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Automatic NVH time signals health verification based on machine learning techniques

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ABSTRACT

In noise and vibrations field (commonly referred as NVH; Noise, Vibration and Harshness), the time signals health verification is a necessary task. Its complexity is low, but time-consuming. The current paper proves that automate the referred activity is possible through the use of a machine learning algorithm, specifically trained for this purpose. The adjusted algorithm solves this work effectively and efficiently, performing the mentioned task in a few minutes, while engineers would spend even days verifying the same amount of time signals.

INTRODUCTION

Noise and vibrations analysis is applicable in many different fields and industries; automotive, aeronautics, railway, naval, building, or industrial equipment. The standard analysis process is based on the study and monitoring of insitu measurements that can be acquired either during product development (e.g: new automotive powertrain development) or once a commercial product is deployed (e.g: vibration levels components monitoring once installed in aircraft). Therefore, time signals acquisition is the first step in the whole NVH analysis process and fully determines the obtained conclusions.

As a result of the acquisition process, time signals are gathered and stored and can be directly used for analysis purposes (e.g: inspection of maximum, mean and energy values per time signal). However, the common practice is to perform the analysis in the spectral domain, to do so, Fourier transform [1] must be computed over acquired time signals.

Anomalies in acquired NVH time signals are very common because the measurement environment can be very hostile. Some of the common causes of anomalies are: wires improperly fixed that could hit surrounding surfaces, excessive temperature in the measurement location, incident airflow (for microphones), unexpected damage of sensors before the measurement interval, etc. Many different anomalies could happen and, therefore, it is required to review acquired time signals before computing its Fourier transform. This verification is necessary because, anomalies detected in time signal could be overlooked when analysing its spectral representation, producing conclusions over signals that seemed to be healthy while there were not, making this verification a key factor in the NVH analysis process.

Reviewing a time signal only takes a few seconds. However, solving this task could require a huge amount of time if it is necessary to verify the health of thousands of signals, which is probably the usual scenario. A standard automotive NVH test performed with 20 sensors could easily produce 500 signals per test day. In the aeronautics field, the amount of gathered data could be an order of magnitude higher. Considering a two days flight test campaign, 10.000 signals would be gathered and its visual review would approximately take 8 working hours (considering 3 seconds as the reviewing time per signal).

The following paper sections explain how the automatic time signals verification has been solved based on machine learning (ML) techniques, structuring the rest of the paper as follows: state of the art, proposed framework, data description, time signals classifier, results and conclusions.

STATE OF THE ART

ML is the part of the data science field that focuses on the design and evaluation of algorithms from extracting patterns from data. ML involves using a variety of advanced statistical and computing techniques and gives a computer the ability to learn from data [2].

In recent years, the use of ML techniques is becoming more popular and the applications fields are growing rapidly. The use of these techniques in the field of noise and vibrations is progressively increasing and one can find good examples of its use in topics as vehicle interior noise [3], vibration control [4], sound insulation [5], sound absorption [6], hall acoustics [7] and even prediction of vibration frequency response [8]. However, no research about automatic NVH time signals classifications based on ML techniques was found.

ML algorithms used in this project are: a) logistic regression (error-based learning; it tries to minimise the absolute error between the predictions and the training samples), b) knn (similarity-based learning; using similarity measures, it identifies most similar samples and makes the prediction based on the dominant category for that subset), c) decision tree (information-based learning; it splits training data with yes/no question (for categorical features) or bigger/lower questions (for numerical features) in order to reduce data entropy after each decision step), d) random forest (information-based learning and ensembles; it uses many decision tree models and perform the prediction by returning the majority vote or the median) [9]. Further information about mentioned algorithms can be found in the following references: [10], [11], [12], [13].

PROPOSED FRAMEWORK

The main goal of this project is the development of an algorithm capable of optimising one of the higher time-consuming steps in the NVH analysis workflow; the visual inspection of acquired time signals health. The proposed workflow, which includes the developed classification algorithm, is shown in Figure 1.

