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Multiresolution analysis of vibration signals acquired from locomotive Diesel engine for classification of engine states basing on signal statistical parameters

The paper presents a method of classification of locomotive Diesel engine states basing on vibration signals taken from an engine body and using chosen statistical parameters calculated for the original signal and it wavelet multiresolution components. The researches presented in the paper concern estimation of an engine states before and after a general repair. The target application of the presented researches is an on-line diagnostic system which can complement standard OBD systems. To this purpose the applied methods should not base on complex analysis of some spectral, time-frequency or scalogram plots but rather on choosing single diagnostic parameters which are suitable for the fast on-line diagnostic. The results have showed the significant difference in distinguishing of engine work before and after a general repair using some chosen statistical parameters applied to vibration signals.

Key words: *vibration signals, Diesel engine diagnostic, multiresolution analysis, classification*

1. Introduction

A combustion engine is an example of a mechanical device which can run down. The engine diagnosis needs estimation of the technical state of an engine during it exploitation. Together with engines used in a car transport the locomotive combustion engines are nowadays also an important source of pollution. To reduce air pollution for passenger cars the OBD (on board diagnostic) norms and systems were introduced. The rail area is also partially regulated with several regulations considering limits on emission of combustion gases (for example, cart UIC 623 1-2-3 in Europe). But all the time there are no obligatory regulations for systems monitoring the emission critical damages that might play a similar role to that of the OBD for cars. Anyway, the coming years will show a tightening of norms and regulations regarding combustion gases emission regarding vehicles with heavy diesel engines like combustion locomotives. It is this imminent perspective that gives an impulse to research new detection methods that would be applicable in diesel locomotives and which base on vibration analysis [1].

The paper presents some researches on classification of different states of Diesel locomotive engine basing on vibration signals taken from an engine body before and after a repair. In the area of vibration signals analysis many specialized methods can be found. It is enough to mention about FFT spectrum, nonlinear analysis, short-time analysis and wavelets (see e.g. [2-9]). The results presented in the paper covers the application of multiresolution wavelet analysis into diagnostic of rail vehicle combustion engine with application of some chosen statistical parameters applied to the original signal and it wavelet multiresolution components.

The proposition of engine diagnostic presented in the paper bases on the indication of some diagnostic parameters which can be useful to distinguish engine different states by signal processing methods without considering details of mechanical engine processes. In this on-line analysis the applied methods cannot base on complex analysis of spectral, time-frequency or scalogram plots but they need choosing single diagnostic parameter which can be applied in a fast on-line diagnostic.

The results presented in the paper showed the significant difference in distinguishing of engine work before and after a repair using some of chosen shape parameters applied to vibration signals taken from an engine.

2. Multiresolution wavelet analysis

Wavelet analysis [7, 10] is nowadays a known signal processing method applied in broad range of problems and disciplines. Wavelets have also found an application in the area of analysis of broad class of mechanical signals (also vibration signals) for diagnostic aim [5, 6, 11–13].

In continuous wavelet transformation CWT [7, 10] the set of wavelets which create orthonormal base can be obtained by transformations of one special mother wavelet. In comparison with Fourier base functions the wavelets series is created by scaling (stretching or compressing) and by translation, while the Fourier base function are only scaled. Wavelets are better from traditional Fourier approach during analysis of signals which contain discontinuities and sharp non-periodic peaks. During processing of unsteady signals the Fourier analysis loses all information about localization in time of the given frequency components. The use of CWT while all calculations are done for all possible scales and translations gives the big amount of data. For this reason in practice the Discrete Wavelet Transformation DWT is used [7, 10]. In DWT a signal is transformed to discrete scales and discrete translations what gives a data reduction. What is worth to underline each DWT transformation can be interpreted as a special case of a filtering function [7, 10].

In effect using DWT transformation to the original signal S can make it decomposition into two terms: high frequency approximation term and low frequency approximation term. This operation can be repeated. For example, the structure of multiresolution decomposition of an original signal S on the level 5 can be described as $S = A_5 + D_5 + D_4 + D_3 + D_2 + D_1$ (see Fig. 1), where D represents low frequency component decomposed with a high scale and A high frequency components decomposed with a low scale.

