Robust Identification of Glass Breaks Acoustic Signals Based on Wavelet Transformation and Rock Solid Attributes

Ireneusz Bemke, Romuald Zielonko

Gdańsk University of Technology, Faculty of Electronics, Telecommunications and Informatics, Department of Metrology and Electronic Systems; Narutowicza 11/12 str. 80-952 Gdańsk,
bemke@merkury.perfect.net.pl, zielonko@eti.pg.gda.pl

Abstract – Analysis of acoustic signals is a popular method of wireless detection of glass breaks in alarm systems. In most cases detection of some frequencies is applied for this purpose. Unfortunately, methods like this are not enough resistant to other (false) signals. Better results can be achieved using of JTFA for signal decomposition. To develop a robust method of glass breaks detection the authors applied Wavelet Transformation (WT). First results presented in [1] and [2] did not meet strong requirements of VdS standard. In this paper a new approach based on Rock Solid Attributes (used in geology) and Wavelet Transformation is presented. The main subject of the paper is the application of instantaneous Rock Solid Attributes to improve detectability of true glass breaks signals, and resistance to false signals.

I. Introduction

Nowadays many alarm systems are based on wireless glass breaks detection by acoustic signal analysis. Proper identification of glass breaks acoustic signal is difficult due to stochastic character of process, its nonlinearity, a lot of varied parameters and strong requirements of VdS standard: over 90% of detection efficiency, and at the same time near 100% of resistance to false signals (when glass hasn't broken). The main difficulty of the problem consist in big amount of signals received by detector: mechanical and fire stimulated glass breaks, traffic jam, environment sounds, sabotage hits and so on; simultaneously, as it was mentioned, detection method must be resistant on all false signals. Most of known methods are based on detection of a few acoustic frequencies, but they do not allow detectors to meet VdS standard requirements. Better efficiency can be achieved using JTFA solution [6], based on Hilbert transformation method – over 97% of detectability.

The authors used a different approach based on Wavelet Transformation to solve the problem. Obtained results have allowed to develop a theory of the solution, but the early methods did not meet expected performance [1]. Distinctive measures of the process were being analysed and reported in [2]. This paper presents application of Rock Solid Attributes (RSA) as a tool for improving the identification method in sense of detectability of true glass breaks signals and resistance to false signals.

II. Theoretical basis

A. Wavelet Transformation

Wavelet Transformation (WT) is a mathematic tool for signal analysis. WT is self-scaling and has good resolution in time and frequency domains. These advantages makes it ideal for analysis of nonstationary signals. In mathematical meaning WT is a correlation between analyzed signal and the set of functions called wavelets, where wavelets are generated by scaling and translating given mother wavelet. The Continuous Wavelet Transformation is expressed by the formula:

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int h^*\left(\frac{t-b}{a}\right) \cdot s(t) \;\; dt, \tag{1}$$

where $h^*(t)$ denotes complex conjugate of the mother wavelet $h(t)$, $s(t)$ is the signal, and a and b are dilatation and translation coefficients, respectively. In Discrete Time domain a dyadic scaling is commonly used:

$$t = n2^{-m} \quad oraz \quad a = 2^{-m}, \tag{2}$$

and the discrete version of Wavelet Transformation can be described by next formula:

$$DWT_x(m,n) = 2^{\frac{m}{2}} \int_{-\infty}^{\infty} \Psi^*\left(2^m \tau - n\right) s(\tau) d\tau \,. \tag{3}$$

In practical applications Fast Wavelet Transformation is used. It is based on iterative Mallat algorithm and has dyadic scaling (Fig.1.). Process consists in the convolution of the input signal with two filters, called quadrature mirror filters. It is possible, to compute various number of approximations for the same signal, but for most purposes few levels are enough. The results of Mallat processing are called approximations and details. They represent low and high-frequency parts of analysed signal respectively.

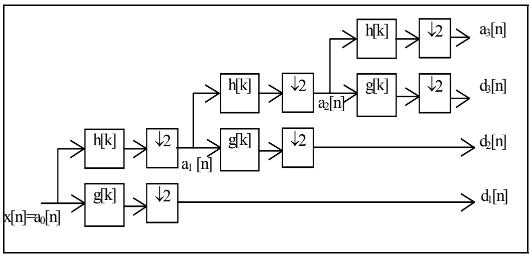

Fig. 1. Iterative Mallat algorithm – Fast Wavelet Transformation

This algorithm can be described by the following two expressions:

$$\begin{aligned} a_{j+1}[n] &= \downarrow_2 \left[a_j[n] * h[k]\right] = \sum_k a_j[2n-k]h[k] \\ d_{j+1}[n] &= \downarrow_2 \left[a_j[n] * g[k]\right] = \sum_k a_j[2n-k]g[k], \end{aligned} \tag{4}$$

