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# Tractor Engine Fault Detection System Based on Vibration and Acoustic Monitoring

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**Abstract:** A tractor gearbox test rig has been used to collect signals from different types of bearing faults. For vibration monitoring accelerometers have been used to obtain vibtation data. For fuel injectors a Bearing Checker has been used in order to collect acoustic data. Least squares support vector machines (LS-SVM) are used for detecting faults when exposed to actual data from the system representing a yet unknown state. Feature extraction was performed using seven features. The feature vectors are then fed to the LS-SVM for training. LS-SVM classification gave promising results (more than 95% correct classification). The fusion of features from both the vertical and the horizontal accelerometer resulted in more accurate separation of classes regarding fault position. In the case of the fuel injectors the feasibility of using one-class SVM has been tested in the detection of signal deviations indicating failure with high detection performance.

**Key words:** Vibration, condition monitoring, SVM, bearing, fuel injector.

## INTRODUCTION

The use of vibration signals is quite common in the field of condition monitoring of rotating machinery. By comparing the signals of a machine running in normal and faulty conditions, detection of faults like mass unbalance, rotor rub, shaft misalignment, gear failures and bearing defects is possible. These signals can also be used to detect the incipient failures of the machine components, through the on-line monitoring system, reducing the possibility of catastrophic damage and the down time. The procedure of fault diagnosis starts with data acquisition, followed by feature extraction, fault detection and identification. Feature extraction is critical for the success of the diagnostic procedure. Extended defects in the inner and outer races are common in rolling element bearings (see an example in Figure 1).

The use of vibration signals is quite common in the field of condition monitoring and fault diagnosis of bearings (Xu et al., 2009). To inspect raw vibration signals, a wide variety of techniques have been introduced that may be categorized into two main groups: classic signal processing (McFadden and Smith, 1984) and intelligent systems (Paya et al., 1997).

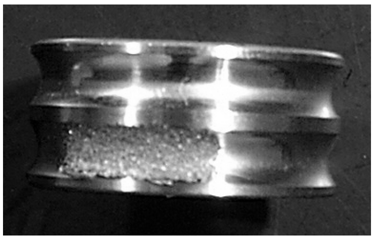

**Figure 1. Example of an extended fault in the inner race**

In the current work vibration monitoring is applied in the health condition monitoring and fault detection of two tractor components, the tractor gear box and the fuel injectors. An approach from artificial intelligence, Support vector machines (SVM) are used in the form of two different implementations. One approach uses Least Squares Support Vector Machines (LSSVM) for identifying bearing faults belonging to two different categories and discriminating them form healthy bearings. The other approach uses One Class SVM for detecting deviations in the acoustic response of fuel injectors associated with malfunction due to wear.

## MATERIALS and METHOD

### Gear box test platform data acquisition

A gearbox test rig has been used in order to collect signals from different types of bearing faults. A photograph of the rig showing the position of the accelerometers and the encoder at the output shaft is shown in Figure 2 (Sawalhi, 2007). Two types of faults (inner race and outer race crack) were tested under a 50 Nm load, while setting the output shaft speed to 10 Hz (600 rpm). Vibration signals were collected using two accelerometers positioned on the top of the gearbox casing above the defective bearing (vertical accelerometer) and sideways respectively (horizontal accelerometer). The 1.35 seconds (65536 samples) signals were sampled at 48 kHz. A photo-reflective switch was placed near the output shaft to measure its speed by providing a once per rev tacho signal. The torque for each case was measured at the input shaft.

### Fuel injector data acquisition

The Bearing Checker (manufactured by SPM Instrument) was used for the injector measurements. Normally, this instrument is used to measure the level of impulse during operation of the machine via an embedded microprocessor impulse analyzer samples from different bearings and record the operational status. The Bearing Checker has a 1.5 mm headphone jack as shown in. The computer's sound card has a corresponding audio input. So the wire with nail jack 1.5 mm was connecting the output of the Bearing Checker to the input of the computer sound card. In this the transfer of sound from the Bearing Checker to the computer. The registration and storage of sound was performed using the free program Audacity. The sound was saved in mp3 format with bit rate 128kbps. To control the audio recording earphones were used which were connected to a computer.