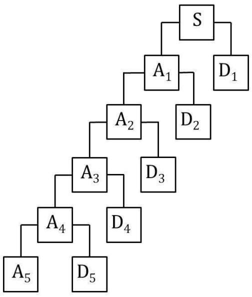


Fig. 1. The exemplary tree structure of multiresolution decomposition on level 5

3. Measurements

All experiments were done on Diesel locomotives ST44. The construction of ST44 locomotives is simple and a service is easy to performance. They have easiness of start in any circumstances and a big force. The ST44 locomotive was a typical combustion traction vehicle for railway in Poland 1949–1991. It appeared irreplaceable in winter conditions. Unfortunately it has also many disadvantages like a big fuel consumption, little fuel tank, high emission of combustion gases and high level of noise. The measurements were performed on two ST44 locomotives – number 2045 and 2061. The main calculations were done for data registered on both locomotives. The paper presents also some calculation performed for each locomotive separately. The number of performed registrations was limited by complexity of measurements and first of all by the general costs of researches.

The examinations were focused on Diesel engine 14D40 no 8849. The measurements were done under loading (on water resistor) for correspondingly adjustment power in determinate measurement points [1, 14]. The researches were performing basing on comparison of vibration signals recorded from an engine before and after the revision repair in a diagnostic station. Periodic repair consisted in full service of damaged parts and in replacement of damaged or wearing elements [14].

The acceleration measurements before repair of a Diesel engine were done by using acceleration sensors EGCS Entran Devices of the range ± 5 g. The signal was registered by cart PCL-818HD ADVANTECH with the sampling frequency f_{Hz} = 1004.0161 Hz/channel. The measurement after repair were done using the same sensors EGCS and new sensors PCB PIEZOELECTRONICS 393B04 where the signal was amplify by 3-channel signal conditioning amplifier and next registered using analogue to digital cart.

The sensors were mounted on an engine body in places which correspond to bearing sites of engine crankshaft (see Fig. 2). Each measurement points registered acceleration in vertical direction and transverse horizontal direction [14]. The measurements before the repair were performed under load on water recoil in the seven measurement points mounted on an engine body near of engine crankshaft bearing. In each measuring point acceleration was registered in two directions: vertical and horizontal transversal. The measurements after repair were also done under load on water recoil but in six points of sensors mounted on engine body. In this case acceleration was registered in the same two directions: vertical (Entran sensors) and horizontal transversal (PCB sensors).

Fig. 2. Sensors mounted on an engine body

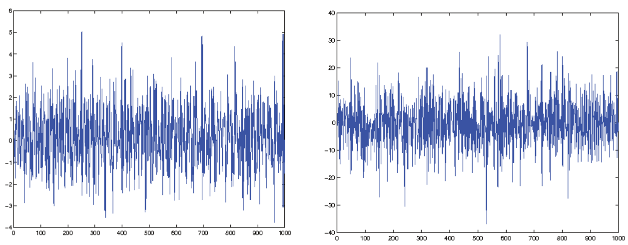
4. Data analysis

Taking into account all configurations and all settings for horizontal case the full measurements gives finally 180 signals registered before and 120 signals registered after. Each of these signals was processing to find it multiresolution components. The calculations were performed in MATLAB for Daubechies wavelet rank 5 and multiresolution decomposition at 5-th level. The type of wavelet was chosen basing on literature remarks and some own experiments. From the point of view of diagnostic aims the 5 level of decomposition seems quite enough, because the analysis is usually performed on-line and this needs not very time consuming calculations.

In the considerations an original signal S after the decomposition consisted of 6 sub signals S = $A_5 + D_5 + D_4 + D_3 + D_2 + D_1$, where D_5 is a low frequency component decomposed with a high scale and successive D_5, D_4, D_3, D_2, D_1 are high frequency components decomposed with a small scale.

