McMaster University

CMHT CENTRE FOR MECHATRONICS AND HYBRID TECHNOLOGIES

EECO MOBILITY

Case Study: Advanced Fault Diagnosis and Detection (FDD)of Spark Plugs

Centre for Mechatronics & Hybrid Technologies

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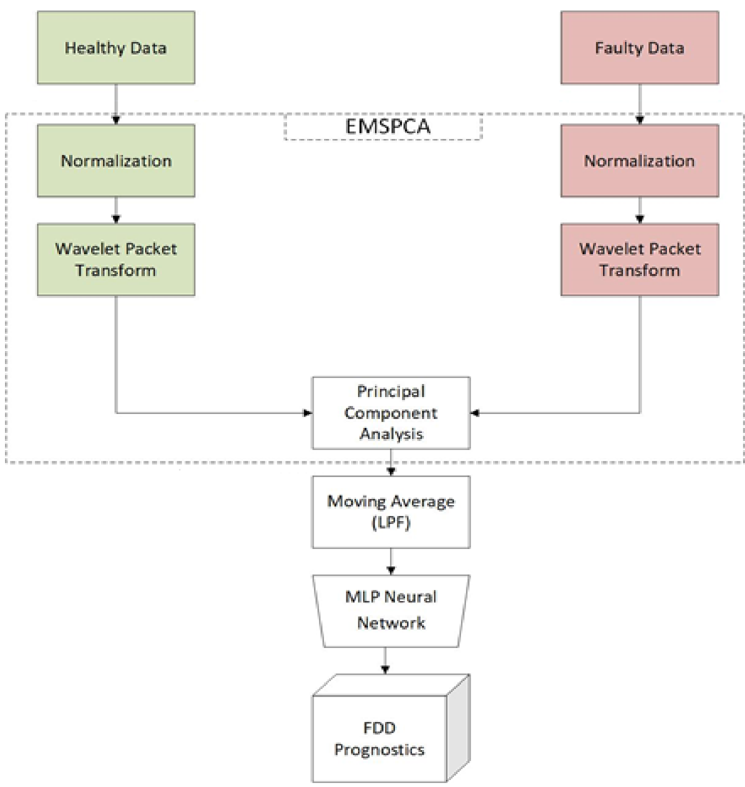
1. Overview

Condition monitoring and fault detection and diagnosis (FDD) tools play an important role in detecting conditions that would affect the operability of the engine. In this software, different signal based FDD techniques are implemented for fault condition monitoring of internal combustion engines (ICE). The implementation of diagnostics for the engine in an automated form has important consequences that include cost savings, higher reliability and reduction of GHG emissions.

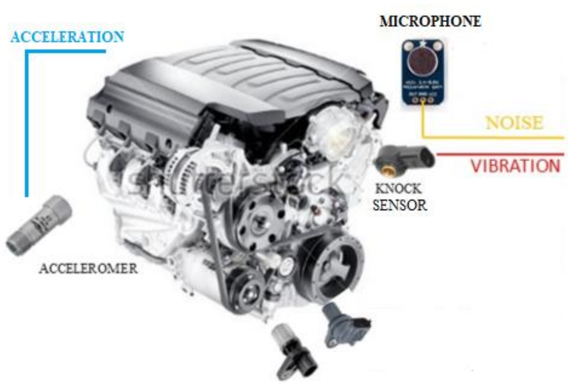
This software includes advanced FDD strategies which combines Fourier Transforms (FT), Wavelet Packet Transforms (WPT), Principal Component Analysis (PCA) and Neural Network (NN). The proposed FDD software was able to achieve 100% accuracy in classifying a set of engine faults. This document contains a description of the FDD strategies implemented in this software along with corresponding MATLAB codes. It consists of 3 main steps as follows: *Data Acquisition, Extra Multi-Scale Principle Component Analysis (EMSPCA) and Classification.*

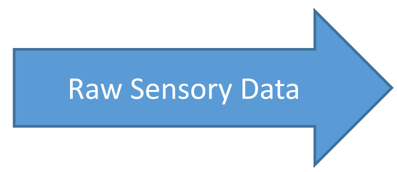


FDD Block Diagram

2. *Data Acquisition*

While the test engine is running, the raw data is collected through different sensors around the engine. Four knock sensors measure vibrations, two accelerometers measure acceleration, a microphone measures noise, a pressure transducer measures pressure and a speed sensor measures the crankshaft speed.





