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MULTI-CHANNEL REGISTERED DATA DENOISING USING WAVELET TRANSFORM

ODSZUMIANIE DANYCH REJESTROWANYCH WIELOKANAŁOWO Z UŻYCIEM TRANSFORMATY FALKOWEJ*

In order to obtain information regarding given phenomenon or object, it is usually necessary to register selected measurement signals obtained using sensors. Unfortunately, obtained signals, apart form desired information, contain disturbances caused by, amongst many other, properties of the measurement channel and processes associated with object operation. In many cases it is necessary to measure the same value in different places and/or directions. Thus, there is a demand for a tool improving signal to noise ration of the multi-channel registered signals.Wavelet transform is a relatively new method of data processing used in different fields (e.g. technique and physics). In case of signals it can be used for denoising, compression, trend detection or discontinuity detection. In this work it was used to denoise vibration signals registered by two three-axis sensors. Object of investigation was the bevel toothed gear. Signals denoising was to improve efficiency of the diagnosis of transmission gears teeth damage.

Keywords: *denoising, wavelet transform, artificial neural network, spiral bevel gear.*

W celu uzyskania informacji o interesującym nas zjawisku lub obiekcie najczęściej rejestrowane są wybrane sygnały pomiarowe otrzymane za pośrednictwem czujników. Niestety uzyskane sygnały oprócz pożądanej informacji zawierają również zakłócenia, które są spowodowane m.in. właściwościami toru pomiarowego i procesami towarzyszącymi działaniu obiektu. W wielu przypadkach zachodzi potrzeba pomiaru takiej samej wielkości w różnych miejscach obiektu i/lub kierunkach. Potrzebne są zatem narzędzia do poprawy stosunku sygnału do szumu sygnałów rejestrowanych wielokanałowo.Transformata falkowa jest stosunkowo nową metodą przetwarzania danych, która znalazła zastosowanie w różnych dziedzinach takich jak technika i fizyka. W odniesieniu do sygnałów może być używana do odszumiania, kompresji, wykrywaniu trendu czy nieciągłości sygnału. W pracy tej transformata falkowa została użyta od odszumiania sygnałów drgań zarejestrowanych z dwóch trójosiowych czujników. Obiektem badań była przekładnia zębata stożkowa. Odszumianie sygnałów miało na celu poprawę skuteczności diagnozy uszkodzenia kół zębatych przekładni.

Słowa kluczowe: *odszumianie danych, transformata falkowa, sztuczne sieci neuronowe, przekładnia stożkowa.*

1. Introduction

In the vibroacoustic diagnosis, like in other fields of science, it is desired to improve achieved results [2]. In the recent years one can observe continuous development of the algorithms of diagnostic computing and signal processing methods [3, 11, 16]. Measuring and computer equipment allow signal measurement with much higher accuracy and from many channels simultaneously.

In case of examining complex objects there is a necessity of registering many signals. At the beginning of the investigation more measurement points are selected to avoid losing important information and obtain best measurement points.

Obtained measurement signals always contain disturbances. In a simple signal model [1, 4, 10] it is assumed that signal contains valuable component (contain useful information) and random component (noise). There are many methods of extracting useful information from the signal, e.g. by signal filtration, PCA main components analysis, signal averaging. Among these method it is worth to mention wavelet transform (WT) that has been found to be useful in signal denoising [14]. Generalisation of the denoising using WT for one signal is a procedure proposed in [1] for many signals – it was used in this work.

2. Test stand

An investigated object is a bevel toothed gear. Its body was equipped with two three-axis vibration acceleration sensors marked with 1 and 2 in Fig. 1. X axis of the sensors is parallel to the direction of input shaft axis and Z axis is an axis of output shaft. The vibrations was registered for the gear in good conditions and with damaged surface of teeth due to seizing. More precise description of the test stand can be found in [9].