The example of signals and it multiresolution components are presented in Figs. 3-4. For each signal and its components, the following parameters were calculated:

- mean M, $X_1 = \frac{1}{n}\sum_{i=1}^{n} x(i)$ (1)
- variance VAR, $X_2 = \frac{1}{n}\sum_{i=1}^{n}\left(x(i) - X_1\right)^2$ (2)
- root-mean square RMS, $X_3 = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x(i)^2}$ (3)



A B

Fig. 3. Exemplary vibration signal before (A) and after (B) an engine repair for horizontal transversal registration (the x-axis units are in number of samples; the y-axis units are in 10 m/s^2 ≈ g (A) and 1 m/s^2 (B))

- mean from absolute values MAV, $X_4 = \frac{1}{n}\sum_{i=1}^{n}|x(i)|$ (4)
- shape coefficient SC, $X_5 = \frac{X_3}{X_4}$ (5)

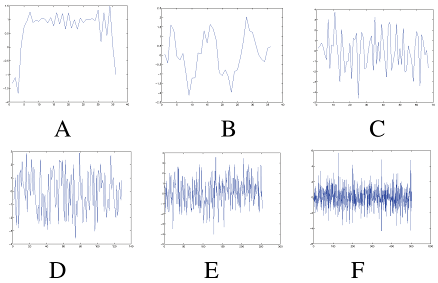


Fig. 4. Multiresolution components of signal A from Fig. 3 (before a repair) (the x-axis units are in number of samples; the y-axis units are in 10 m/s^2 ≈ g)

5. Results

The general results for signal S and decomposition components A5, D1, D2, D3, D4 and D5 were showed that the most interesting are results are for horizontal registration (see Table 1). The Table 1 presents the averaged values of parameters X_1, X_2, X_3, X_4 and X_5 calculated for all signal cases (180 signals registered before and 120 signals registered after). Generally all parameters (except "Mean") for horizontal registration show the increase of parameter value after the repair. The values of parameters after a repair are higher in comparison with values before a repair, but only for horizontal registration. It is worth to underline that the values "before" represent a worn-out engine in a general bad state while values "after" represent the repaired engine in better general state.

The next step of the researches was a creation of a simple classifier to test if the chosen parameters can play a role of diagnostic parameters distinguishing engine state before and after the repair. Basing on the above observations above the three parameters: X_2 (Variance VAR), X_3 (Root-Mean Square RMS) and X_4 (Mean From Absolute Values MAV) for components S, D1 and D4 were chosen to build a classifier. It needs to define a threshold to distinguish the states of right and fault work of an engine and at the beginning the simplest way was taken into account.

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Table 1. The full results from two locomotives for horizontal registrations

		X_1	X_2	X_3	X_4	X_5
S	Before	0.054	3.298	1.733	1.547	1.257
	After	0.075	65.853	72.862	8.727	5.499
A5	Before	0.054	0.009	0.160	0.145	1.142
	After	0.075	2.268	1.879	1.172	1.265
D1	Before	-0.0000002	1.227	1.032	0.800	1.291
	After	0.000004	33.179	32.276	5.844	3.799
D2	Before	-0.0000005	1.114	0.987	0.767	1.291
	After	-0.000001	21.074	28.197	4.801	3.491
D3	Before	0.000003	0.676	0.768	0.611	1.256
	After	-0.0000005	8.109	9.955	2.954	2.390
D4	Before	-0.000006	0.243	0.471	0.374	1.265
	After	-0.00001	4.312	4.191	1.942	1.001
D5	Before	-0.000002	0.029	0.164	0.133	1.239
	After	0.000009	2.048	1.747	1.145	1.238

Table 2. The means and standard deviations of distribution of parameters X_2, X_3, and X_4 calculated for the cases before and after

		X_2	X_3	X_3
S	Before	3.298 ±2.298	1.733 ±0.571	1.547 ±0.513
	After	65.853 ±93.607	72.862 ±129.779	8.727 ±5.307
D1	Before	1.227 ±1.079	1.032 ±0.404	0.800 ±0.313
	After	33.179 ±43.655	32.276 ±52.626	5.844 ±3.425
D4	Before	0.243 ±0.142	0.471 ±0.144	0.374 ±0.119
	After	4.312 ±5.348	4.191 ±4.557	1.942 ±1.114

