitoring system, Support Vector Machine.

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INTRODUCTION

Monitoring the condition of the in-service mechanical transmission system is an important issue for reliability, where their components deteriorate over the time and affected much when subjected to varying loads. This is led in continues improve of maintenance strategies from breakdown and periodic maintenance to CBM and predictive maintenance in order to sustain reliability and reducing the periodic maintenance costs. Also, in some applications there is more demanding aspect such as saving man's life other than reliability [1]. Smith [2], has defined the causes of transmission vibration and its transmission path, including factors such as manufacturing error, design error and gear tooth deflection, which combine to introduce a transmission error (TE), which is the primary source of the vibration.

Over the past decade, vibration analysis proved to be a trustworthy diagnostic technique that can provide reliable information. However, in the last 10 years researchers devoted a much effort to support CBM actions using vibration information [3-13].

The work focused on the development of reliable features using a suitable signal processing techniques can be grouped in two groups; time domain vibration features including: statistical parameters, time synchronous averaging based methods, filter based methods, stochastic methods and other model based methods. The second group is the frequency domain and time frequency domain features including: first order; (FFT), correlation of spectrum, signal averaging, short time Fourier transform (STFT), continuous wavelet transform (CWT), discrete wavelet transform (DWT), discrete wavelet packet analysis (DWPA), time-averaged wavelet spectrum (TAWS) and time-frequency scale domain (TFS). Second order; power spectrum, Power cepstrum (logarithm of Power spectrum), cyclostationarity, spectrogram Wigner distribution and scalogram. Third order; Bicoherence spectrum, bilinearity and Wigner bi Spectra. Fourth order; Wigner tri Spectra [29].

The authors of this paper continued their research by developing multi sensors fusion algorithms to fuse vibration analysis information with other sensory data, such as acoustic emission and oil debris analysis to minimize false alarms that may occur in failure prediction [14-17]. Also, other researchers devoted efforts to build intelligent algorithms based on vibration features including Expert systems, ANN's, Genetic algorithm, and fuzzy logic [18 - 28]. Intelligent health monitoring systems incorporate AI algorithms, where AI can be defined as "the science of making machines do things that would require intelligence if done by humans" [33]. To develop an IHMS, the running system condition must be recognized and classified. Researchers have devoted considerable effort to the application of various different soft computing methods to develop IHMSs, and have shown that this can be achieved using methods such as neural networks, fuzzy logic and mathematical modelling based on parametric approaches. All of these methods can provide important tools in the field of intelligent systems which can learn, adapt, and make decisions concerning the system they are in charge of [33].

Artificial neural networks (ANNs) have been used with different HMS techniques such as vibration and acoustic monitoring. An ANN requires input data of the healthy and faulty conditions to be pre-processed, and then these features are used to model the system's behavior. Fenton et al [36] mentioned that there are two main basic network architectures: feed-forward and recurrent ANNs. Feed-forward ANNs do not have feedback between layers, and previous inputs are not remembered, whereas recurrent ANNs involve feedback between layers and previous inputs are remembered and can be used to reconstruct correlative memory. The two standard neural network architectures used in transmission diagnostics are the feed-forward back propagation network, and the Kohonen feature map which is also known as the self-organizing map (SOM) [37]. Fuzzy logic was developed by Zadeh in the 1960s to characterize types of knowledge that cannot be represented by classical Boolean algebra to cover approximate knowledge in describing the behavior of systems which are difficult to describe mathematically [33].

Currently, the authors of this paper is devoting their efforts in developing smart CBM systems that can use one analysis technique only such as vibration or acoustic emission analysis along with intelligent algorithms to predict the onset of failures; this is to reduce costs of different sensory requirements [30-32]. This paper builds on the author's previous work to develop an online wireless vibration analysis tool for testing automotive mechanical transmissions. The online operation of this system can lead to the wide spread of using such systems with other rotating machinery.

Parametric methods based on mathematical modelling is to fit measured time series waveform data to a parametric time series model, and then extract features based on this model [34]. Two models are currently in use: the auto regressive (AR) and auto-regressive moving average (ARMA) models. The advantage of mathematical modeling based on parametric methods over the neural networks model-based method is its ability to deal with time series data directly without the need for a signal pre-processing step to extract useful features that can be modeled to represent the system [14]. However, they can only be used to model a time series signal such as a vibration signal, and cannot be applied to combined information from several techniques (vibration, AE and ODA) such as in the case of fuzzy logic.