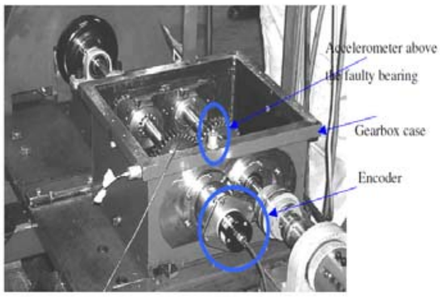


**Figure 2. The spur gear rig**

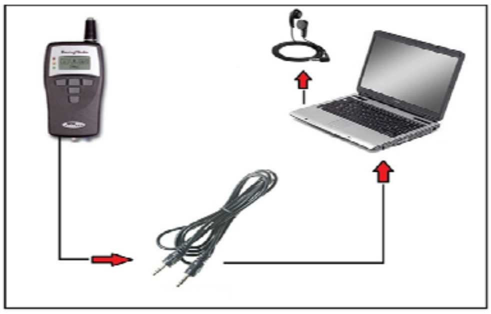

**Figure 3. Data acquisition setup for sounds emitted from malfunctioning injectors. The Bearing Checker (by SPM Instrument) is shown on the left.**

Data acquisition of injector sounds was performed on the injectors of a New Holland TN65N multipurpose tractor, three injectors controlled electronically, one healthy (injector1), one slightly damaged (injector2) and one audibly deviating from a healthy state (injector3).

Additionally, data acquisition of injector sounds was performed on the injectors of a Zetor 7711, used for viticulture, four injectors controlled mechanically, injectors4-5-6-7 all deviating from healthy state. All malfunctioning injectors needed cleaning to restore their functionality. Additionally, a newly installed injector8 was added for testing the developed techniques.

**Signal processing and feature determination acquisition**

To inspect raw vibration or sound signals, a wide variety of techniques have been introduced that may be categorized into two main groups: classic signal processing and intelligent systems. To make mention of a few, FFT, Wigner–Ville distribution, wavelets, blind source separation, statistical signal analysis, and their combinations are classic signal processing methods. Neural network based, genetic algorithm based, fuzzy logic based, various similar classifiers, expert systems, and hybrid algorithms can be classified as intelligent systems. Feature extraction was performed using seven features. The first six features were introduced in (Lei et al., 2009): Kurtosis, Skewness, Crest, Clearance, Shape and Impulse Indicators. A newly proposed feature consisting of the line integral of the acceleration or the sound signal is introduced in this work. All the used features provide statistical information about the nature of data, and were found to be reasonably good features for bearing fault detection. The Kurtosis is the fourth moment about the mean normalized with variance and for N points is given by Eq. 1. All other features are given from Eqs. 2-6.

$$Kurtosis = \frac{\sum_{i=1}^{N}(x_i - \mu_X)^4}{N\sigma_X^4} \qquad (1)$$

$$Skewness = \frac{\sum_{i=1}^{N}(x_i - \mu_X)^3}{N\sigma_X^3} \qquad (2)$$

$$Crest\ Indicator = \frac{\max|x_i|}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}} \qquad (3)$$

$$Clearance\ Indicator = \frac{\max|x_i|}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{|x_i|}\right)^2} \qquad (4)$$

$$Shape\ Indicator = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2}}{\frac{1}{N}\sum_{i=1}^{N}|x_i|} \qquad (5)$$

$$Impulse\ Indicator = \frac{\max|x_i|}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}|x_i|}} \qquad (6)$$

In Eqs. 1-6 $\mu_X$ and $\sigma_X$ refer to mean value and standard deviation. The new line integral feature for *N* sampling points is given by Eq. 7:

$$\begin{aligned} LI &= \int_a^b ds \approx \sum_{i=1}^{N}\left\|\vec{r}(t_i + T_s) - \vec{r}(t_i)\right\| \\ &= \sum_{i=1}^{N}\sqrt{\left(x(t_i + T_s) - x(t_i)\right)^2 + T_s^2} \\ &\approx \sum_{i=1}^{N}\left|x(t_i + T_s) - x(t_i)\right| \end{aligned} \qquad (7)$$

where *N* is the number of sample points (equal to 500) in the window used to calculate Kurtosis and the other features and the newly proposed line integral feature and $T_s$ is the sampling period. The presented features were used for both the case of vibration signals from the gearbox test rig and the sounds collected from the injectors.

