Review report

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Overview

This report is organized so that a quick overview of some relevant work can be obtained be reading the “Executive summary”. The following sections contain more specific discussions of methods and individual resumes of the relevant sources.

Contents

1 Executive summary

The reviewed articles show that acoustic emission and machine learning is a powerful combination in condition monitoring of machinery.
The systems in general consist of preprocessing followed by machine learning. Furthermore everybody seems to use the same methods: PCA for feature extraction, followed by neural network classifiers (sometimes layered, or combined into ensembles.)

Fog [1998] and Ypma [2001] describe numerous ways to extract features, and how to build and train pattern recognizer's with good generalization. This include simple regularizationschemes, complicated resampling methods as bootstrapping, and adaptive structures.

Another way to increase generalization is ensembling. Sharkey et al. [2000] creates an ensemble by combining neural networks into a majority voting system. Even though their ensembles are created by random combination, the general idea is to combine precise *and* diverse neural networks in a controlled way. Diversity can be obtained by (a) using information from different types of sensors and (b) reusing the data to create neural networks that differ in various ways: bagging, boosting, resampling, etc. Precision can be obtained by applying regularization etc.

Neill et al. [1998] show that AE is superior to pressure- and vibrationinformation wrt. signal to noise ratio, and that the AE is sufficient in a more realistic industriallike setting. This has also been reported by Fog et al. [1999]. We note that experiments where AE has been omitted, have been constrained to laboratory like settings.

It is not clear whether a conventional PC is able to record raw AE data for a longer period. It depends on the true bandwidth of the observed signal, as it is likely to exceed to transfer limits of a harddrive — this also determins wheter realtime processing is possible on a PC.

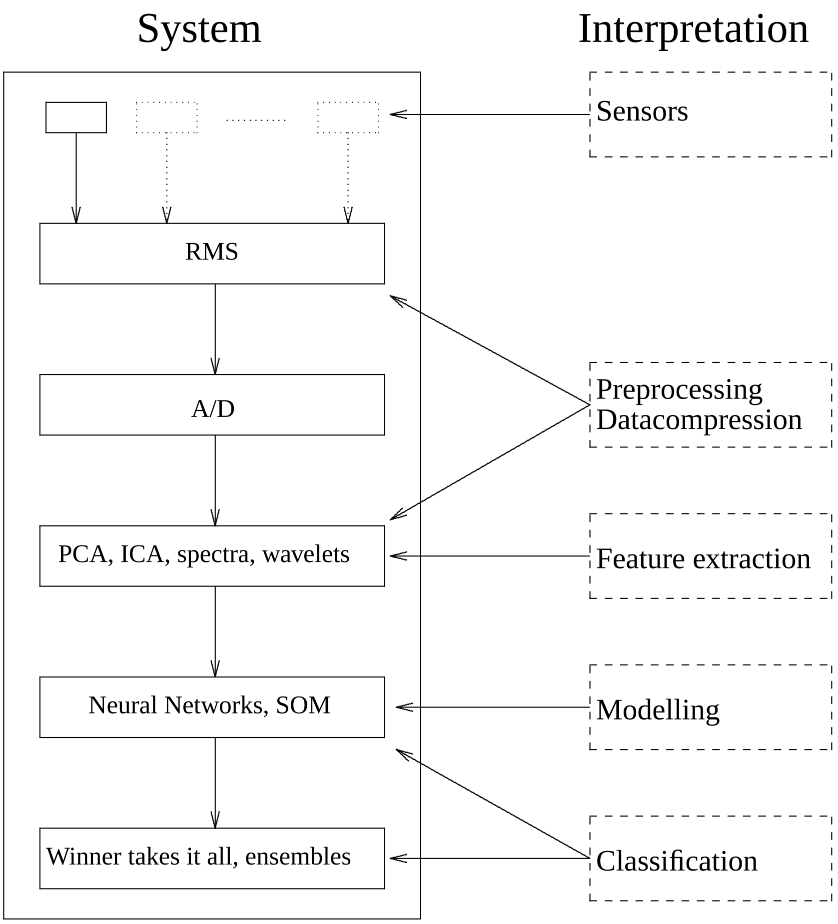

Figure 1: Overview and interpretation of a general AE-classification system

2 Methods

Figure 1 show how we interpret the parts of a general AE-clasification system. The discussed methods are grouped and compared according to this figure.