3. Discrete wavelet transform (DWT)

In case of the Continuous Wavelet Transform (CWT) the wavelet coefficients are computed for each scale what generates large amount of data and requires long computations. Dis-

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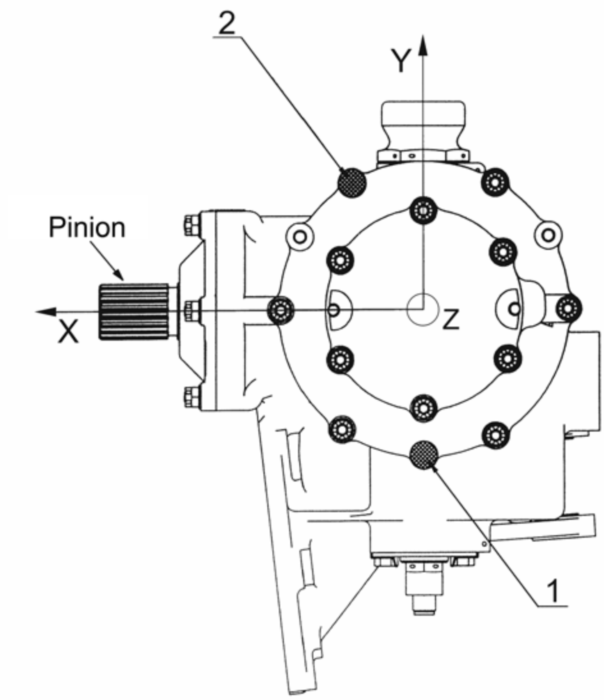

Fig. 1. View of the examined gear with marked position of the vibration sensors

crete Wavelet Transform is based on CWT and allows scale selection. DWT can be defined as [17]:

$$DWT(j,k)=\left|S_0^j\right|^{-1/2}\sum_k x|k|\psi\left(\frac{t-k\tau_0 S_0^j}{S_0^j}\right) \tag{1}$$

where:
$S_0 > 1$, $\tau_0 > 1$,
ψ – basis wavelet,
$x|k|$ – investigate signal,
j, k – positive integers.

For fast and efficient computations of DWT one can use an algorithm introduced by Mallat [12,15], known as multi-resolution analysis (MRA). As a result of its operation we obtain multi-resolution representation of the signal in a form of approximations and details. Complete theoretical basis of the MRA can be found in Mallat's work [12] and the dependency describing it is expressed by formula [17]:

$$x(t)=\sum_{\tau} S_0(\tau)\phi(t-\tau)+\sum_{\tau}\sum_{j=0}^{j-1} d_j(\tau)^{j/2}\psi(2^j t-\tau) \tag{2}$$

where:
τ – shift coefficient,
S_0 – scale coefficient,
d_j – wavelet coefficient for j scale,
$\phi(t)$, $\psi(t)$ – scaling and wavelet function.

Details and approximations are computed thanks to filtration with a two-channel set of filters (quadrature reflection filters [5,6]). In order to obtain signal decomposition into a few levels the filtration operation should be iterated (Fig. 2). Using low-pass filter we obtain approximation A_j (low frequency signal component) and using high-pass filter we obtain detail D_j (high frequency signal component)[7]. Fig. 2 shows sample signal registered with 10kHz frequency. Decomposition resulted in signal in 0 – 5kHz range at the first level of approximation A_1 and detail D_1 - range 5 – 10 kHz. If the original signal consisted of 100 samples then the filtration results in obtaining a detail with length equal approx. 100 samples and an approximation with length equal approx. 100 samples. A sum of the resulting signals is approximately twice larger than original signal. To avoid this increment of number of samples decimation is used (removing every second sample from the obtained signal). Then we can perform further decomposition. Usually, an approximation is analyzed in order to obtain next detail and approximation. Signal decomposition is performed for finished number of levels due to signal length or physical sense of obtained details and approximations [18]. Usually, decomposition level does not exceed 8.