In Addition, researchers have devoted considerable effort to the application of various different soft computing methods to develop heath monitoring systems HMSs for gear box transmission systems summarized in data mining techniques. These methods can provide important tools for the field of intelligent monitoring which can learn, adapt, and make decisions concerning the system they are in charge of TakehisaYairi et al. [45] evaluating a variety of dimensionality reduction algorithms and compare between them, without using the cross-validation.

Artificial neural networks ANNs in combination with other soft computing methods have been the most predominant to date [42, 43]. However, ANN techniques are characterized as black box approaches which model the relationship between different sensory data and a desired response without giving any information about the process. In addition, issues associated with collinearity and dimensionality needs to be specifically addressed in these techniques. Solving many of these limitations can be addressed through the use of multivariate statistical analysis, which is a data-driven modelling approach [43]. Iverson et al. [38, 39, 44] discuss several data driven software tools that successfully applied to space mission operations using data mining tool which searches for unusual data points, or outliers, in multivariate data sets in the spacecraft system data that may indicate malfunctioning system components. John



MacGregor et al. [45] established the advantages applying of multivariate latent variable monitoring and fault diagnosis methods contrasted with other techniques as Independent Component Analysis (ICA), Artificial Neural Networks (ANN), and Support Vector Machines (SVM).

The simplicity of multivariate statistical analysis approach is that there is no need for a fundamental model of the system and only data from normal operation needs to be used, which is generally available in some form for most machines. Among the approaches used in multivariate analysis are: two-projection methods called principal component analysis PCA, projection to latent structure PLS [48, 49, 50]. Many applications of these two techniques have been successfully applied in other fields of process monitoring.

This paper outlines the use of the Support Vector Machine SVM approach, to develop a framework for monitor heath status of transmission system under study.

SYSTEM CONFIGURATION

An automotive mechanical transmissions gear test rig is currently being developed for this ongoing research. The rig comprises 130mm centre distance gearbox. Table1 provides the basic geometry specification for the gears. The system is driven by a 7.5Kw variable speed electric motor controlled by an inverter to provide a speed variation of 1750 rpm. The load is applied via a mechanical breaking mechanism.

Specifications	Gear number									
	1		2		3		4		5	
	Р	W	Р	W	Р	W	Р	W	Р	W
Module (mm)	9.5	9.5	9.5	9.5	8	8	8	8	8	8
Gear Type (H-S)	S	S	Н	Н	Н	Н	Н	Н	Н	Н
Number of teeth	21	40	19	35	30	33	38	25	43	20
Face Width (mm)	25	25	25	25	25	25	25	25	30	30
Gear Ratio	4.095		3.96		2.365		1.414		1	

 Table 1. Gears basic geometry.

The rig can generate a load torque on the test gears in the range of 0 - 200Nm. The torque is measured using calibrated strain gauges installed on the shaft and the measured torque values are transmitted to the control program by telemetry in order to provide torque control of the loading mechanism on the mechanical transmissions. The test rig is shown in Figure 1. The testing system has been developed for this research work, and is capable of on-line monitoring, automatic measurement, and analysis. Also, any changes in the gears and bearing conditions due to degradation



during the operation can be identified. The advantage of developing the system arises from its ability to enhance online analysis methods for vibration technique to provide robust information about the system's condition. Two temperatures were measured: gearbox oil temperature and bearing temperature using RTD temperature sensors (10mv/C). The input shaft speed and motor current were also monitored as a precaution. The test rig operating conditions were monitored and it is flexibly changed according to the required test conditions using LabVIEW's virtual instrument scalable architecture features.

As shown in Fig. 1, the process is simply a multistage automotive gearbox. The gearbox is derived by a 3-phase electrical motor. The system is loaded through a mechanical braking system and controlled with an AC motor inverter. The system is equipped with five sensors, two accelerometers at two different positions (input and output of the gear system), temperature sensor (immersed in the gearbox oiling system), wireless strain gauge for torque measurements (on the output shaft) and a proximity sensor for speed measurement (at the gearbox input shaft).



1. Speed sensor 2. Accelerometer 1 3. Temperature sensor 4. Accelerometer 2 5. Torque sensor.



Fig. 1. Multistage gearbox System Scheme.



The Vibration analysis system incorporated a 24-bit NI wireless DSA data acquisition card (NI 9234 with cDAQ-9191) to acquire the vibration signal, speed and temperature. The vibration signals were acquired using two DJB Piezotronic constant current source accelerometers (model no. Acc103 -10mV/g) mounted adjacent to the tested gear bearings transversely to the gearbox casing, and a shaft speed sensor was used to acquire the shaft rotation reference. The sensors location diagram over the test rig is shown in Figure 2. The vibration signals are then acquired continuously and transmitted to the base unit using an IEEE 802.11b/g (Wi-Fi) wireless communication interface (frequency range 2.412–2.462 GHz). The system can send the data from a range up to 30 m for indoor measurements and 100 m for outdoor operation as long as the line of sight of the wireless signal is provided. The system can also provide Ethernet cabling measurements up to a distance of 100 m. The test rig sensor-actuation system layout is shown in Figure 3.



