Machine learning application to fault diagnosis of diesel engines using audio signals

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ABSTRACT

The present work aims to analyze machine learning techniques applied to pattern recognition of diesel engines audio files captured with a smartphone. Audio samples from 3 different engines were recorded, under 3 different operating conditions: normal operation, leaking hose and injector failure. Several combinations of data processing, audio feature extraction and classifiers were evaluated. The results show that this approach is very promising for fault diagnosis of diesel engines.

RESUMO

O presente trabalho tem como objetivo a análise de técnicas de machine learning aplicadas ao reconhecimento de padrões em arquivos de áudio contendo sons de motores a diesel capturados a partir de um smartphone. Foram gravadas amostras de áudio de 3 motores distintos, em 3 condições de operação diferentes: motor com funcionamento normal, com a mangueira furada e com falha no injetor. Várias combinações de tratamento dos dados, de atributos extraídos do áudio e de classificadores foram testadas. Os resultados mostram que essa abordagem é bastante promissora para diagnosticar falhas em motores a diesel.

INTRODUCTION

The Brazilian automotive aftermarket moves around 100 billion brazilian reais per year and is expected to grow between 6% and 7% by 2023. This growth directly follows the mechanical maintenance industry, which is mostly carried out through workshops places that are responsible for correctly identifying in vehicles the components that need repair. In general, the most common resource for diagnosing which component should be repaired are scanners, electronic equipment that receives and drives, in real time, all the vehicle's electronic injection operating parameters, with the function of detecting eventual failures in the system. However, this equipment has an extremely high cost, in addition to requiring hardware and qualified technical knowledge of the mechanic who operates it.

To solve this problem, initially inspired by [1], which dealt with the application of artificial intelligence for the diagnosis of COVID-19 using only the cough recording, the idea arose of evaluating similar methods for the application of artificial intelligence for the diagnosis of failures in vehicles with diesel engines through the use of sound. The main focus of the research initially is to study diesel injection commercial vehicles such as pick-ups, buses and trucks, a fleet that in 2020 represented around 15% of all vehicles in Brazil. In these analyses, different machine learning methods are evaluated in order to understand which one provides the greatest accuracy when applied to fault diagnosis in light, medium and heavy commercial vehicles. In other words, a methodology is established for collecting data from vehicles and classifying their engine failures. This procedure includes data analysis and processing, as well as defining the parameters and machine learning methods that are most appropriate for solving the problem.

The remaining of this work is organized as follows: a brief literature review is presented in the next section. Then a methodology section takes place to explain the machine learning (ML) strategy used to fault diagnosis of diesel engines, followed by a database section, a section detailing the experimental setup, the results section and, last but not least, in the final section conclusions are stated.

LITERATURE REVIEW

According to Henriquez *et al.* [2], condition monitoring (CM) has an important role in fault diagnosis of mechanical components and directly influences the operational continuity of a given process. One of the main approaches of CM is to use measurement data, like vibration and acoustic signals, in conjunction with machine learning techniques to diagnose anomalies in machinery functioning. Furthermore, Zhao *et al.* [3] present a review of studies which used deep learning (DL) techniques with different data processing methods in order to classify flaws in machineries. These studies indicate good potential in using this type of approach to motors and engines health monitoring.

In a recent comprehensive review, Soother *et al.* [4] point out the importance of feature extraction and processing in order to improve classifier's performance in CM of motors. They analyze different DL architectures, such as multilayer Perceptron (MLP), autoencoders (AE), deep Boltzmann machine (DBN), convolutional neural networks (CNN), recurrent neural networks (RNN) and generative adversarial neural networks (GAN), with input features covering raw vibration, acoustic and sound signals, time domain features, frequency domain features and time-frequency domain features, addressing some well-known transformations such as fast Fourier transform (FFT), short-time Fourier transform (STFT) and wavelets. They end up concluding that choosing the right features for a given ML method directly impacts on the generalization potential of the classifier, even more than the volume of the available data. Moreover, they encourage further studies on correlated topics, since it is a relatively new subject.