**Support vector machines**

SVMs (Vapnik, 1998) correspond to a relatively new computational intelligence technique, related to the machine learning concept. SVMs are used in pattern recognition as well as in regression estimation and linear operator inversion. In contrast to many classical neural network training algorithms which exhibit many local minima, SVMs are always able to find a global minimum and they have a simple geometric interpretation. More specifically, in order to estimate a classification function such as:

$$f : \mathbf{x} \to \{\pm 1\} \qquad (8)$$

The most important is to select an estimate $f$ from a well restricted so-called *capacity* of the learning machine. Small capacities may not be sufficient to approximate complex functions, while large capacities may fail to generalize, which is the effect of what is called "overfitting".

In the case of support vector machines, regularization is used to avoid overfitting. However, overfitting in SVMs is limited according to the statistical theory of learning from small samples (Vapnik, 1998). The simpler decision functions are the linear functions. In case of SVM, the implementation of linear functions corresponds to finding a large margin separating of separation between two classes. This margin corresponds to the minimum distance of the training data points to the separating surface. The procedure that is followed in order to find the maximum margin of separation is formulated as a convex quadratic problem (Vapnik, 1999). An additional parameter enables the SVM to misclassify some outlying training data in exchange for obtaining a larger margin between the rest of the training data, without however affecting the optimization of the quadratic problem. The input data are projected into a feature space $F$ using a map such as:

$$\phi : \mathbf{x} \rightarrow F \qquad (9)$$

Then a linear learning machine can be extended to a non-linear one. In SVMs the latter procedure is applied implicitly. What has to be supplied is a dot product of pairs of data points $\phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j) \in F$ in the feature space. Thus, in order to compute these dot products, one has to supply the kernel functions that define the feature space via:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \phi(\mathbf{x}_i) \cdot \phi(\mathbf{x}_j) \qquad (10)$$

It is not necessary to know the mapping $\phi$ since it is performed implicitly. SVMs can also learn which of the features implied by the kernel are distinctive for the two classes. The selection of an appropriate kernel function may boost the learning process.

### Least Squares Support vector machines

LSSVM (Suykens and Vandewalle, 1999) builds a similar classification model as the SVM based on the function in Eq. 8 which uses basis functions $\varphi$.

The following model is taken:

$$f(\mathbf{x}) = w^T \varphi(x) + b$$

$$\min_{w,b} J(w,b) = \frac{\mu}{2} w^T w + \frac{\zeta}{2} \sum_{i=1}^{N} e_i^2, \qquad (11)$$

S.T. $y_i[w^T \varphi(x_i) + b] = 1 - e_i$

$i = 1, \ldots, N$

with regularizer $\gamma = \zeta / \mu$.

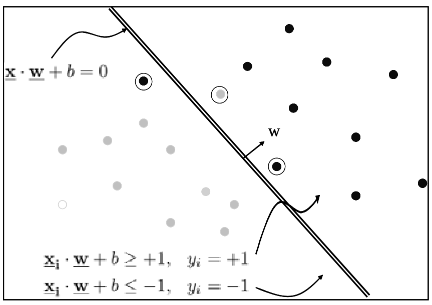


**Figure 4. Interpretation of the LSSVM classifier**

Instead of inequality it is subject to equality constraints which lead to a formulation of Langrange multipliers. The support vectors can then be found by solving a linear system:

$$\begin{bmatrix} 0 & 1_v^T \\ 1_v & \Omega + \gamma^{-1} I_N \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \qquad (12)$$