Fig. 2. 1. Inverter, 2. Electric motor, 3. Fixable coupling, 4. 130 mm center distance Gearbox, 5. Mechanical coupling, 6. Loading Mechanism.



Fig. 3. The test rig sensors - actuation system layout.

SUPPORT VECTOR MACHINES METHODOLOGY

Support Vector Machines Methodology

Support vector machines (SVMs) are a group of learning machines for solving pattern recognition problems efficiently. SVMs try to find the hyperplane, which separates optimally the training patterns according to their classes (i.e. hyperplane with maximum boundary margin). This is performed by using what is commonly known in machine learning as the "kernel trick" when using SVM's. Kernel function is chosen to map the data from its original space to feature space. It can be chosen arbitrarily so as to best suit the data and at the same time reduce the computational burden involved with generating the mapped values by direct evaluation. "Support vectors" correspond to those points that lie along the margin or closest to it. The maximum margin between classes is found by solving a guadratic optimization problem. SVMs have a good generalization performance over traditional approaches, since their training is based on the principle of structural risk minimization (SRM) (i.e. minimizing the upper bound on the expected risk), while the training traditional approaches are based on empirical risk minimization (i.e. minimizing the number of the training error). SVMs have a high computational efficiency in terms of speed and accuracy. They are also more preferable when dealing with high dimensional data as they are more robust than traditional approaches, which may over-fit the data. However, they still have negativeaspects in terms of giving information about the system output and no physical explanation and interpretation of the process itself. The description of SVMs classification can be explained as follows:

Consider the training data $\{x_i, y_i\}$, where: i=1,..., N, $y_i \in \{+1,-1\}$ corresponding to the class of x_i ($y_i = 1$ for class A, $y_i = -1$ for class B). The principle of operation of SVMs classifier will be modified according to the type of the data samples as follows:

Linearly Separable Data

Figure 4 shows the hyper plane H which separates the two classes of data (separating hyper plane). This hyperplane H satisfies the following equality

$$b + w^{t} \cdot x_{i} = 0$$

(1)

where: w is a normal vector on the hyperplane, and b is a bias representing the distance from the origin.



Fig. 4. Optimal separating hyperplane of SVMs for separable data.



$$b + w^t$$
. $x_i \ge 1$ and $b + w^t$. $x_i \le -1$ (2)

The two inequalities in (2) can be combined as follows:

$$y_i (b + w^t. x_i) \ge 1 \tag{3}$$

The equalities of (3) define hyperplanes H1, and H2 respectively, and any training data belongs to class A or class B and lying on H1 or H2 is called support vectors (SVs). From figure 4 the geometry and the separating margin of hyperplane H is given by:

$$m_r = \frac{1}{\|w\|} \tag{4}$$

The SVMs classifier tries to find the separating hyperplane with the largest margin (optimal hyperplane). This can be formulated as follows:

$$\operatorname{Minimize} \frac{1}{2} \|w\|^2 \tag{5}$$

ands.t. constraints in (3).

Using the Lagrangian formulation of the problem

$$L_{p} = \frac{1}{2} ||w||^{2} - \sum_{i}^{N} \alpha_{i} y_{i} (b + w^{t}. x_{i}) + \sum_{i}^{N} \alpha_{i}$$
(6)

Lp will be minimized with respect to w, b and all the derivatives of Lp with respect to all the Lagrangian multipliers, α i will vanish. All of these multipliers are subjected to the following constraints:

$$\alpha_i \ge 1 \tag{7}$$

The calculations can be simplified by applying Karush-Kuhn-Tucker (KKT) condition, which allows applying dual formulation of the problem. This implies that the maximum of Lp is subjected to same constraints in (7) and acquiring that the gradient of Lp with respect to w and b vanishes which results in (6) and (7):

$$w = \sum_{i} \alpha_{i} y_{i} x_{i}$$
(8)

$$\sum_{i} \alpha_{i} \mathbf{y}_{i} = \mathbf{0} \tag{9}$$

Substituting (8) and (9) in (6) results in:

$$L_{D} = \sum_{i} \alpha_{i} - \frac{1}{2} \sum_{i,j} \alpha_{i} \alpha_{j} y_{i} y_{j} x_{i} x_{j}$$
(10)

s.t. constraints in (7) and (9). Once α is obtained from (10) (using a quadratic programming (QP) solver), the dimensions of the classifier w, b are determined using



(3) and (8). Substituting the obtained values of w and b in (11) allows the classification of any unknown sample.

$$y$$
 unknown= sign(b + w^t. x unknown)

The number of variables in (10) is the number of the training data. All the training data associated with the Lagrangian multipliers satisfying the inequality of (7) are the SVs. The number of SVs is considerably less than the number of the training data.