Even though ML techniques applied to fault diagnosis of engines, motors and similar systems is a recent topic, there are some relevant researches being published in the literature. Sun *et al.* [5] used an unsupervised DL technique based on a sparse auto-encoder (SAE) to classify an induction motor faults with noisy vibration signals acquired by an acceleration sensor. They achieved good prediction accuracies by using a denoising auto-encoder algorithm and a dropout layer to make the prediction more robust. A study carried out by Yang *et al.* [6] compares a support vector machine (SVM), a deep neural network (DNN) and a CNN classifiers using statistical-based features and mel-frequency cepstral coefficients (MFCC) extracted from segmented audio signals in order to classify belt conveyor rollers condition. Jena and Panigrani [7] use statistical-based features extracted from raw acoustic signals and continuous wavelet transform (CWT) to compare a MLP and a SVM piston-bore fault classifiers of a motor bike engine.

Additionally, there is an increasing body of literature addressing specifically CM of internal combustion engines, analyzing different components faults with a ML approach. Jafari *et al.* [8] classify different valve conditions using statistical-based features extracted from acoustic emission techniques in conjunction with a MLP. They end up concluding that using these statistical-based features achieves better performance than using the time and frequency analysis. A comparative study driven by Ahmed *et al.* [9] evaluates different estimation strategies to efficiently train a MLP to detect and classify some selected faults. They compare back propagation (BP), Levenberg-Marquardt, Quasi-Newton, extended Kalman filter (EKF) and the smooth variable structure filter (SVSF) methods, the latter being the one which helds best results. Hou *et al.* [10] propose a simple model to diagnose cylinder faults, which uses some primary monitoring parameters, such as temperature and pressure, to train a MLP using BP and Levenberg-Marquadt. Ramteke *et al.* [11] use FFT in vibration and acoustic signals to extract statistical features to detect liner scuffing faults. In a recent study, Ramteke *et al.* [12] deepened their analysis by using a STFT in conjunction with MLP to classify liner scuffing fault, piston scuffing fault and a combination of both. A different approach is suggested by Shiblee *et al.* [13], consisting of using empirical mode decomposition to find intrinsic mode functions (IMFs) of vibration signals measured by four strategically positioned sensors. These IMFs are then used to obtain statistical-based features from cumulative mode functions, which are used to train a MLP to diagnose cylinder faults. Furthermore, they highlight the increasing number of researches in applying wavelet transforms to feature extraction of signals in recent years.

This approach of using wavelet transform to extract features from an audio or vibration signal in conjunction with a ML procedure is one of the CM of internal combustion engines strategies which holds the most promising results for numerous types of components faults. Ravikumar *et al.* [14] compare different forms of feature extraction of vibration signals along with ML techniques to identify gearbox faults, including a CWT approach. They end up concluding, among other things, that extracting statistical features from CWT in conjunction with decision tree algorithms has good potential to CM of engines. Ayati *et al.* [15] investigate the use of FFT and wavelet packet transform (WPT) of vibration signals to extract uncorrelated features which are used to train and compare the performance of a SVM, a MLP and a K-nearest neighbors (KNN) classifiers in a injection fault detection problem. They conclude that wavelet mothers of the Daubechies family provide features with high classification potential. Shatnawi and Al-Khassaweneh [16] propose an interesting approach by using stereo recordings of engines, dividing the right and the left channels to extract WPT statistical-based features. Then they compare the fault classification performance for different architectures of MLPs. In a similar study, Wu and Liu [17] computed the Shannon entropy of each WPT node of audio signals to use as input feature to train a MLP to diagnose various types of faults. This analysis is tested for idle, 2000RPM and run-up functioning conditions. Furthermore, they compare the db4, db8 with db20 Daubechies wavelets and BP with generalized regression techniques to see which approach yields the best results.

METHODOLOGY

The present work approach is based on studies that used a wavelet transform approach to investigate faults in diesel engines components [14-17]. WPT statistical-based features are extracted from audio recordings of the engines and are used to train a classifier. In this work, 4 different classifiers were tested: Random Forest, Gradient Boosting, SVM and MLP. Besides that, a CNN that uses MFCC as input feature [5] was also tested.