Table 3. The results of classification for signal S for gauss thresholds separately for locomotive 2045 and 2061

	X_2 Number (percentage) of classification as a		X_3 Number (percentage) of classification as a		X_4 Number (percentage) of classification as a	
	Proper	Improper	Proper	Improper	Proper	Improper
After both	95 (79%)	25 (21%)	110 (92%)	10 (8%)	110 (92%)	10 (8%)
2045	60 (100%)	0 (0%)	49 (82%)	11 (18%)	60 (100%)	0 (0%)
2061	40 (67%)	20 (33%)	50 (83%)	10 (17%)	50 (83%)	10 (17%)
Before both	11 (6%)	169 (94%)	4 (2%)	176 (98%)	16 (9%)	164 (91%)
2045	6 (7%)	84 (93%)	0 (0%)	90 (100%)	6 (7%)	84 (93%)
2061	13 (14%)	77 (86%)	0 (0%)	90 (100%)	4 (4%)	86 (96%)

Table 4. The results of classification for signal component D1 for gauss thresholds separately for locomotive 2045 and 2061

	X_2 Number (percentage) of classification as a		X_3 Number (percentage) of classification as a		X_4 Number (percentage) of classification as a	
	Proper	Improper	Proper	Improper	Proper	Improper
After both	108 (9%)	12 (10%)	110 (92%)	10 (8%)	110 (92%)	10 (8%)
2045	60 (100%)	0 (0%)	60 (100%)	0 (0%)	60 (100%)	0 (0%)
2061	41 (68%)	19 (32%)	50 (83%)	10 (17%)	50 (83%)	10 (17%)
Before both	13 (7%)	167 (93%)	11 (6%)	169 (94%)	12 (7%)	167 (93%)
2045	6 (0%)	84 (93%)	0 (0%)	90 (100%)	9 (10%)	81 (90%)
2061	0 (0%)	90 (100%)	2 (2%)	88 (98%)	5 (6%)	85 (94%)

Table 5. The results of classification for signal component D4 for gauss thresholds separately for locomotive 2045 and 2061

	X_2 Number (percentage) of classification as a		X_3 Number (percentage) of classification as a		X_4 Number (percentage) of classification as a	
	Proper	Improper	Proper	Improper	Proper	Improper
After both	110 (92%)	10 (8%)	110 (92%)	10 (8%)	110 (92%)	10 (8%)
2045	60 (100%)	0 (0%)	60 (100%)	0 (0%)	60 (100%)	0 (0%)
2061	50 (83%)	10 (17%)	50 (83%)	10 (17%)	50 (83%)	10 (17%)
Before both	9 (5%)	171 (95%)	7 (4%)	173 (96%)	6 (3%)	174 (97%)
2045	1 (1%)	89 (99%)	46 (51%)	44 (49%)	1 (1%)	89 (99%)
2061	7 (8%)	83 (92%)	5 (6%)	85 (94%)	6 (7%)	84 (93%)

for components S, D1 and D4 were chosen to build a classifier. It needs to define a threshold to distinguish the states of right and fault work of an engine.

At the beginning the simplest way was taken into account. The threshold was considered as a center between the parameter averaged value for the case before and the case after the repair. The results for this kind of thresholds appeared not perfect. But analyzing the original data more detailed it was noticed that resolutions of values for the state “after” was concentrated very broad in comparison with the values for the state “before” (see Table 2). Taking the “center” threshold gives a bad classification for signals before but better for signals after.