Non-Separable Data (Noisy Data)

Figure 5 shows an example of non-separable data, which contains noise. The classification is performed by introducing a positive slack variable ξ_i which defines the distance between the margin and the input vector xi lying on the wrong side of the margin, and i =1,..., N, as well as introducing a penalty C due to errors. The larger the value of C, the larger is the margin mr and, hence, the smaller is the number of misclassified samples. Now the optimization problem is modified as follows:

$$\text{Minimize } \frac{1}{2} \|w\|^2 + C \sum_i^N \xi_i \tag{12}$$

s.t.
$$y_i (b + w^t. x_i) \ge +1 - \xi_i$$
, for i=1,....,N (13)

and
$$\xi_i \geq 0$$
 for all i



Fig. 5. Optimal separating hyperplane of SVMs for non-separable data.

The calculations can also be simplified by applying KKT condition as in (10) subject to the constraints in (9) where:

$$c \ge \alpha_i \ge 0 \tag{15}$$

The only difference between (7) and (15) is that there is an upper bound C on the Lagrangian multipliers.



(11)

(14)



Non-Linear Data

In the case of non-linear input data, kernel functions are used. They map the nonlinear input data into a higher dimensional space, where linear separation is possible. Kernel functions also called "kernel trick" are defined as follows:

$$k(x_i, x_j) = \phi(x_i). \phi(x_j)$$
(16)

$$\left(b + w^{t}.k(x_{i}, x_{j})\right) \ge +1, \text{ for } i = 1, \dots, N$$

$$(17)$$

Substituting (16) into KKT condition of (10) results:

$$L_{D} = \sum_{i} \alpha_{i} - \frac{1}{2} \sum_{i,j} \alpha_{i} \alpha_{j} y_{i} y_{j} k(x_{i}, x_{j})$$
(18)

s.t. constraints in (15) and (9).Again, α is obtained from (18) (using a quadratic programming QP solver) and the dimensions of the classifier w, b are determined using (8) and (17). Substituting w, b in (11) allows the classification of any unknown sample. Figure 6 shows non-linear kennel function mapping philosophy and the two kernel non liner functions are:

1. Polynomial: $k(x_i, x_j) = (x_i^T \cdot x_j + 1)n$, n > 0

where: n is the degree of inner product kernel.

2. Gaussian Radial basis function (RBF):

$$k(x_i, x_j) = \exp\left(\sigma \left\|x_i^{\mathrm{T}} - x_j\right\|^2\right), \sigma > 0$$
(19)

where: $\sigma = \frac{-1}{2y^2}$ and γ is the kernel width parameter.



Fig. 6. Kernel function (non linear case).



RESULTS AND DISCUSSION

This section discusses the results of the experimental study, showing the application of the SVM algorithm to real stored sensory data, for normal and anomalous operation periods.

Measurements were driven through three conditions as shown in Fig. 7. Figure 7 shows Kurtosis, Crest factors and temperature of the input gearbox shaft through the different conditions. First, the system was run under normal condition (observations 1-100), then external excitations were applied at one position (input shaft: 101-200). The system was then subjected to a high temperature (201-300).



Fig. 7. Kurtosis, Crest factors and Temperature at the input gearbox shaft for 300 samples experiments.

There are several evaluation schemes for selection of training and testing sets including hold-out, leave-one-out, cross-validation and bootstrap. In our article the selection is based on hold-out method. So, the 300observations are divided into 225 observations as training set and 75 observations as testing set. The division percentage is 75 % for training set to 25% for testing set.

Nonlinear Support Vector Machines Results

In this section, the generalization of the non-linear SVMs classification algorithm to the gearbox state-of-health data and its performance is investigated. The training technique generated in this design work is adapted to train 225 observations (80 normal, 145 faulty) as training set (Set-1). Subsequently, the model is tested and validated on a subset (Set-T) of the remaining 75 observations (20normal, 55 faulty) and their corresponding normalized values are directly used as the input features for SVMs. The corresponding output y1 is (1 for a normal condition, 2 and 3 for faulty conditions).