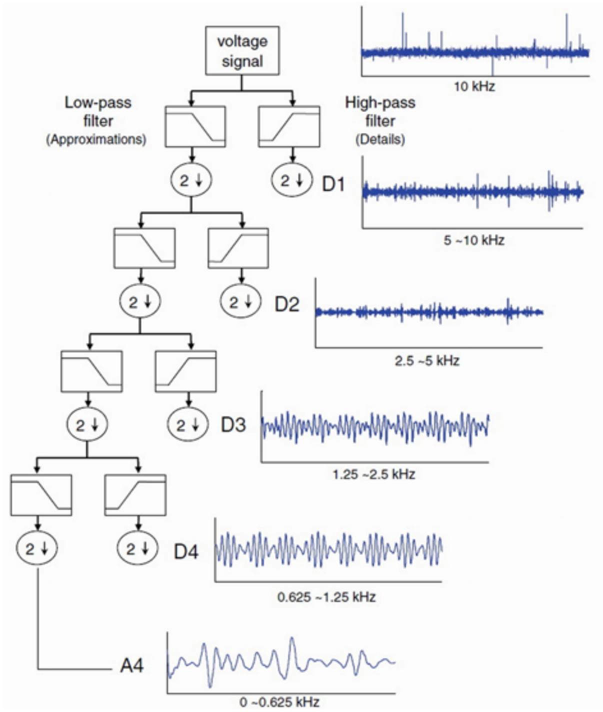

Fig. 2. Signal decomposition using multi-resolution analysis algorithm [17]

Removing irrelevant information (noise) after wavelet decomposition can be realized using a few methods. Next signal approximations contain signal component with lower and lower frequencies, thus the selection of proper approximation as a signal representation is then noise elimination method. Other possibility is simple modification of first detail (or details) by changing wavelet coefficients to zero. These methods of signal denoising are not very precise. More sophisticated denoising algorithms base on zeroing detail wavelet coefficients basing on a criterion calculated separately for each detail. Apart from selection of the proper threshold criterion (below which wavelet coefficients are set to zero) it is also necessary to select a method of threshold realisation. Hard thresholding method realizes denoising process by setting zero value for the elements which absolute value are below threshold value (other elements are not changed). A variation of this method is soft thresholding, in which not zeroed elements are also changed what