For each crank angle, 10 samples are collected. The sampling rate varies based on the engine speed as follows:

$$Sampling\ Rate = \frac{N.\ of\ Samples}{Crank\ Angle}\ X\ \frac{N.\ of\ Crank\ Angles\ per\ Revolution}{N.\ of\ Revolutions}\ X\ \frac{N.\ of\ Revolutions}{Minute}$$

- ***Example:***

If the engine is running at a constant speed of 3500 rpm, the sampling rate will be:

$$Sampling\ Rate = \frac{10\ \text{samples}}{1\ \cancel{CA}}\ \text{X}\ \frac{360\ \cancel{\text{CA}}}{1\ \cancel{rev}}\ \text{X}\ \frac{3500\ \cancel{\text{rev}}}{\cancel{1\ min}}\ \text{X}\ \frac{\cancel{1\ \text{min}}}{60\ sec} = \frac{360\ \text{x}\ 10\ \text{x}\ 3500\ \text{samples}}{60\ sec} = 210\ \text{KHZ}$$

a. Data Dictionary

Column	**Sensor**
UNI	Right Front knock sensor
UNI_A	Left Front knock sensor
UNI_B	Right Rear knock sensor
UNI_C	Left Rear knock sensor
UNI_D	Microphone
UNI_E	Accelerometer 1 (Perpendicular)
UNI_F	Accelerometer 2 (Parallel)

b. Data Sample

The following table represents a data sample of the different sensors mentioned above:

	A	B	C	D	E	F	G	H	I	J
1	Cycle number	Crank angle	SPEED_HIRES	UNI	UNI_A	UNI_B	UNI_C	UNI_D	UNI_E	UNI_F
2	[-]	Crank angle [°CA]	Speed [1/s]	Voltage [V]	Voltage [V]	Voltage [V]	Voltage [V]	Voltage [V]	Voltage [V]	Voltage [V]
3	1	-360		0.2482646	0.2540233	0.25402335	-0.2412296	-0.1046459	0.633607	-0.1587432
4		-359.9		0.3979922	0.2712996	0.40375097	-0.2585058	-0.1141712	0.9889144	0.0665019
5		-359.8		0.3634397	0.2309883	0.36343969	-0.2181946	-0.1258132	0.91222179	-0.0068288
6		-359.7		0.2482646	0.3173696	0.24826459	-0.3045759	-0.1422179	0.86389494	-0.1528599
7		-359.6		-0.039673	0.3346459	-0.0396732	-0.3160934	-0.1541245	1.02421401	-0.0919261
8		-359.5	58.85122411	-0.246988	0.2885759	-0.2469883	-0.2815409	-0.164179	1.05131907	-0.0595681
9		-359.4		-0.258506	0.2943346	-0.2585058	-0.2872996	-0.1692062	1.12485992	0.0150233
10		-359.3		-0.212436	0.1618833	-0.2124358	-0.1490895	-0.1689416	1.22529572	0.0240584
11		-359.2		0.0351907	0.2194708	0.03519066	-0.2009183	-0.1668249	1.17318677	-0.1167198
12		-359.1		0.2885759	0.3404047	0.28281712	-0.3218521	-0.1623268	1.1698249	-0.1473969
13		-359		0.3691984	0.3000934	0.36919844	-0.2872996	-0.158358	1.11687549	-0.1202918
14		-358.9		0.2770584	0.3864747	0.28281712	-0.3736809	-0.1543891	0.8897393	-0.334821
15		-358.8		0.2079533	0.6225837	0.20795331	-0.6155486	-0.1501556	0.7365642	-0.412144
16		-358.7		0.2079533	0.77807	0.20795331	-0.7652763	-0.146716	0.79350584	-0.2030778
17		-358.6		0.3691984	0.9220389	0.3749572	-0.9092451	-0.1459222	0.86284436	-0.3192724
18		-358.5	58.66478939	0.6628949	0.8990039	0.65713619	-0.8862101	-0.1498911	0.75547471	-0.5304397
19		-358.4		0.8068638	0.6513774	0.80110506	-0.6328249	-0.1546537	0.69958366	-0.3018327
20		-358.3		1.060249	0.403751	1.06024903	-0.3909572	-0.1607393	0.86599611	-0.0045175