The wavelet transform is a convolution method which produces flexible time-frequency resolution representation of a signal. There is a wide variety of wavelet shapes, divided by families, and the chosen shape for the convolution procedure is often called the wavelet mother. While the traditional discrete wavelet transform (DWT) focus on decomposing only the low-frequency information of a signal, providing a relatively low resolution in the high-frequency domain, the WPT is a type of DWT that decomposes both low and high-frequency regions, which overcomes the difficulty in differentiating detailed transient components [18-20]. The WPT can be defined as follows [21]:

$$W_{2n}^{(j)}(t) = \sqrt{2}\sum_{k} h(k)\, W_{n}^{(j)}(2t - k), \tag{1}$$

$$W_{2n+1}^{(j)}(t) = \sqrt{2}\sum_{k} g(k)\, W_{n}^{(j)}(2t - k), \tag{2}$$

where $W_0^{(0)}(t)$ represents the scaling function, $W_1^{(0)}(t)$ is the base wavelet function and the superscript j stands for the jth level of the transformation, generating 2^j WPT nodes. Furthermore, $h(k)$ and $g(k)$ represent the low and high-pass filter coefficients, respectively. A schematic representation of the procedure can be seen in Figure 1.

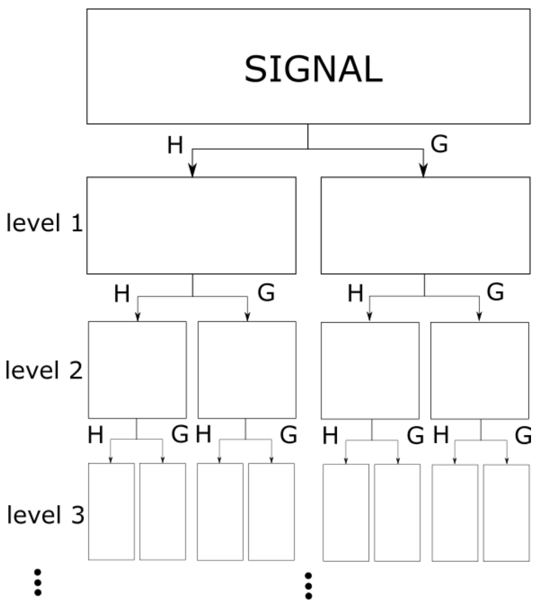

Figure 1. The WPT schematically represented, where H and G stand for low and high-pass filters, respectively.

The raw signal is segmented into short duration chunks and then WPT is applied, resulting in 2^j transformed signals for each chunk. After that, statistical-based features are computed for each transformed signal. Many statistics can be extracted from the node's signal, such as kurtosis, skewness, mean, wave length, mean cross-count, amount of change and square root average. Then the feature extraction is succeeded by a feature selection algorithm, which selects the features of each WPT node by analyzing the correlation between the features and the output (classes) and among the features themselves. This procedure discards unwanted and redundant features, such as those with low correlation with the output or those highly correlated among themselves. Finally, the selected features are used as input of the ML classifier under analysis. An overview of the whole methodology is presented in Figure 2.

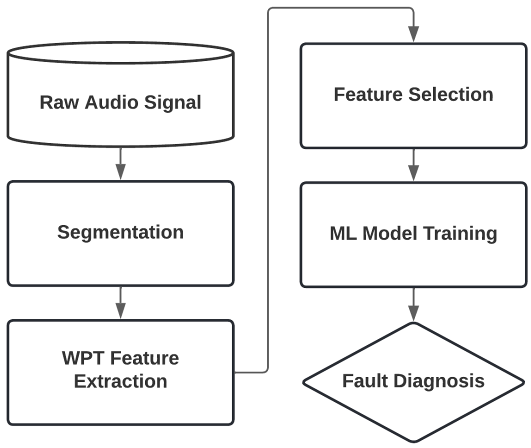

Figure 2. Flowchart of the proposed methodology.

DATABASE

Thinking about practical feasibility and ease of use for the final user, the audio data is recorded with a smartphone from idling engines (~800-1000RPM). Therefore, it is important to note that, as the equipment used for data acquisition is not dedicated to this specific purpose, the collected data is inherently noisy, which makes the classification procedure more challenging. As for engine running condition, 3 targets were considered: normal condition, damaged injector and leaking hose.