SVM Models Design

The SVM models are designed during the training process by trial and error. The



training process involves different Kernel functions as well as several values of each Kernel parameters in order to obtain the SVM classifier with the best performance. The SVM and Kernel methods coded in MATLAB is used for the SVMs training and testing.

Selection of Kernel Function and Kernel Parameters

The SVMs classification technique is tested for two different Kernel functions during the training process namely, the polynomial and Gaussian RBF kernel functions of (19). According to the performance of these Kernel functions, the suitability of the SVMs as an intelligent classifier is judged.

The selection of the optimum parameters for SVMs is done during the training process (Set-T). The SVM classifier with the best performance is obtained by testing different values of the Kernel parameters. These parameters are varied in the following manner; γ is varied with values of 0.1, 0.2, 0.3, 0.5, 1, 3, 5. The order of the polynomial Kernel n is varied in the range with steps of 2. The penalty due to the error C is also varied with values of 1, 10, 100, 500 and 1000. The tolerance condition for the QP solver is 0.0000001. The performance of the two SVMs is assessed on each of these values by calculating the training percentage performance efficiency defined by:

 $\eta = \frac{\text{No. of samples correct classified}}{\text{Total No. of samples}} \times 100$ (23)

From these results, the SVM classifier with the highest training percentage performance efficiency is selected. The testing process is then performed, during which the generalization performance of the classifier is examined using testing set (Set-T) by evaluating the testing percentage performance efficiency.

Training and Testing the Results

Figure 8 shows the best performance of kernel functions during the training process of the training set (Set-1). The best performance is introduced in terms of the percentage training efficiency of equation (23), with respect to the variation of the kernel parameters γ , and n as well as the penalty due to the error C. The corresponding number of SVs and the training time are also illustrated.

From the results illustrated in Figure 8 the following clarification are worth noting: **1. Effect of penalty due to the error C**

- a. For the Kernel functions under investigation, the best performance is obtained at high values of C = 500 and 1000. In addition, as C increases the training efficiency increases.
- b. The maximum training efficiency is 96.98% at C= 1000.

2. Effect of the Kernel parameters

a. For the polynomial Kernel, as n increases, both of the number of SVs and the training time decrease, while the training efficiency increases. The best performance for the polynomial Kernel function is 96.13% for C = 1000, n = 10.





- Fig. 8. Best performance obtained during training of SVMs with for normal and faulty data and for different values of Kernel parameters for Gaussian and polynomial Kernel.
 - b. For the Gaussian Kernel, as γ decreases, both of the number of SVs and the training efficiency increase, while the training time decreases. The best performance for the Gaussian Kernel function is 96.98% for C = 1000, γ = 0.1.

3. Effect of the type of the kernel function

- a. The best training efficiency was obtained with the Gaussian Kernel function (96.98% during SVM training).
- b. The shortest training time was obtained for the polynomial Kernel function (7.4 second during SVM training and the smallest number of SVs was obtained for both the polynomial and Gaussian Kernel function (10 SVs during SVM training).

Figures 9 and 10 demonstrate samples of contour plots for non-linear SVM classifier using Gaussian Kernel functions.



C=1000, Gaussian, KO =2, lambda=1e-7

Figure 9. Non-linear Gaussian SVMs contour plots.



C=1000, Polynomial, KO =2, lambda=1e-7

Figure 10. Non-linear Polynomial SVMs contour plot.

CONCLUSION

The study has presented a wireless vibration measuring system that was able to detect different conditions of gears in automotive gearbox and clearly identify its condition using two accelerometers at two different positions (input and output of the gear system) but only one was used in analysis, temperature sensor (immersed in the



gearbox oiling system), wireless strain gauge for torque measurements (on the output shaft) and a proximity sensor for speed measurement (at the gearbox input shaft)for model building and testing. The study has focused on monitoring the progression of gear faults in spur and helical gears, using multiclass SVM. The online information about the transmission condition can provide a solution for PHM systems. The system solved a major problem for application those sensing points are far from acquisition and analysis point. The system is being developed for use on 130mm automotive manual transmissions, but could be adapted for other transmission or machinery systems rotating machinery. The model was tested under different conditions including: normal condition, external excitations at one position (input shaft), high temperature and was able to successfully differentiate between them.

For future applications, another data driven monitoring to explore, is the use of supervised learning methods to help identify fault signatures. Among these methods Projection to latent structure discriminant analysis PLS-DA based technique, may be able to analyze the data and distinguish between different types of fault behavior and normal operation as linear and nonlinear classifiers.

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