It can be seen from Table 7 that the standard deviations of parameters are approximately ten times bigger for the set of data “before”. From the classifier construction point of view, it means that the threshold cannot be taken as a center of distance between before and after cases. To find the right threshold the Gaussian distribution was taken into consideration (find out that a mean and a standard deviation are enough to define a Gaussian distribution). This way a threshold should be define as a value, which is a coincidence point between two adjacent Gauss distributions, one for proper and the second for improper case. In other words, the threshold is a solution of equation created by equate two Gauss distribution with different means and standard deviations

$$G(x)_{\mu 2,\sigma 2} = G(x)_{\mu 2,\sigma 2} \tag{6}$$

These kinds of thresholds are calling in the paper as “gauss” thresholds. The results of classification for gauss thresholds were better but they all the time not satisfactory. The problem was in the fact that the set of all signal data were recorded on two locomotives but considered together. That’s way the calculations were repeated for each locomotive separately.

Taking into account the center thresholds for each locomotive separately and classify all cases as improper (while the value of a parameter is below threshold) or proper (while the value of a parameter is above a threshold) separately for locomotive 2045 and 2061 give the results which are not satisfactory the same as for the analysis of data from two locomotives jointly. Here also can be noticed that resolutions of values for the state after are concentrated very broad in comparison with the values for the state before. Taking into account the means and standard deviations of distribution of parameters X_2, X_3, and X_4 calculated for the cases before and after for each locomotive separately the gauss threshold was using (threshold calculated basing on Gauss distributions). Considering gauss thresholds and classify all cases as improper (while the value of a parameter is below a threshold) or proper (while the value of a parameter is above a threshold) separately for locomotive 2045 and 2061 give the results of classification which are presented in Tables 3–5. These results are really the best and give a good perspective for using the above parameters and methods for classification of Diesel engine state.

Find that for classification performed in the paper a case was classified as improper while a corresponding value was below threshold and as a proper while the corresponding value was above a threshold. The state “before” represents a worn-out engine in bad conditions while state “after” represents the repaired engine in better general conditions. It strictly means that the values of Variance X_2, Root-Mean Square X_3 and Mean From Absolute Values X_4 of horizontal signal S and of it multiresolution components D1 and D4 are higher for proper engine working. At the same time the above parameters before the repair have significantly lower values (sometimes 10 or even 100 times) of standard deviation in comparison with the values for the same parameters for the case after repair. The resolutions of values for the state “after” are concentrated very broad in comparison with the values for the state “before”. The bigger values of Variance, Root-Mean Square and Mean From Absolute Values show that the range of variability of the vibrations for repaired engine is higher. From practical point of view it seems that for the bigger values of the above parameters the engine is working “better”. The sensors mounted on an engine body registered vibration signals which represent the influence of many vibration processes taken place in an engine, like combustion processes and functioning of engine parts. This is no way to distinguish between them and presented in the paper diagnostic base on the general indication of useful diagnostic parameters without finding the relation to real mechanical engine processes. We can just say that the "better" working of an engine corresponds to better combustion and better working of engine parts.

6. Discussion

The analysis presented in the paper was performed to distinguish between different engine states corresponding to engine state before and after a repair using signal processing methods. For this analysis three parameters were eventually selected: Variance, Root-Mean Square and Mean From Absolute Values. The horizontal registration signals were chosen to analysis and in the calculations the original signal S and the two multiresolution components D1 and D4 were considered. The best results of classification were obtained for considering separately data from different locomotives. This shows that in this case the individual attributes of each signal can differ significantly for different signal source. In practice it means the classification and determination of thresholds should be performed separately for each locomotive engine. The even superficial analysis of the results is interesting and gives perspectives to practical application in combustion engine diagnostic. Although the results are very promising the great complexity and variety of possible measurement schemas need more experiments and researches before practical application in an on-line OBD diagnostic system.

Nomenclature

14D40	engine type
2045, 2061	locomotive numbers
A1–A5	multiresolution high frequency components of S
CWT	continuous wavelet transformation
D1–D5	multiresolution low frequency components of S
DWT	discrete wavelet transformation
FFT	Fast Fourier Transformation
M/X1	mean
MAV/X4	mean from absolute values
OBD	on board diagnostic
RMS/X3	root-mean square
S	original signal
SC/X5	shape coefficient
ST44	type of Diesel locomotive
VAR/X2	variance

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