2.1 Analogue data acquisition

Acoustic Emission as well as vibration can be measured by mounting repectively PZT-transducers and accelerometers on the surface of the machinery. Both measurements are obtained non-intrusive. The pressure (and also temperature) can only be measured inside the machine. AE can also be derived from accurate measures of the distance between source, object and reciver using laser and and advanced optics (an inferometer).

The AE signals are ultrasonics (appr. range 50 kHz. -10 MHz.). Some AE signals have a more concentrated spectrum, for instance Chandroth and Sharkey [1999] find that their data can be sampled at 2 MHz., where Reuben [1998] state that 10 MHz. is necessary. The implication of this is that only some AE signals can be recorded and processed using a PC. The frequencyrange of AE is also important, as tells whether a narrow band - high sensitive or broad band - lower sensitivity PZT-transducer is most appropiate.

2.2 Feature extraction

Feature extraction is motivated by the idea that the classificationalgorithms can be more efficient if it is presented with relevant features instead of raw data. In many cases it is a matter af necessity since the amount of raw data is enormous — for instance with AE.

The raw AE can be compressed by applying "Root Mean Square" (RMS), done by Fog et al. [1999], Fog [1998], Neill et al. [1998], where its applied prior to AD-conversion. The chosen time-constant should be chosen so that important features are preserved and so that the AD-converter is capable of the new datarate.

Given a set of timeseries we can try to find a preferably sparse basis that express most of the data. Principal Component Analysis (PCA) is a way to obtain such a basis. Given a "sufficient" set of timeseries, PCA can propose a basis that is optimal for this system — as opposed to Short Time Fourier Transformation (STFT) and wavelets where the basisfunctions are defined in advance. Given the basisfunctions PCA and time-frequency analysis works in the same way, as the new data is transformed into coefficients corresponding to the basisfunctions.

2.3 Modelling and classification

Self organized maps (SOM) and unsupervised NN's rely on the ability to correctly group and separate equivalent and differing states. The learning phase needs to include sufficient variants of the states that we want to classify.

The experiments with Neural Networks (NN) by Chandroth et al. [1999a,b], Fog et al. [1999], Neill et al. [1998], and Sharkey et al. [2000] have been *supervised*, i.e. based on training with known labels. These labels can "only" be produced by an expert; which is not all ways a feasible task.

The states presented to the algorithms during the learningprocedure (called the training set) is a sampling in the true distribution of states, hence it doesn't tell everything. If the model adapts very good to the training set it is also likely to adapt very good to the observed noise, meaning that the ability to generalize decrease — this is called overfit. Overfit is normally reduced by constraining the learningprocess so that it cannot adapt fully to the training set. The can be done by resampling (bootstrapping), regularization (weight decay), or optimization of architecture (pruning).

Generalization can also be achieved by combining networks in ensembles. Sharkey et al. [2000] have tried to generate ensembles that differ by either

- Combining networks based on different sensors
- Randomizing the initial conditions (useful when you only have a limited number of examples)
- Varying the architecture (pruning)
- Exposing the different networks to different examples (resampling)

Ensembles is not bound to work — for instance an ensemble of "experts" at our department predicted that France would win the football world cup this year.

3 Resumes

3.1 On Condition Monitoring of Exhaust Valves in Marine Diesel Engines (Fog et al. [1999])

The paper show that acoustic emission (AE) data is superior to pressure, vibration and temperature-data, leading to improved classification.

The paper also addresses the fact that the AE-data obtained from the outside of the combustionchamber, i.e. the method is non-intrusive.

The AE-data is preprocessed with PCA.

The obtained subspace, consisting of the selected principal components, is fed into either neural networks or linear discriminators.

The Neural Networks are optimized aiming at improved generalization by Optimal Braindamage (OBD) pruning.

3.2 Condition Monitoring And Fault Diagnosis in Marine Diesel Engines (Fog [1998])

Methods used and briefly discussed in other papers is more deeply discussed here. These extended discussions is on how to select the number of components in PCA, and how to train and evaluate and optimize the performance of Neural Networks.