where $a_{j+1}[n]$ represent approximation, and $d_{j+1}[n]$ details of input signal $a_j[n]$ convolved with filters h[k] and g[k]. The filters coefficients depend on selected wavelet [3], [7], and presented below system of equations (formula 5) describes the necessary conditions of wavelet filters. Formula 6 describes the relationship between the low-pass and high-pass filters:

$$\begin{cases} \sum_{n=0}^{N-1} h(n) = \sqrt{2} \\ \sum_{n=0}^{N-1} h(n)h(n-2k) = \delta(k) \qquad k = 0,1...(N/2)-1 \end{cases} \tag{5}$$

$$g(n) = \pm(-1)^n h(N-1-n). \tag{6}$$

By selecting mother wavelet (wavelet filters) it is possible to get out different features of the signals [4]. Important property of Wavelet Transformation is orthogonality of the results. Approximations and details are orthogonal both on the same level, and between different levels. This property is used in analysis and investigation of the method.

B. Rock Solid Attributes

Rock Solid Attributes were developed as an application to compute and output numerous physical and geometric attributes from seismic data. RSA allow users to generate many advanced 3D seismic attributes. Some of them are showed below.

Trace Envelope and Time Derivative of Envelope:

$$E(t) = \sqrt{f^2(t) + g^2(t)}\,; \quad d[E(t)]/dt = E(t) * diff(t). \tag{7}$$

Instantaneous Phase and Frequency:

$$Ph(t) = \arctan\left[\frac{g(t)}{f(t)}\right]; \qquad F(t) = \frac{\partial Ph(t)}{\partial(t)}. \tag{8}$$

In original case (seismic data analysis) RSA are computed for complex values of signal samples received by Hilbert transformation of real signal. The complex seismic trace is represented by mathematical formula:

$$S(t) = g(t) + if(t), \tag{9}$$

where: *f(t) = - Hilbert[g(t)],*
g(i) is acoustic signal recived by geophone.

C. Description of the investigation method

In papers [1] and [2] the results of distinctive measures of glass breaks acoustic signals are presented. As it was shown, simple measures as mean value, RMS value, local maximum and some more are not enough distinctive to meet requirements of popular standards. In authors opinion discontinuity and nonstationarity of geological signals make them similar to glass breaks signals. Therefore, RSA as a family of parameters used for identification of thresholds, edges, and discontinuity can be suitable for glass breaks signals analysis. The novelty of application of RSA, for this purpose, is using of WT as an initial processing - computation of analytical signal (Fig 2). Analytical signal for this purpose can be constructed in several ways, it means: of elements of the same approximation level, or elements of different levels. Authors propose to calculate RSA as a result of computation of signal composed of approximations and details on given level of Mallat algorithm:

$$S[n] = a_j[n] + id_j[n], \tag{10}$$

where a_j[n] is vector of approximation, and d_j[n] vector of details of signal on given approximation level.

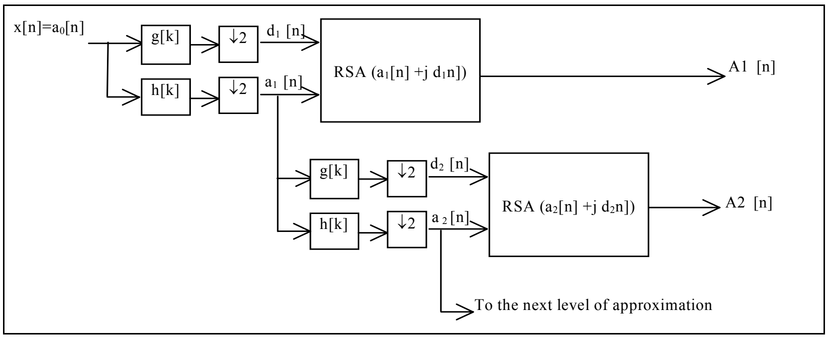

Fig. 2. The algorithm of RSA calculation from FWT.

To analyse glass breaks signal, special software was elaborated. Software uses Matlab environment, and enables to analyse input signals by STWT, CWT, DWT and FWT. Over 40 different wavelets are available for analysis. Software can cut signals and compare results of calculation of different signals. It is possible to show results on 2D and 3-D scalograms, or reconstructed bands of signals with selectable resolution. Since the beginning of investigation the software is successively developed. For purposes presented in this paper new module of RSA calculation has been made and tested.
The authors had analysed over 70 acoustic signals, recorded on real glass break research, with three sample rates: 25, 50 and 100kS/s. Signals, as it was described in [1] and [2], had been conditioned (converted to its amplitude, power and energy) and ROI (Region of Interest) limited.
Input signal had been shorted from 100ms (at the begin of the investigation), down to 2,5ms. Similarly the number of approximation levels had been fixed too. The results obtained for signals with sample frequency 100kHz had been analysed on 4 levels, and slower sampled signals only on 3 levels of approximations. Like in papers [1] and [2] only results obtained from signals with 100kS/s sample rate are interesting.
To check if other wavelets apart from selected in [1] and [2] (dmey, symlet, bior) get distinctive results, initial research has been done for nearly 40 wavelets., and finally only five wavelets were used.