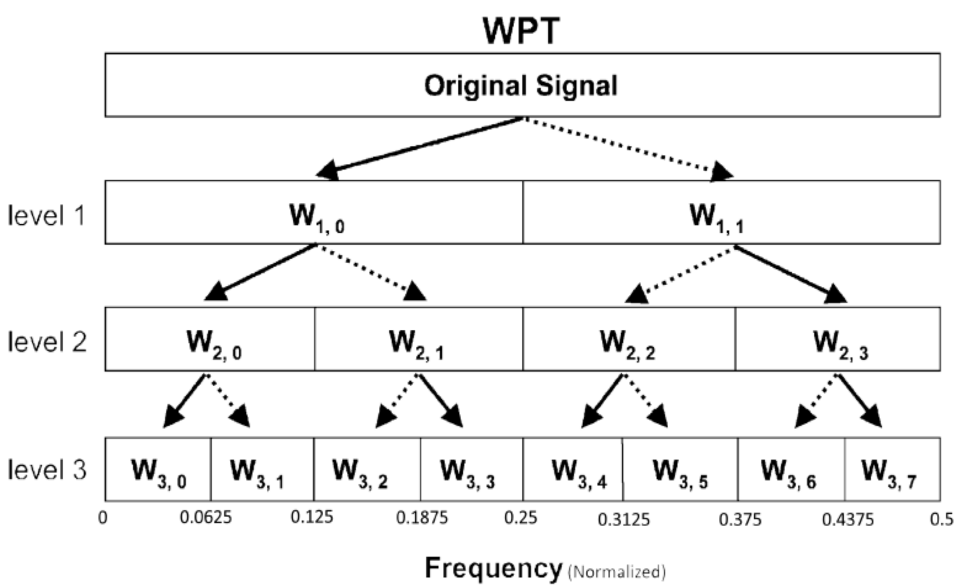
3. *Extra Multi-Scale Principle Component Analysis (EMSPCA)*

a) ***Input***

Raw sensory data from (i).

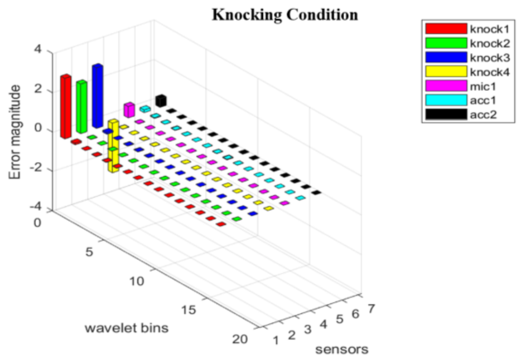
b) ***Model Description***

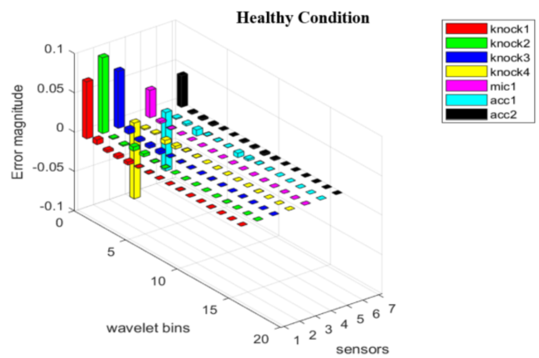
The EMSPCA model is in charge of extracting features from the engine data. It normalizes raw sensory data of both healthy and faulty samples and transforms them to the frequency domain. Discrete Wavelet Transform (DWT) is used to highlight high frequency contents while Wavelet Packet Transform (WPT) is used to break down the frequency spectrum equally. Each level of wavelets splits the previous signal equally into smaller portions. The same process is implemented on the healthy base sample as well as all the train and test samples. The number of levels can be adjusted by the user depending on the desired deepness of the analysis.