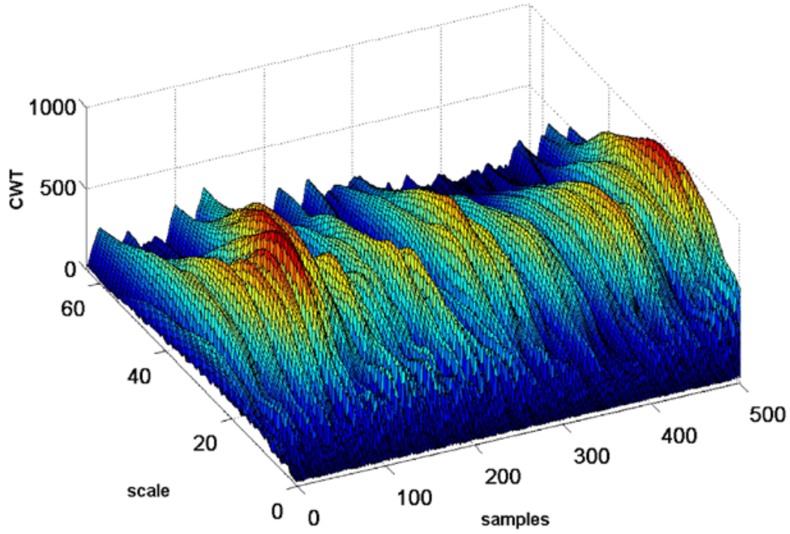

Fig. 3. 3D plot of vibration signal

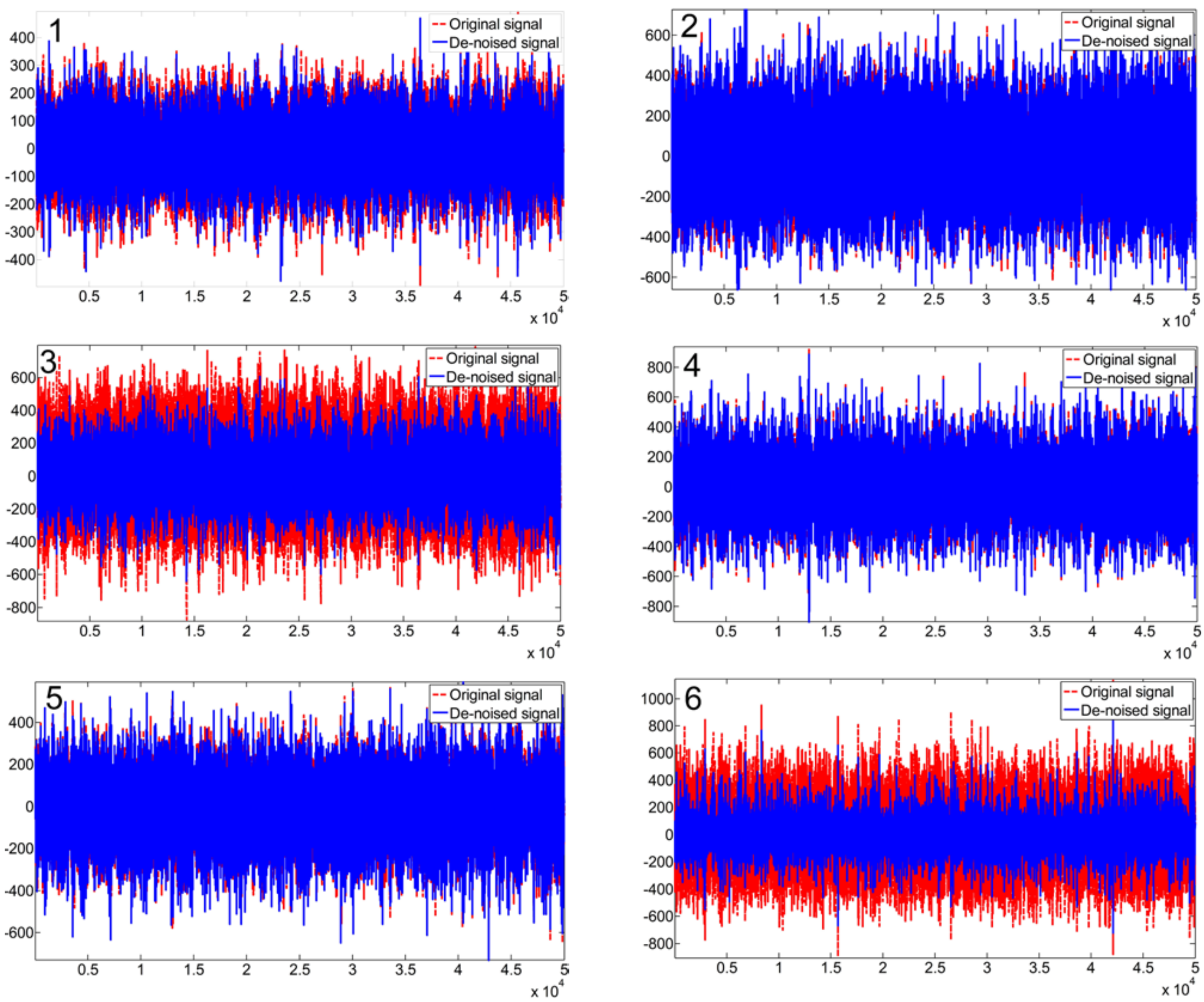

Fig. 4. Vibration signals for the damaged gear from first to sixth channel before and after denoising

eliminates discontinuities in the location where the elements have values equal to threshold value [13]. Signal reconstruction is performed similarly to the decomposition. One should oversample details and approximations before synthesis in the filters (their selection is critical for complete reconstruction of the original signal).

3.1. Denoising procedure

Denoising procedure for the multi-dimensional data is a generalisation of single dimension data denoising. The considerations are in accordance with Aminghafari et al. [1].

Let us assume the following p-dimensional signal model:

$$X(t) = f(t) + \varepsilon(t),\ t = 1,\dots, n \tag{3}$$

where:
$X(t)$, $f(t)$, $\varepsilon(t)$ are of 1x p dimension,
$f(t)$ – signal to be denoising,
$\varepsilon(t)$ – Gaussian noise with unknown covariance matrix $E(\varepsilon(t)^T \varepsilon(t))=\Sigma_\varepsilon$.

Every component $X(t)$ has form for $1 \le i \le p$:

$$X^i(t) = f^i(t) + \varepsilon^i(t),\ t = 1,\dots, n \tag{4}$$

where:
f^i – belongs to certain functional space (most often L^2 or Besov's).

Covariance matrix Σ_ε that is to be additionally defined, shows stochastic dependence between $X(t)$ components and spatial correlation models.