The recording procedure was performed outside the vehicles, next to the engine, and in an open environment, i. e., the recordings are susceptible to different types of environmental noise. The audio files were recorded with a sampling rate of 22.05 kHz in .ma4 format, and were converted to .wav. Engines from 3 different vehicles (2 pickup trucks and 1 medium duty) were used in the recordings. For each vehicle and condition, 2 audio tracks were recorded, with little duration variation among them.

The total recorded audio duration of each vehicle and condition can be seen in Table 1.

Table 1. Recorded audio length in relation to the engine type and condition.

Engine	Total audio length per condition		
	Ok	Injector	Hose
Pickup Truck I	7min21s	7min15s	7min21s
Pickup Truck II	10min03s	10min04s	10min01s
Medium Duty	10min03s	10min59s	10min56s

The short size of the available database, especially in the number of recorded tracks per engine condition, impose a hard challenge for research. Moreover, the generalization capability of the proposed methods cannot be properly assessed with such database. Besides that, one can list many other variables that affect such systems in the real world that are not covered by this database, such as different smartphone models, different recording environments, and higher number of engines and faults.. This occurs due to the inherent intricacies of data acquisition, such as the viability of having access to a good amount of vehicles, the difficulty of collecting audio data with different models of smartphones and the difficulty of having access to a variety of engine faults.

EXPERIMENTAL SETUP

In the experimental setup, different tracks are used for training/validation and test purposes, in order to avoid biased results. Furthermore, each audio is segmented in 1s chunks and are normalized in relation to the training data. Regarding the WPT parameters used to extract the features for each vehicle under analysis, it is considered a level 6 decomposition, generating 2^6 wavelet packet nodes, and db20 of the Daubechies family as the wavelet mother. Then statistical-based features are extracted from each wavelet packet node. After a series of experiments, it was found that the statistical-based features which best work for each vehicle under analysis may vary, having to carry out a separate analysis for each case. This results in different extracted features for each vehicle under analysis, which can be seen in Table 2.

Table 2. Extracted statistical-based features for each vehicle.

Vehicle	Extracted Features
Pickup Truck I	skewness, mean, wave length, mean cross-count and square root average
Pickup Truck II	kurtosis, skewness, wave length, mean cross-count and amount of change
Medium Duty	kurtosis, skewness, mean, mean cross-count and amount of change

After the statistical feature extraction procedure, a feature selection is made based on the correlation matrix filter method, i.e., the more relevant extracted statistics per wavelet packet node are selected by eliminating unwanted features, such as low correlated with the output, or redundant features, such as high correlated among others. This procedure reduces our classifier input size from the order of hundreds to an order of tens. The filter values for each vehicle under analysis can be seen in Table 3.

Table 3. The correlation filter values for each vehicle.

Vehicle	feature-output filter	feature-other features filter
Pickup Truck I	< 10%	> 99%
Pickup Truck II	< 10%	> 95%
Medium Duty	< 30%	> 99%

Moreover, as stated in the methodology section, 4 classification algorithms (MLP, SVM, Gradient Boosting and Random Forest) are analyzed and compared with a MFCC-CNN traditional approach. The choice to use the MFCC-CNN approach as a comparative basis against the other models comes from the fact that it is a well established method in the literature for vibration, acoustic and sound signals classification, as can be seen in [1, 5, 22-28], among many other works. After some preliminary experiments, optimal parameters for each model under investigation were chosen, as follows:

- The MLP architecture which worked best is composed of an input layer with the size of the selected features (see Figure 2), an hidden layer with 20 ReLU neurons, a 20% dropout layer and a softmax output layer, with the size of the considered targets. Furthermore, the loss function is computed based on the Kullback Leibler divergence and the optimization algorithm used is the Stochastic Gradient Descent (SGD).
- The SVM model is constructed as a multi-class classifier, using the one-vs-one approach with a limit of 1000 iterations.

- The gradient boosting model is multi-class oriented, constructed with 31 leaves in each tree, learning rate of 0.1 and 255 max bins.
- The random forest model used 800 decision trees and the entropy criterion to measure the quality of the split.
- The CNN architecture is composed of five blocks of ReLU convolutional and max pooling layers, followed by a ReLu fully connected output layer, using the cross entropy loss and the Adam optimizer. Regarding the MFCC parameters, it is used a FFT window length of 2048, 128 Mel filter banks and 512 number of samples between consecutive frames.