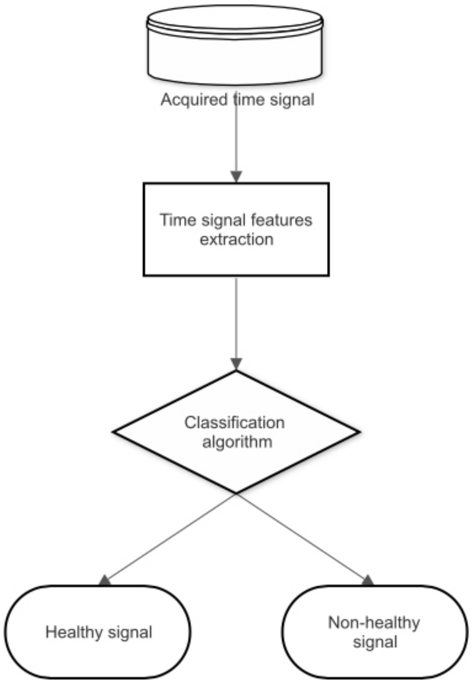

Figure 1. *Flowchart for automatic time signal classification.*

Acquired time signal

Once NVH tests are finished, stored time signals are loaded and used as inputs for the previously shown workflow. Commonly used storing time signals formats as wav, unv, hdf5 can be loaded easily.

Features extraction

Extracted features compactly represent each time signal, and are used as inputs for the classification algorithm. Based on an iterative process, 20 features were defined to describe each time signal. Some of these features are the time signal mean, median, standard deviation, quantiles, and some others specifically developed features (patent pending).

Additionally, the use of these features to describe each time signal produces a significant reduction in the amount of data to work with. For example, a 10 seconds time signal acquired using a sampling rate of 1024 Hz is represented by just 20 values, instead of 10240 values, reaching a reduction ratio of 512. The reduction ratio is Ns/Nf (where Ns is the number of samples of the raw time signal and Nf is the number of features extracted per signal).

Classification algorithm

A previously adjusted model receives the set of features extracted per time signal. The model computes the probability of that signal belonging to the target class (non-healthy signal) and it chooses the predicted class (healthy or non-healthy signal). Model implementation details are explained later.

DATA DESCRIPTION

Types of time signals used for the project and, therefore, utilised as algorithm input are: a) stable time signals (considered as healthy signals), b) signals with overload or transient impacts (both considered as non-healthy signals). Figure 2 shows an example for each of the different types of time signals used:

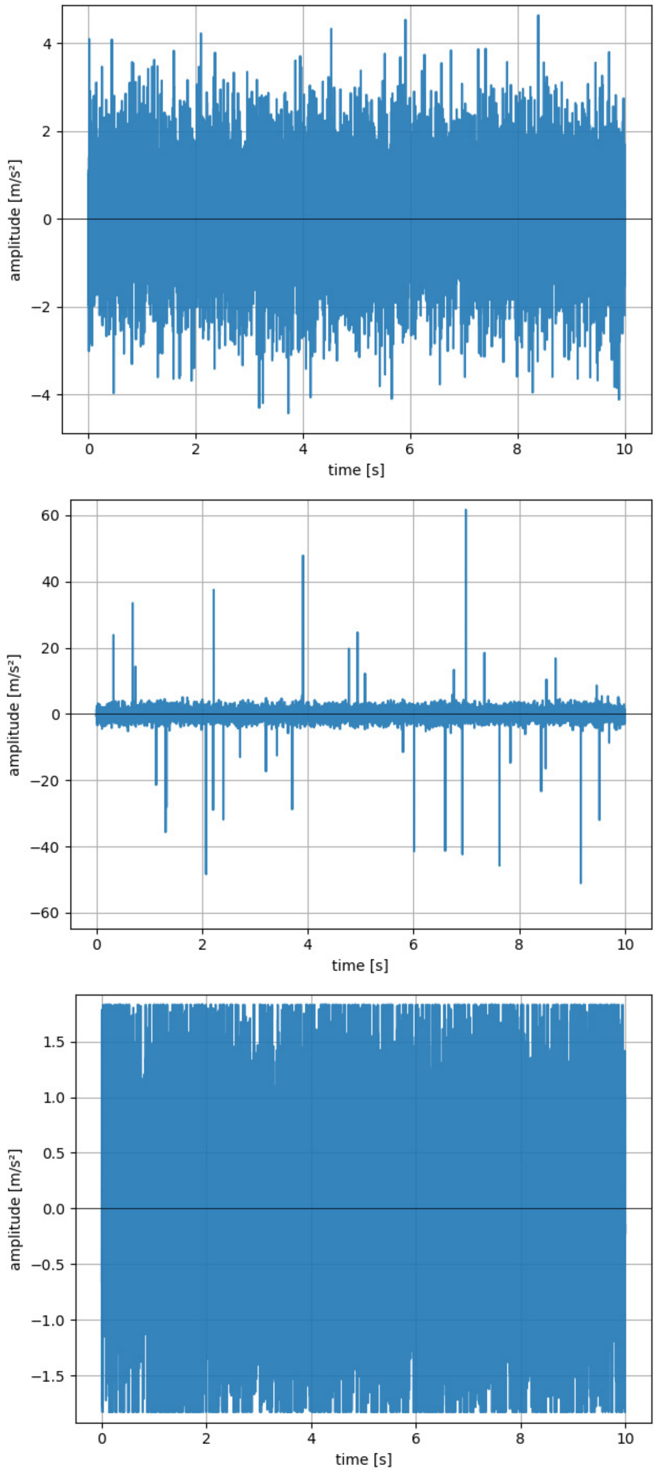

Figure 2. From top to bottom: stable signal (healthy), signal with impacts (non-healthy), signal with overload (non-healthy).

During the development phase (model training and evaluation) 2400 time signals, with a time duration of 10s and 1024Hz as sampling rate, were used. Those signals were manually labelled (as healthy and non-healthy) and then split into train and test samples according to 80%-20% proportions respectively, keeping the same target feature proportions in both subsets of data (Table 1, Table 2).

Table 1. Train samples division.

Signal type	Target feature	Total samples
Stable	Healthy	697
Impacts	Non-healthy	1002
Overload	Non-healthy	206

Table 2. Test samples division.

Signal type	Target feature	Total samples
Stable	Healthy	183
Impacts	Non-healthy	233
Overload	Non-healthy	61

To avoid correlations between features (detrimental to logistic regression algorithm), their relations were crosschecked. Additionally, transformations over features were applied when necessary, in order to reach standardised features (mean equal to zero and standard deviation equal to one). This data processing is required for algorithms working with similarity metrics (knn algorithm in this project). As a result, 20 features were obtained and then used to train the model, getting a robust algorithm capable of classifying time signals with different amplitude, time duration and sampling frequency.

TIME SIGNALS CLASSIFFIER

The objective of the classification algorithm is to properly identify non-healthy signals (target class for the target feature). To do so, different algorithms were explored and adjusted. Studied algorithms are a) logistic regression, b) knn, c) decision tree, d) random forest. To reach robust algorithms adjustments, train data were split into 5 subsets in order to use the k-folds cross-validation technique [14].

According to performance metrics to reach, it was set, as a target value, a true positive rate (TPR) equal to or greater than 0.98. It means that 98% of non-healthy signals of the training dataset might be properly identified. Additionally, if different explored models reached the target TPR, the one with the lowest false positive rate (FPR; the ratio of healthy signals classified as non-healthy) would be considered the model with the best performance.

Furthermore, if it was required to analyse anomalies produced in non-healthy signals, the information gathered in the data field 'Signal type' (Table 1 and Table 2) could be used to develop another algorithm. In that case, the developed model could detect generalised anomalies produced while a test campaign is in progress and, perhaps, detected issues could be fixed before finishing the test campaign.

