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WAVELETS AND GRAPHICAL PROGRAMMING IN SEISMIC SIGNAL PROCESSING

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Abstract − The numerical methods based on a wavelet analysis and their application in seismic signals for the purpose of denoising and automatically identifying of the P phase arrival are presented. The methods implemented in the computer program and the results are presented. The methods are used for the low-amplitudes, therefore noisy signals, which were usually rejected because of the problem with the proper P phase arrival identification.

Keywords: wavelets, seismic signal processing, graphical programming.

1. INTRODUCTION

The seismic events detection is very important in coal mining. These events – mainly a rock mass vibration and tremors – can produce a rock burst. The prediction of the rock burst is the most important for the safety of mining and protection of human lives. Therefore the seismic events are registered in a dedicated hardware and the locations of these events are performed.

The seismic signal – the seismogram – has several features that represent various types of phases (see Fig. 1). Some of the most significant, especially for the seismic event location, are the P and S arrivals. Accurately determining the times of these arrivals are important in accurately determining the seismic event location.

In the Polish coal mines mainly the P phase arrivals times are used in the seismic event location methods. The times of arrival from at least fife seismograms for the particular seismic event are required [1]. Therefore the events are registered in 8 to 16 channels system.

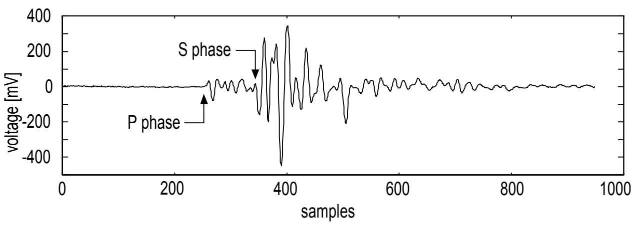

Fig. 1. Example of one-component seismogram registered in a coal mine. The P and S phases times arrivals is depicted

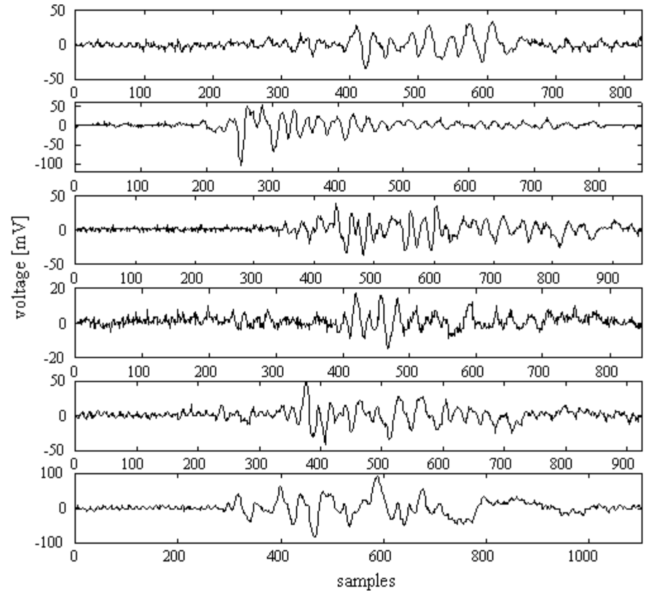

Fig. 2. Seismograms with low amplitude and the ambiguous P phase arrival.

Typically, there is no problem with the P phase time arrival identification in clear, noiseless signals. The noisy, low amplitude signals are rejected. The reason is, that signals with low amplitude have usually the ambiguous P phase arrival, and therefore the seismic event cannot be located. The examples of such the signals are presented in Fig. 2. Such the signals are interesting, but the methods of denoising of the signals and the P phase identification are required. The important is, that the method of signal denoising cannot introduce the phase shift. One of the methods is based on a wavelet analysis.

2. WAVELET ANALYSIS

2.1. Wavelet representation

The wavelet analysis is a very useful tool in the analysis of nonstationary and finite energy signals. There are lots of publications on wavelets; some of them are described in the references [2, 3]. The main advantage of the wavelet transform is that it provides information on transients localized in a time.

The fundamental idea behind wavelets is to analyse according to a scale. The scale is connected with a resolution. First scale corresponds to the highest resolution – details in signal can be observed – and the last scale corresponds to the lowest resolution – only low-frequency features of the signal can be observed.

In this paper the implementation of the multiresolution (MRA) analysis is presented, first introduced by Mallat [4]. The MRA allows us to decompose a signal *f(t)* into a sum of its details *D(t)* and approximations *A(t)* at different levels of resolution (see Fig. 3). The approximations are the low-resolution representations of the original signal while the details are the difference between two successive low-resolution approximations.