c) Output

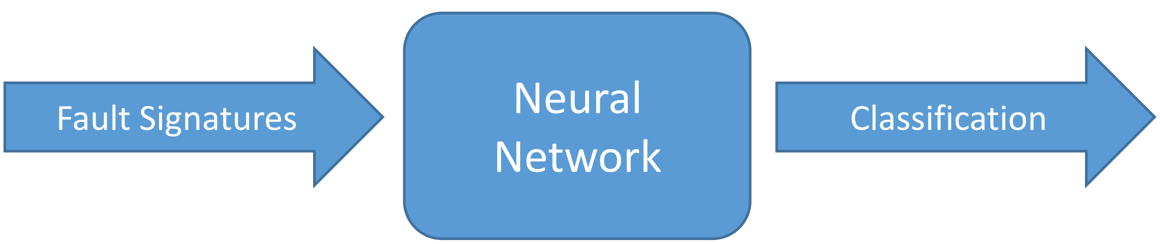
The EMSPCA model generates fault signatures which represent 8 different classes (7 faults and a healthy condition). Figure (a) shows an example of a knocking condition fault signature while (b) shows an example of a healthy condition signature.





(a) Knocking Condition ***(b) Healthy Condition***

4. Classification



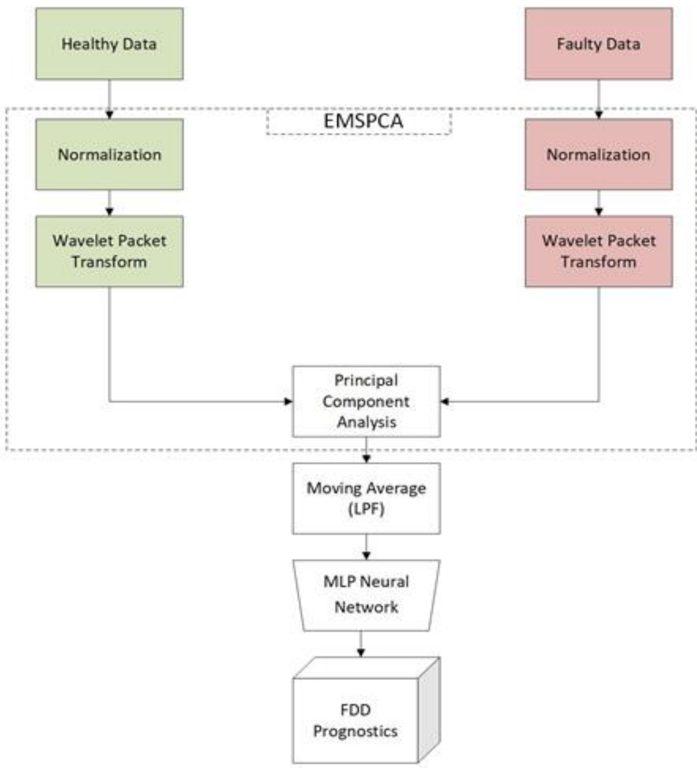
a) <u>Input</u>

Fault Signatures representing 8 different classes (7 faults and a healthy condition) from section (2).

b) <u>Model Description</u>

The final step in the EMSPCA technique is to use the obtained F_c coefficients (a.k.a. Fault signatures) to give an intuitive output from the algorithm. For this purpose, a multi-layer perceptron neural network dynamic classifier is applied along with three training algorithms: LM, SVSF, and EKF.