RESULTS

To exhaustively evaluate models performance, ROC curves [9] were inspected for each of the trained models. The main advantage of ROC curves is that they show how TPR and FPR progress according to classification threshold, allowing the identification of the optimal classification threshold per model and, additionally, giving an overview of the general model performance. This threshold increases progressively from 0 to 1 providing the corresponding TPR and FPR values. A common practice is to just use confusion matrix [15] to evaluate model performance, when this is the case, only a value per evaluation metric is provided (just the one computed using 0.5 as classification threshold), giving a more limited model evaluation analysis. Obtained ROC curves per trained model are shown in Figure 3.

To focus the performance analysis in high TPR values (equal to or greater than 0.98) and confirm produced error rates, Table 3 gathers obtained FPR for different TPR values (0.98, 0.99, 1). Additionally, to explore FPR stability, mean and standard deviation values were computed per model. These values were used to set a models ranking (last table column).

As a result of exploring ROC curves (Figure 3) and TPR metrics (Table 3), it can be stated that the model providing better performance is the random forest. It reaches a TPR of 0.98 with a FPR of 0.04. If those TPR

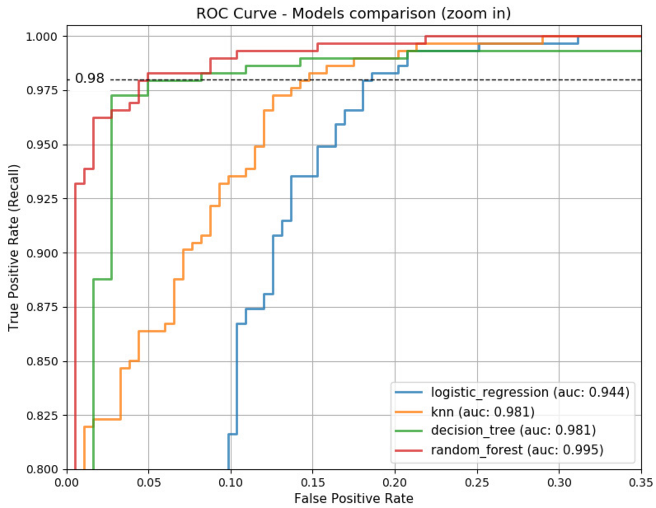

Figure 3. *Obtained ROC curves for the trained classification algorithms.*

and FPR values needed to be adjusted (e.g: higher TPR), obtained model would work as well, just the classification threshold should be modified (the exploration of the ROC curve would provide the corresponding value).

Finally, it was evaluated the required time to automatically classify 10.000 signals through the use of the trained random forest model. This exercise allows the evaluation of the algorithm speed and shows how faster is the algorithm compared with a visual inspection performed by an engineer. Computed time includes time signals loading, features extraction and signal classification (workflow gathered in Figure 1). The total time employed by the algorithm was 7 minutes, classifying 24 signals per second. An engineer would, on average, spend 3 seconds per signal. Therefore, the developed algorithm is 70 times faster than an engineer solving the time signals health verification task.

CONCLUSIONS

Thanks to the use of machine learning classification algorithms, it was possible to automate the detection of

Table 3. *FPR values for different TPR (0.98, 0.99, 1). Mean and standard deviation computed for model FPR.*

	TPR			Mean FPR	Standard FPR deviation	Ranking
	0.98	**0.99**	**1**			
Logistic regression	0.19	0.20	0.31	0.23	0.054	3
KNN	0.14	0.17	0.29	0.20	0.065	2
Decission tree	0.05	0.14	1	0.39	0.428	4
Random forest	**0.04**	**0.09**	**0.21**	**0.11**	**0.071**	**1**

non-healthy time signals. Different algorithms were explored and trained, obtaining a better classification performance with the random forest model. It correctly classifies 98% of the non-healthy signals (TPR = 0.98). Furthermore, the classification speed was evaluated; the trained random forest algorithm solved the classification task much faster than an engineer, classifying 10.000 signals in just 7 minutes (approximately 70 times faster than the usual visual inspection).

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