Denoising procedure can be expressed using three steps [1] for the X matrix that has $n \times p$ dimensions and consists of p signals (columns of X matrix) in a way that $n>>p$:

- For each column of X matrix perform a wavelet decomposition of J-th degree. In this degree $J+1$ matrixes $D_1,\dots,D_J$ are obtained – they contain degree detail coefficients from 1 to J of p signals and approximation coefficients A_J of p signals. The matrixes D_j and A_J have dimensions $n2\text{-}j \times p$ and $n2\text{-}J \times p$;
- Determine the estimator $\hat{\Sigma}_\varepsilon$ of the noise covariance matrix and perform SVD (singular value decomposition) of the $\hat{\Sigma}_\varepsilon$ matrix using orthogonal V matrix where $\hat{\Sigma}_\varepsilon = VAV^T$. Then change the basis using transformation matrix V (precisely calculating $D_j V$, $1 \le i \le p$) and perform single-dimensional filtering using threshold $t_i = \sqrt{2\lambda_i \log(n)}$ for the i-th column of the matrix $D_j V$;
- Perform reconstruction of the denoised matrix using simplified details matrix and approximation through basis changed using V^T matrix and reciprocal wavelet transform.

4. Test results

Vibration signals registered during tests were denoised using the procedure described above. Denoising was performed for the signals recorded for transmission in good condition and for damaged one (6 channels were registered). Figure 3 shows a graph of wavelet coefficients which illustrated the change of frequency vibration signal in time.

Denoising results in time domain for the damaged gear are shown in Fig. 4. Basing on the graphs for the axes of sensors according to the direction of output shaft axis one can notice that corresponding signals exhibit the highest level of noise.

Signal decomposition level was equal three and for the basic wavelet the Coiflet 1 was chosen (Fig. 5)

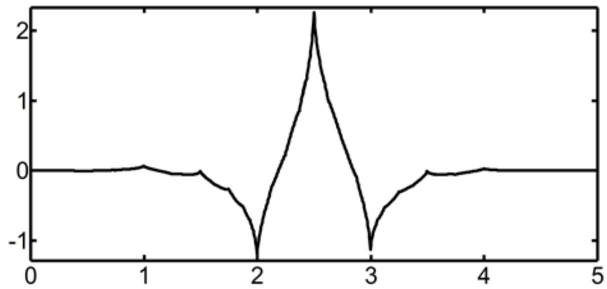

Fig. 5. Wavelet Coiflet 1

For the same criterion of calculating thresholds for the signal details the denoising was realized using soft and hard thresholding. Then the features of signals were computed and eight of twenty of them were selected using an algorithm presented in [8]. Selected features:

- average value,
- RMS value,
- peak value,
- peak factor,
- backlash factor,
- standard deviation,
- energy ratio,
- FM0.

In order to compare the efficiency of signals denoising the same features were computed for the signals without processing. Condition classification was performed using artificial neural network - multi layer perceptron (MLP).

Table 1. Condition classification results for the unprocessed signal

Network name	Quality (learning)	Quality (testing)	Quality (validation)	All trials
MLP 8-4-2	89,88	91,66	91,66	90,41

Table 2. Condition classification results for the denoised signal (soft thresholding)

Network name	Quality (learning)	Quality (testing)	Quality (validation)	All trials
MLP 8-4-2	95,53	95,83	95,83	95,62

Table 3. Condition classification results for the denoised signal (hard thresholding)

Network name	Quality (learning)	Quality (testing)	Quality (validation)	All trials
MLP 8-9-2	97,02	94,44	94,44	96,24

Network classification results are given in the tables above. Classification efficiency for the unprocessed signal reached approx. 90% and for the denoised signal – approx 5% better. Differences between hard and soft thresholding were insignificant.

5. Summary

The work presents a method of denoising vibration acceleration signals registered simultaneously for the same object. Comparison of the signals before and after denoising showed that for both sensors (in the same direction of vibration registration – along the axis of the input shaft) there were the highest amount of noise.

Signal denoising was performed using two methods - soft and hard thresholding. Then the neural network was to recognize gear's condition. Both methods resulted in similar and satisfying output. Classification quality achieved approx 96%. In order to verify efficiency of the method, similar procedure was performed for the original (unprocessed signal). Classification correctness was then smaller by approximately 5%.

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