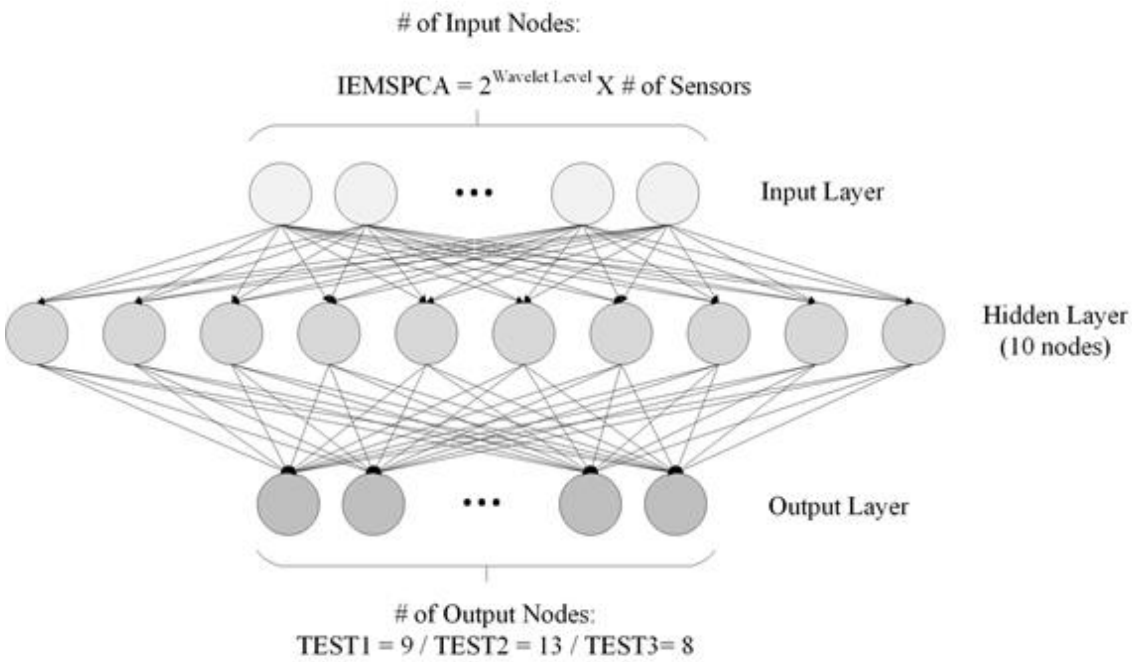
To improve both the training speed, and the classification performance of the network, an additional moving average window is applied to the results obtained from EMSPCA. Averaging the features is applicable as they are derived from the same engine cycle. With that, the following block diagram summarizes the processing steps that make up the EMSPCA FDD technique.



FDD Block Diagram

c) Output

The classifier can be trained using an extensive dataset of labelled faults, such as misfire, knocking, and pre-ignition. By comparing the new measurement to the trained database, the neural network labels the fault in the new measurement based on its signatures which correlate with the past trainings. The output is the class (a.k.a. health condition: Healthy/ type of fault) of the test sample.



5. *How to use the FDD software*

1. Extract a copy of the "FDD Software" folder to your local computer.
2. If this is your first time using the FDD software on your computer: Open your Matlab, go to Home > Set Path > **Add with Subfolders** > navigate to the "FDD Software" folder > Single-Click the "prt" folder > Select Folder > Save. Otherwise, go to step 3.

3. In the "FDD Software" folder, open "EMSPCA_Main" with Matlab and click Run. The model takes several minutes to train and test the provided samples.

   *** If you get an error about the wavelet toolbox not installed, click on Wavelet Toolbox in the error itself and follow the instructions to install the toolbox in your Matlab.

   - The results will be generated in form of bar charts, which represent the estimated labels for each sample, and will be saved in the same folder:

- *Sample 0 represents the healthy baseline against which all the test samples are compared.*
- *Sample A represents a sample of class 1 (Spark Plug gap = 0.040")*
- *Sample B represents a sample of class 2 (Spark Plug gap = 0.020")*
- *Sample C represents a sample of class 3 (Spark Plug gap = 0.080")*

Each bar chart shows the probabilities of the sample to belong to each of the 3 possible categories. The label with the highest probability is considered as the final predicted label for that sample.

The fault signatures of each of the 3 categories will also be generated and saved in the same folder as well as the fault signatures of each test sample.

If you want to try the software with your own customized data, please contact us through the following options:

6. *Contact us*

- For technical support on accessing more Spark Plug data on our CMHT server, please contact *Cam Fisher*, cfisher@mcmaster.ca .

- For technical support on using the FDD software, please contact *Essam Seddik*, seddikeh@mcmaster.ca .

- For inquiries regarding data collection, please contact *Ghabi Neame*, neameg@mcmaster.ca or *Hosna Geraei*, geraeih@mcmaster.ca .

- For business inquiries, please contact the director of CMHT: *Dr. Saeid Habibi*, habibi@mcmaster.ca .