The basis for this decomposition is formed from mother wavelet $\psi(t)$ and scaling function $\phi(t)$

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t-k)\,;\, j,k \in \mathbf{Z} \tag{1}$$

$$\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t-k)\,;\, j,k \in \mathbf{Z}\,, \tag{2}$$

where j is a scale factor representing the level of the resolution and k is a shift factor. The connection between these two functions is given by

$$\phi(t) = \sum_{k\in Z} h_k \phi(2t-k) \tag{3}$$

$$\psi(t) = \sum_{k\in Z} g_k \psi(2t-k)\,. \tag{4}$$

In (3) and (4), two coefficient sets $\{g_k\}$ and $\{h_k\}$ represents the high pass G and the low pass H analysis filters. These filters commonly with the high pass G^* and the low pass H^* synthesis filters, which are derived, for orthonormal wavelets, from analysis filters, give the decomposition tree. An example of decomposition tree is shown in Fig. 3, for the case $j = 2$, and the example of low-amplitude seismic signal decomposition for the first 4 scales is shown in Fig. 4.

2.2. Denoising

It is generally impossible to filter out all of the noise without affecting the information in the signal. In on-line filtering for seismic signals in the case of the P phase time arrival identification the important is a phase shift. The conventional filtering also cuts-off certain frequencies, which can contain an important information.

In this work the conventional wavelet domain denoising methods are used based on thresholding wavelet coefficients (details coefficients) below a certain value [5, 6].

If a signal has its energy concentrated in a small number of wavelet dimensions, its coefficients will be relatively large compared with a noise that has its energy spread over a large number of coefficients. This means that, during the thresholding, the low amplitude noise can be removed in the wavelet domain. The reconstruction will then retrieve the desired signal with little loss of details.

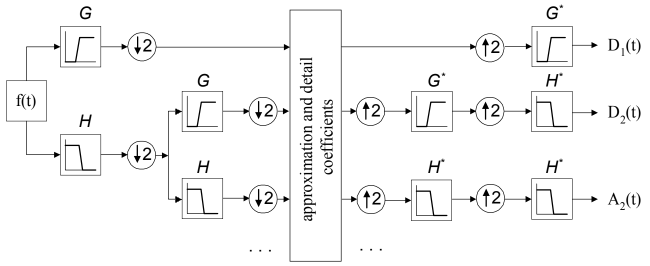

Fig. 3. Decomposition of signal f(t) to approximations $A_i(t)$ and details $D_i(t)$. Symbols ↓2 and↑2 represent dyadic down- and up-sampling.

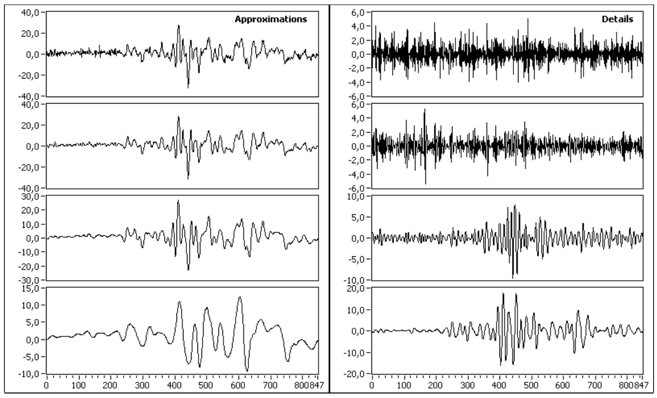

Fig. 4. Example of low-amplitude seismic signal decomposition for the first 4 scales.

If we denote by *cD(t)* the details coefficients before thresholding and by $cD^*(t)$ the details coefficients after thresholding, the hard (5) and the soft (6) thresholdings can be write as follow

$$cD^*(t) = \begin{cases} cD(t) & for\,|cD(t)| > T \\ 0 & for\,|cD(t)| \le T \end{cases}, \tag{5}$$

$$cD^*(t) = \begin{cases} cD(t) - T & for\; cD(t) \ge T \\ cD(t) + T & for\; cD(t) \le -T \\ 0 & for\; cD(t) \le T \end{cases}, \tag{6}$$

where T is a threshold.

In other words, the hard thresholding is setting the details coefficients whose absolute values are less than the threshold to zero. For the soft thresholding, the details coefficients whose absolute value are lower then the threshold is set to zero, and then the nonzero coefficients remaining are shrunk towards zero.

There are several methods of the threshold selection. In this work the most popular fixed form threshold is used according to formula

$$T = \sigma\sqrt{2\log N}\,, \tag{7}$$

where N is the number of data points in the thresholded signal and σ is the noise level.