$Y = [y_1, \ldots, y_N]^T, 1_v = [1, \ldots, 1]^T, e = [e_1, \ldots, e_N]^T,$

$\alpha = [\alpha_1, \ldots, \alpha_N]^T, \Omega_{ij} = \varphi(x_i)^T \varphi(x_j) = K(x_i, x_j)$

e.g. RBF kernel: $K(\mathbf{x}, \mathbf{z}) = \exp\{-\|\mathbf{x} - \mathbf{z}\|^2 / \sigma^2\}$

Resulting in the classifier:

$$y(x) = sign[\sum_{i=1}^{N} \alpha_i y_i K(x, x_i) + b] \qquad (13)$$

This approach simplifies SVM due to linear system formulation can be solved efficiently with numerical methods. This implementation has been used for bearing fault classification in the current work.

### One Class Support vector machine

In the case of the injectors there is no unique description of the faults but there are available a number of injectors that are either new or in different stages of malfunctioning behaviour which can not be quantified exactly. Therefore, contrary to the approach followed for the bearings where there are three classes clearly defined, in the case of backs only the healthy new injectors were used as target classification class and subsequently one-class classification methods were preferred.

One-class classification has the following characteristics:

- Only information of target class (not outlier class) are available;
- Boundary between the two classes has to be estimated from data of only genuine class;
- Task: to define a boundary around the target class (to accept as much of the target objects as possible, to minimize the chance of accepting outlier objects).

As shown if Figure 5, given a target domain $X_T$ there are two errors that can be defined $E_I$ related to false rejected target objects and $E_{II}$ related to false accepted outlier objects. The circular area corresponds to the rough description of the target domain by the selected one class classifier.

Using a uniform outlier distribution also means that when $E_{II}$ is minimized, the data description with minimal volume is obtained. So instead of minimizing both $E_I$ and $E_{II}$, a combination of $E_I$ and the volume of the description can be minimized to obtain a good data description.

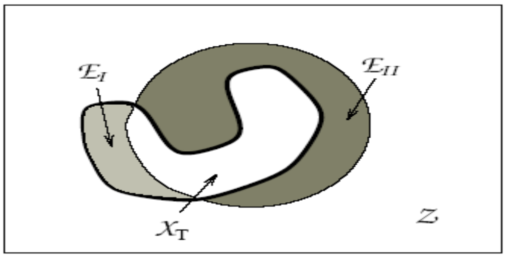


**Figure 5. Domains of target dataset and one-class classifier**

The one-class SVM (OCSVM) builds a model from training on normal data and then classifies test data as either normal or outlier based on its geometrical deviation from the normal training data (Scholkopf et al., 2001). The effect of the spreading parameter of the RBF in $K(\mathbf{x},\mathbf{z}) = \exp\{-\|\mathbf{x}-\mathbf{z}\|^2 / \sigma^2\}$ can be interpreted based on the fact that a large spread denotes a rather linear class of target data while a large number of support vectors and a small spread denotes a highly nonlinear case.

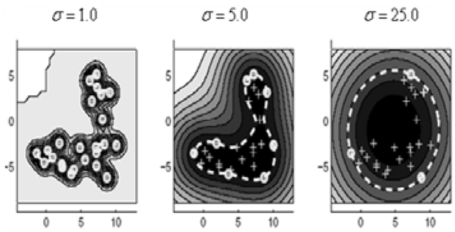


**Figure 6. The effect of the spreading parameter of the RBF in the one class SVM behaviour**

## RESULTS and DISCUSSION

For the bearing fault recognition an LSSVM was used. A validation set was used to test the generalisation performance of the LSSVM. To test the effectiveness of LSSVM, the 75% have been used for training while the 25% have been used in order to test the generalisation of the LSSVM. The implementation used the LS-SVMlab Matlab toolbox (Pelckmans et al., 2002). The method that has been used for obtaining the multiclass LSSVM classifier was the "one-versus-one" which relies on building a set of one versus one classifiers and choosing the class that is selected by the most classifiers. Seven features of the same type from each accelerometer were used. The same order has been used for the horizontal accelerometer in order to build the fusion vector. The fusion (by direct concatenation) of 14 vibration features from both the vertical and the horizontal accelerometer, due to their complementary nature, results in more accurate separation of classes regarding fault position as one can deduce from the results presented in Table 1. The complementarity of features was expected because the vibration modes were measured in two orthogonal directions (vertical and horizontal) which carry projections of the vibration shapes on these independent axes.