3.3 The Role of Acoustic Emission in Industrial Condition Monitoring (Reuben [1998])

As stated in the abstract "This paper offers a review of the role of acoustic emission in engineering condition monitoring".

First the fundamental sources that generate AE is listed: cracking, constricted flow, and surface impacts; these as well as the secondary sources: cavitation, wear, friction, and corrosion can all be related to some "degenerating" events.

It is also pointed out that the stress waves contain insufficient power to make significant measures away from the body.

Yielding there is a relatively small amount of noise from other sources in the ultrasonic frequencies, since "background noise" from other machinery is damped.

Most commercial AE transducers is based on peizoelectric elements (just as some condensermicrophones), that divided into two types, a) narrow band, high sensitivity, or b) broad band, low(er) sensitivity.

The type, size and shape of the peizoelectric element influence the bandwidth and sensitivity.

Another type of transducers is peizopolymer films that relatively inexpensive, and it is easy to produce arrays of sensors.

Laseroptics can also be used to measure AE, which has been done using the "Sagnac interferometer".

The datarate of the raw AE is around 10 MHz, which (at the writing point) cannot be written continuously to a hard disc. Off-line applications can obtain the raw AE-data using an analogue videotape.

A common workaround for realtime applications (used by Fog et al. [1999] and Neill et al. [1998]) is to apply analogue averaging (i.e. RMS) before processing/recording.

Detection of fatigue cracks using AE may involve source locating techniques that not only reveal the defect, but also reject noise from insignificant sources.

3.4 The relative merits of acoustic emission and acceleration monitoring for detection of bearing faults (Neill et al. [1998])

This paper show that AE measurements are superior to acceleration measures wrt. sensitivity and noise ratio.

The result is obtained by inducing errors into bearings, and measuring the AE and the acceleration in two environments.

Moreover the results is compared to theoretical findings obtained by calculating "defect frequencies".

It is also marked that "AE seems to be more sensitive to small defects and less sensitive to contamination by periodic or aperiodic ambient noise."

3.5 Utilising the rotational motion of machinery in a high resolution data acquisition system (Chandroth and Sharkey [1999])

This paper describe a system that obtain AE, pressure-, and vibrationdata, as well as crank angle from rotating machinery.

Obtained data

The datasampling is triggered independently by time and crank angle (two datasets obtained).

The events in a combustionprocess happen at specific "angular" positions,

that for instance locate the combustionzone independently of rotational speed. The data obtained with the system is used in Chandroth et al. [1999a,b], Sharkey et al. [2000].

Datatype	Samplerate (Time)	Samplerate (Angle)
Vibration	50 kHZ	10 degrees^{-1}
Pressure	no data	10 degrees^{-1}
Acoustic Emission	2 MHz	10 degrees^{-1}

3.6 Cylinder Pressures and Vibration in Internal Combustion Engine Condition Monitoring (Chandroth et al. [1999a])

In this paper datafusion and decision fusion is used classify engine condition.

Two sensors are used (a) *pressure sensor* and (b) *vibration sensor*.

The data from the AE-sensors are not used and discussed. The aim is to use as few sensors as possible.

Various ways of datafusion (e.g. summing, multiplying, interleaving) is discussed, ending up with fusing pressure and vibration by summing.

Decision fusion is done by training 3 independent neural networks, one net using pressuredata,

one using vibrationdata and the last using the fused (summed) pressure- and vibrationdata.

The three nets are combined into a majority voting system which outperforms all of the individual nets.

Experimental setup

The data is crank anlge labbeled collected as described in Chandroth and Sharkey [1999] and consist of five classes.

Based on the crank angle only data from 180^o to 200^o is used (TDC + 20^o, i.e. where the combustion takes place).

The 200 datapoints from this angle area is by subsampling reduced to 50 points.

Operating conditions: The 4 defect conditions (E, I, B, and L) is constructed by inducing artifical errors in the machinery.

N Normal condition

E Leaking exhaust valve

I Leaking air inlet valve

B Blocked fuel injector (1 out of 4 holes)

L Poor fuel atomisation

Dataset: The examples are obtained after an initial period of running-in, and consist of 12000 examples of pressure- and vibrationdata. The examples are divided into three parts:

a trainingset with 7500 examples.

a testset with 3000 examples.

a validationset with 1500 examples.