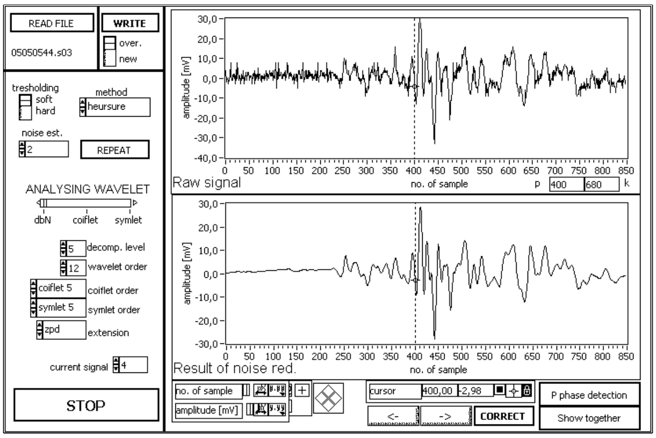

Fig. 5. Example of noise reduction in seismic signal.

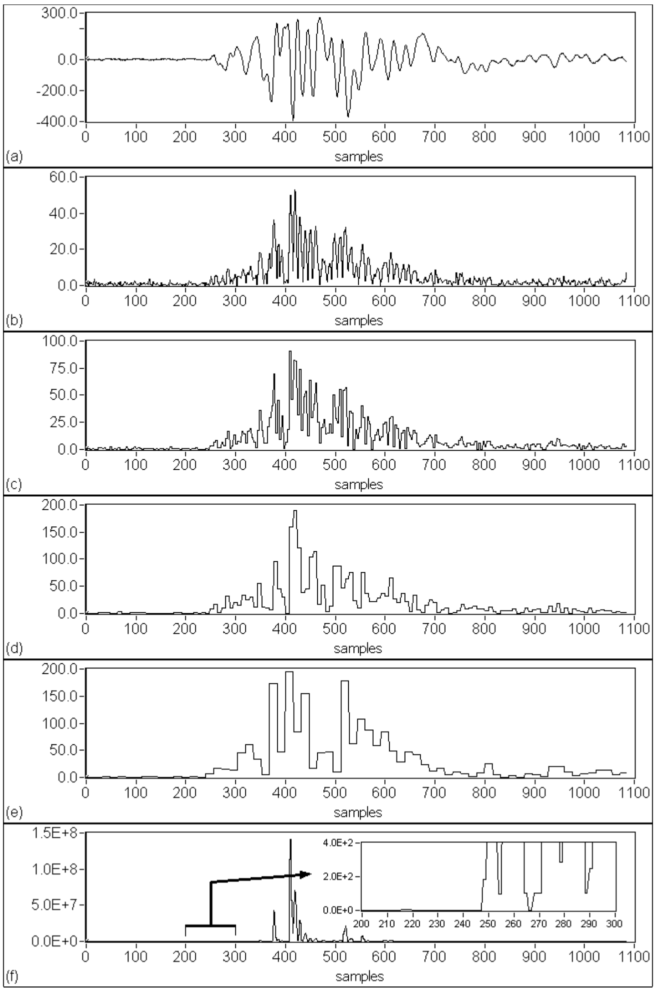

Fig. 6. The P phase arrival identification: (a) seismic signal; (b)–(e) details *D(t)* at first 4 scales; (f) absolute value of product *p(t)* of first 4 scales.

If we assume that the details coefficients in the first scale are essentially noise (see Fig. 4) with standard deviation equal to σ, the median absolute deviation of the coefficients is a robust estimate of σ. If a non white noise is expected, the threshold must be rescaled by a level-depended estimation of the noise at each scale.

There are also other methods of the thresholding selection used in this work: one based on the Stein's unbiased risk estimate (SURE) and the heuristic method (HEURSURE), which is a mixture of the SURE and fixed form threshold (7).

An example of noise reduction in low amplitude seismic signal is shown in Fig. 5. The wavelet used for denoising in this example was the Daubechies wavelet with the vanishing moment 12, that is, db12. The HEURSURE method of thresholding selection was used, rescaled by a level-depended estimation of the noise.

2.3. *P phase arrival identification*

We can treat the arrival of the P phase in the registered seismic signal as a kind of discontinuity. Such the discontinuity can be observed in the details *D(t)* as a rapid jump in their value across the scales.

To obtain a sharp and a rapid jump effect, the Haar (8) wavelet was used. This wavelet has the most compact support among others and gives the best time location.

$$\psi(t) = \begin{cases} 1 & 0 \le t < \frac{1}{2} \\ -1 & \frac{1}{2} \le t < 1 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

To gain the jump effect, the absolute value of the product can be considered

$$p(t) = \left| \prod_{j \in Z} D_j(t) \right|, \tag{9}$$

illustrated in Fig. 6.