**Table 1. Results of LSSVM based classification of bearing faults**

| Real | | Estimated percentage | | |
|---|---|---|---|---|
| | | Healthy | Inner race fault | Outer race fault |
| | Vertical | | | |
| Healthy | | 99.61 | 0.00 | 0.39 |
| Inner race fault | | 0 | 96.08 | 3.92 |
| Outer race fault | | 0.39 | 0.39 | 99.22 |
| | Horizontal | | | |
| Healthy | | 90.59 | 9.41 | 0.00 |
| Inner race fault | | 9.02 | 90.59 | 0.39 |
| Outer race fault | | 0.78 | 0.00 | 99.22 |
| | Fusion | | | |
| Healthy | | 100.00 | 0.00 | 0.00 |
| Inner race fault | | 0.00 | 100.00 | 0.00 |
| Outer race fault | | 0.00 | 0.00 | 100.00 |

The OCSVM was used to classify the injectors to a target class corresponding to healthy injectors and detect outliers indicating injectors that are malfunctioning. As target class, features belonging to injector1 have been used. All other injectors have been used for testing the performance of the OCSVM. The OCSVM was calibrated by splitting the data to 75% training and 25% testing sets has resulted in 99.82% correct classification for the target class of injector1 and 100% when using injector7 as outlier class for testing. These were results for a spread parameter of 1.97 which gave the best reslts by testing different spreads between 0 and 10. Further testing of the obtained OCSVM classifier was performed using all available injectors. Results are shown in Table 2. It is evident that all injectors have been identified correctly based on their respective condition. The slightly damaged second injector has also been identified as midway to damage which is accurate according to the expert opinion based on the sound emission from that injector.

**Table 2. Results of OCSVM based classification of injector condition**

| Injector no. # | Actual condition | OCSVM classifies as healthy (percentage) | OCSVM classifies as outlier |
|---|---|---|---|
| 1 | Healthy | 99.74 | 0.26 |
| 2 | Slight damage | 48.95 | 51.05 |
| 3 | Damaged | 1.32 | 98.68 |
| 4 | Damaged | 8.16 | 91.84 |
| 5 | Damaged | 10.09 | 89.91 |
| 6 | Damaged | 2.63 | 97.37 |
| 7 | Damaged | 1.75 | 98.25 |
| 8 | Healthy | 96.75 | 3.25 |

## CONCLUSIONS

It has been shown that the LSSVM can perform data fusion from accelerometer sensors through combining vibration features. These features can be used to detect faults in roller bearings and discover the position of the faults, and can therefore prove to be a powerful tool for bearing health monitoring. Different bearing faults can be detected with high accuracy by using the collective response of several features and the fusion of different sensors, which may not be obvious by just looking at the data using other diagnostic techniques. The use of several features and a newly introduced feature, the line integral of the acceleration signal has given promising results in detecting the position of bearing faults. The feature based fusion of the vertical and horizontal accelerometer signals has increased the accuracy of fault detection to 100% for different fault types. This result represented a substantial increase in discrimination performance of at least 10% for certain types of fault. In the case of injector malfunctioning detection, the same set of features has been used.

Due to the nature of the problem, relying only on acoustic signatures from healthy injectors, one-class classification has been used. An one-class SVM has been used and has given very promising results. Further it was possible to detect correctly the condition of all the injectors that were presented to the one-class SVM. This result indicates that OCSVM is a robust classifier and can be used for detecting injector malfunction with high confidence. It is planned that this work be extended to include more real data, different features and fault types for bearings and gear boxes and also different types of injectors.

## ACKNOWLEDGEMENTS

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