3.7 Vibration signatures, wavelets and principal components analysis in diesel engine diagnostics (Chandroth et al. [1999b])

This paper focus on what we label as *preprocessing* or *feature extraction*: wavelets, PCA and "Domain expertise".

The data are the same as in Chandroth et al. [1999a], and again the AE-sensor data is not used.

The waveletsection (2) is confusing due to the unpleasant fact,

that all references to tables and figures is missing (in the form: *shown in figure* ??).

The domain expertise is as in Chandroth et al. [1999a], using only the data from the combustionzone (180^o to 200^o).

The finding of this paper is that the wavelet preprocessing performs best,

but that the *Majority voting system* performs best when all three preprocessors train a net.

A *Majority voting system* is briefly explained, but that aspect is further discussed in Sharkey et al. [2000].

3.8 The "test and select" approach to ensemble combination(Sharkey et al. [2000])

In this paper the pressure, vibrationdata as well as the fused pressure and vibrationdata is fed into different neural networks.

In contrast to Chandroth et al. [1999a,b] the datafusion is done by appending the data, so that the pressure- and vibrationdata consist of 50 samples and the fused data consist of 100 samples. Also the dataset is split into 4 parts, as individual testsets are needed for the network- and ensemble-testing.

The outputs of these networks are combined to perform decision fusion, i.e. just like in Chandroth et al. [1999a].

The ensemble creation consist of two layers of "ensembling", the sensorlayer and the networklayer, that gives two parameters: *datatype* and *networktype* that be paired to generate different networks.

- Datatype
  - Pressure
  - Vibration
  - Fused pressure and vibration

- Networktype

    - Randomized initial conditions

    - Architecture (# of hidden units)

    - Bootstrapping

Each pair of parameters is used to train 5 networks, giving a total of 45 networks.

The optimal ensemble is found by creating 100 random combinations of the 45 nets.

Three types of constraint is tested:

- None
- One from each datatype
- All from same datatype

The best ensemble comes from the unconstrained pool and consist of two "fused-network" and one pressurenetwork.

The contribution of this paper is that different combinations of networks is explored, so that an optimal combination can be found.

The ensembles are created by performance, and the authors find and claim that such ensembles perform better wrt. generalization than ensembles constructed by following "archtechtural" rules.

3.9 Learning methods for machine vibration analysis and health monitoring (Ypma [2001])

This PhD-thesis describe several methods for feature extraction and machine learning.

The described methods for feature extraction is classical windowed Fourier analysis (and wavelets), several parametric methods, and PCA.

Also several learning paradigms is discussed, including experiments and discussions on Hidden Markov Models, Neural Networks, and Self Organized Maps.

4 Groups

Figure 2 outline some groups that have published relevent work on health monitoring and AE. It is not intended to be complete (yet), but to give a quick overview of what we have taken into account. The connected groups have published articles together.

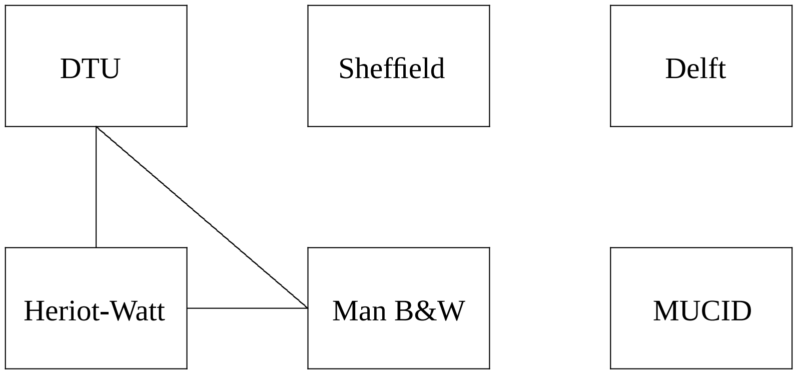

Figure 2: Some groups that work with health monitoring and AE

MUCID - MULTIUNIVERSITY CENTER FOR INTEGRATED DIAGNOSTICS, *consist of Georgia Institute of Technology, Northwestern University, and University of Minnesota.*

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