3. IMPLEMENTATION IN COMPUTER PROGRAM

The presented methods have been implemented in the computer programs for the multiresolution signal decomposition, for the seismic signals denoising and the P phase arrival identification. All the figures, except Fig. 1 were prepared with these programs.

The graphical language – LabVIEW, by *National Instruments* was used. The great advantage of such a programming approach is that the source code is made as a block diagram, with icons – a graphical representation of different numerical, string, file and many other functions. The programming is to make the proper connections between these icons, so that the data flows amongst them to accomplish a desired purpose. The created program is called the Virtual Instrument – the VI. After creating the VI, it can be used in the form of an icon as a subroutine in the block diagram of the higher level VI.

The created computer programs were thought as the tools for investigation the efficiency of the MRA in low-amplitude, noisy seismic signals processing. The programs enable to test many parameters of the analysis. Three types of orthogonal wavelets were implemented – the Daubechies, the coiflet and the symlet. The series of procedures, called the virtual instruments, have been built, for realization of the

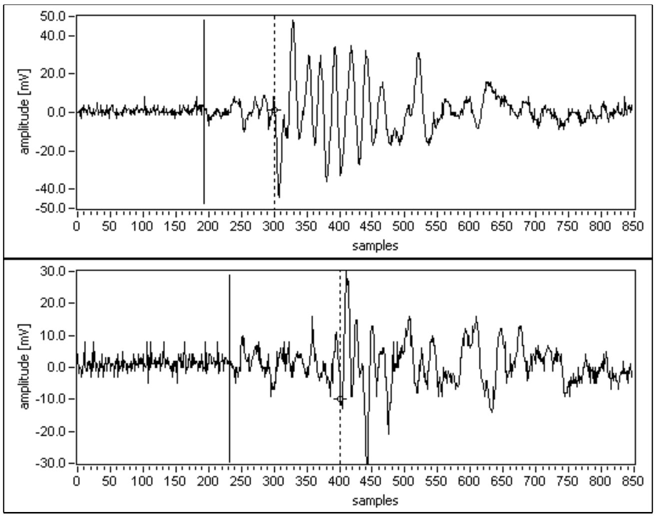

Fig. 7. Examples of the P phase arrival identification in low-amplitude seismic signals. Dashed lines – the result of non-wavelet method, solid lines – the result of wavelet approach.

following tasks: decomposition and approximation coefficient calculations, reconstruction of the details and the approximations, denoising via soft or hard thresholding with chosen thresholding rules and noise estimation, denoised signal reconstruction, the P phase arrival identification.

The described computer programs and subroutines are dedicated not only for the seismic signal processing but can be used also for any signals.

4. CONCLUSION

The description of wavelet methods for the seismic signal denoising and the P phase arrival identification in low-amplitude and noisy signals were presented and their implementation in the computer programs. The programs will be tested in one of the coal mine in The Upper Silesia Coal Basin in Poland.

The comparison between algorithms for the P phase identification – the one based on the signal envelope, working at present in coal mine tremor stations, and the second, described in this paper, based on MRA – shows that for low-amplitude, noisy signals the MRA approach gives better results. The example of comparison between these two methods is shown in Fig. 7. The solid line represents the proper P phase arrival. The preliminary denoising of the seismic signal is performed before the P phase arrival identification. It results with the lower value of the product *p(t)* before the P phase arrival, therefore the jump of the *p(t)* at the arrival time is more visible.

The future work will focus on the implementation of the presented methods in the apparatus working in coal mine tremor stations. We are expecting that the methods of on-line filtering and the P phase arrival identification using the MRA will allow registering and locating the weaker seismic events with present hardware.

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REFERENCES

[1] M. D. G Salamon, G. A. Wiebols, "Digital location of seismic events by an underground network of seismometers using the arrival times of compressional waves", *Rock Mechanics*, vol. 6, No. 3, pp 141-166, 1974.

[2] A. Teolis, "Computational signal processing with wavelets", *Birkhuser*, Boston, 1998.

[3] S. Mallat, "A wavelet tour of signal processing", *Academic Press*, London, 1999.

[4] S. Mallat, "A theory of multiresolution signal decomposition: the wavalet representation", *IEEE Trans. Pattern Anal. Mahcine Intell.*, vol. 11, pp. 674-693, 1989.

[5] D. Donoho, "De-noising via soft thresholding", *IEEE Trans. On Inf. Theory*, vol. 41, pp. 613-627, 1995.

[6] D. Donoho, I. Johnstone, "Adapting to unknown smoothness via wavelet shrinkage", *J. American Statistic. Assos.*, vol. 90, pp. 1200-1224, 1995.

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