For each classifier under analysis, 100 realizations of the proposed methodology are made (see Figure 2), randomly picking training and validation samples from each segmented data with a training-test-ratio of 75%. In order to compare results, accuracy and F1 score are computed, as well as precision vs.recall curve is plotted for visual analysis.

RESULTS

The results are presented for 3 different diesel engine vehicles, 2 pickup trucks and 1 medium duty.

PICKUP TRUCK I – For this vehicle, the shortest audio recordings were available (see Table 1) and they were the noisiest among the 3 vehicles studied in this work. The performance scores of the investigated models are shown in Table 4.

Table 4. Statistical scores for the Pickup Truck I, where **μ** and **σ** stand for the mean and the standard deviation, respectively.

Classifier	Relative Runtime	Accuracy (%)		F1 Score	
		μ	**σ**	**μ**	**σ**
MFCC-CNN	1	42.14	3.03	0.341	0.045
MLP	0,522	82.16	4.18	0.817	0.046
SVM	0,055	74.73	6.11	0.741	0.064
Gradient Boosting	0,058	52.19	1.71	0.479	0.024
Random Forest	0,057	65.71	5.91	0.636	0.066

By analyzing Table 4, one can notice that the MLP is the model which yields the best classification performance, while the MFCC-CNN is the worst one. Moreover, there is a reduction in computational cost (relative runtime) of approximately 48% in relation to the CNN approach. In order to analyze the MLP performance per class, a precision and recall values map for all 100 realizations is presented in Figure 3.

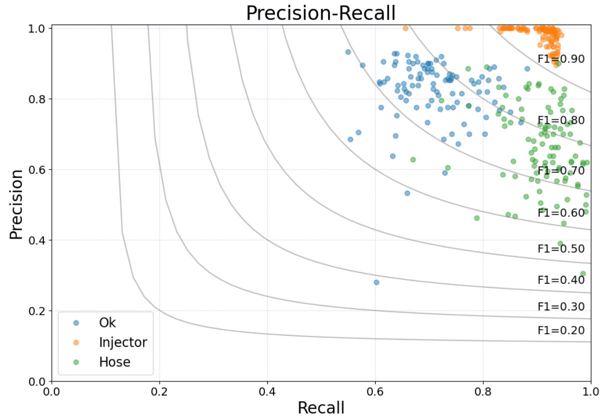

Figure 3. The precision and recall measures for each condition of the pickup truck I engine. The F1 contour lines represent the F1 score value for a given combination of the precision and recall.

As can be seen In Figure 3, the injector fault is the class with the best prediction scores, while the other 2 are more scattered on the plot, with a larger variance.

PICKUP TRUCK II – The second pickup truck has less noisy signals compared to the first one, although there is still a presence of noticeable noises and transient regime chunks. The performance scores of the investigated models are shown in Table 5.

Table 5. Statistical scores for the Pickup Truck II, where **μ** and **σ** stand for the mean and the standard deviation, respectively.

Classifier	Relative Runtime	Accuracy (%)		F1 Score	
		μ	**σ**	**μ**	**σ**
MFCC-CNN	1	39.92	3.94	0.289	0.057
MLP	0.727	83.52	3.69	0.834	0.039
SVM	0.020	84.24	3.10	0.843	0.031
Gradient Boosting	0,023	51.81	3.50	0.43	0.031
Random Forest	0,021	60.63	4.34	0.552	0.04

By analyzing Table 5, one can notice that the SVM is the ML model which yields the best classification performance, closely followed by MLP, while the

MFCC-CNN is still the worst one. Furthermore, there is a considerable reduction in computational cost (relative runtime) of approximately 98% in relation to the CNN approach. In order to analyze the SVM performance per class, a precision and recall values map for all 100 realizations is presented in Figure 4.

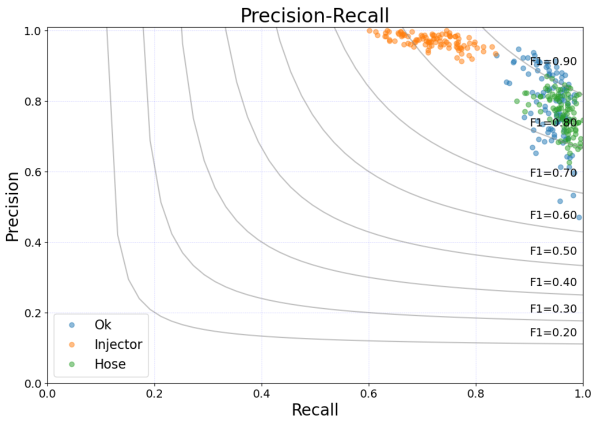

Figure 4. The precision and recall measures for each condition of the pickup truck II engine. The F1 contour lines represent the F1 score value for a given combination of the precision and recall.

As can be seen in Figure 4, the normal condition engine and the hose fault are the classes with the best prediction scores, with a small advantage to the normal condition class. Opposedly to the previous vehicle, the injector fault is not diagnosed as well. The results are slightly better than the pickup truck I, although the predictions still have a considerable variance.

MEDIUM DUTY – This vehicle has the less noisy audio signals, having practically only non transient sections. However, here we raise the hypothesis that, since this vehicle is a medium duty, opposedly to the other 2, the engine functioning could be so loud as to suppress any external noises. The performance scores of the investigated models are shown in Table 6.

Table 6. Statistical scores for the medium duty, where **μ** and **σ** stand for the mean and the standard deviation, respectively.

Classifier	Relative Runtime	Accuracy (%)		F1 Score	
		μ	**σ**	**μ**	**σ**
MFCC-CNN	1	33.93	0.11	0.17	0.002
MLP	0,688	86.63	1.98	0.866	0.02
SVM	0,021	68.13	0.56	0.561	0.005
Gradient Boosting	0,023	95.42	1.49	0.954	0.015
Random Forest	0,022	96.02	1.04	0.960	0.011

By analyzing Table 6, one can notice that the Random Forest is the ML model which yields the best classification performance, closely followed by Gradient Boosting, while the MFCC-CNN is still the worst. Furthermore, there is a considerable reduction in computational cost (relative runtime) of approximately 98% in relation to the CNN approach. In order to analyze the Random Forest performance per class, a precision and recall values map for all 100 realizations is presented in Figure 5.

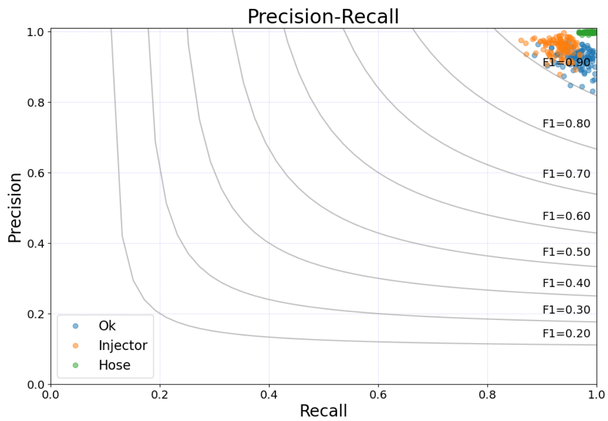

Figure 5. The precision and recall measures for each condition of the medium truck engine. The F1 contour lines represent the F1 score value for a given combination of the precision and recall.

As can be seen in Figure 5, this is the vehicle which got the best scores for the predictions of the considered classes, having predicted correctly practically all of the hose fault data. Furthermore, it is the analyzed case with the lowest variance, showing that it is a more robust classification procedure.

CONCLUSIONS

The present work explores the viability of a diesel engine fault diagnosis task by using a simple everyday tool, such as a smartphone. A WPT-ML-driven methodology is proposed and results show the viability of the proposed approach. By analyzing each model performance for 3 different vehicles, it is not clear if this approach is more suitable for trucks or if the collected data is more standardized for this specific case, making the classification procedure easier. Moreover, different combinations of selected features and ML models worked best for each vehicle, showing that an unique model that works well for any type of vehicle is not possible yet with the available dataset. Therefore, the authors strongly recommend that further studies should be conducted using a more robust dataset, even though the analyzes performed in the present work are still valid to verify the feasibility of the proposed approach. In addition, the potential of the proposed approach in CM of other types of machinery should be investigated in future works.

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