III. Results

This paper describes instantaneous parameters only (wavelet and geometrical attributes will be analyzed in the future). Instataneous attributes were computed sample by sample of input signal, and obtained data were analyzed on a few ways: amplitudes, periods and delays of peaks. The results of such investigation shows distinctivity of several attributes, moreover they are helpful for designing parameters, and time points of signal for practical identyfication algorithms.
The instantaneous attribute group contains few ones which results depend on input signal amplitude (like: Real and Imaginary part, Instantaneous Envelope, Time Derivatives of Envelope) and these which are independent of input signal amplitude (Instantaneous Phase, Instantaneous Frequency, Band Width and Instantaneous Q factor). These two subgroups are analysed separately, to show their properities for long (from 10ms to 100ms) and short (up to 5ms) input signals.

Original records were 2,5 sec. long, but in this paper only 2,5ms to 100 ms after break were analysed. Due to need of precision cuts of the signals, the first problem of analysis was detection of break points, and synchronization of the signals. To do this a simple algorithm, based on amplitude analysis was elaborated. To check its results, the normalized amplitude of true and false signals were calculated. In Fig. 3a the first 0.6ms of signals are showed. Graphs b, c, d present normalized amplitude calculated for wavelet Bior1.3. As we can see, all signals have similar shape between 50th and 60th sample on first level of approximation, and significant differences in amplitudes in top graph. Authors assumed that the obtained synchronization is precise enough to compare the different attributes. Second difference (but not very distinctive) between signals is time of first wave – for true signals about 0.1ms and for false 0.15ms.

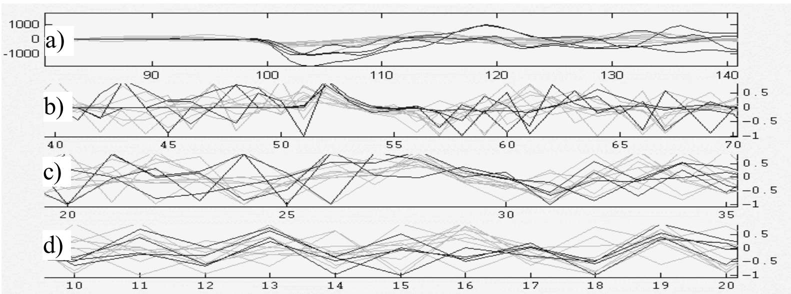

Fig.3. Real amplitude (a), and Normalized amplitude (b, c, d) of signals on different levels of approximation; signal interval 0,6ms; wavelet Bior1.3.

In the first step of investigation, signals of 10-100ms period were analysed. Fig. 4 (left) shows Instantaneous Envelopes of first 10ms after hits of true (dark) and false (light) signals. It is clear shown that all signals have similar time-scale spectrum. Although there are differences of signals amplitudes, they are not very distinctive features because of unknown distance between glass pane (signal source) and microphone (detector).

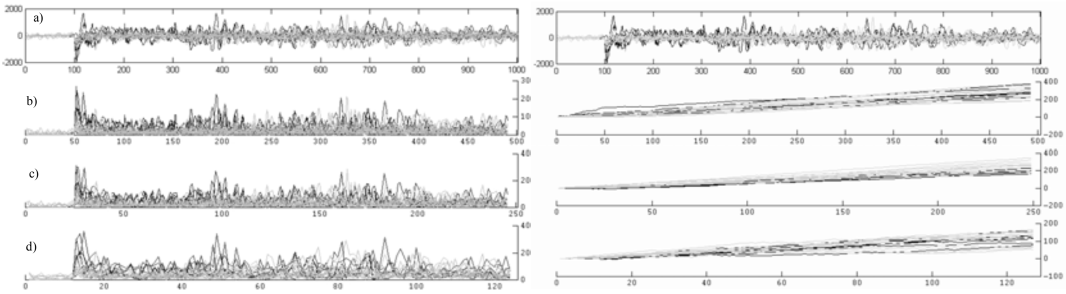

Fig.4. Typical true (dark) and false (light) Instantaneous Envelopes (left) and Instantaneous Phase (right) on different levels of approximation b), c), d); wavelet Bior1.5.

Due to similarity of time-scale spectrum of false and true signals, and big number of samples they are not easy to direct compare. Similarly, results obtained for attributes independent of signal amplitudes were not very distinctive or were difficult to interpretation. Fig. 4 right shows Instantaneous Phase of signals on three levels, for wavelet Bior 1.5, and time period of 10ms. As we can see, true and false signals have similar values of phase.

TABLE I. Selected amplitude sensitive RSA, long signals analysis

Attribute	parameter	level of distinct	best wavelets
Real part	amplitude	low (<20%)	Bior.1.3, 1.5, 2.6
Imaginary part	amplitude	low (<20%)	Bior.1.3, 1.5, 2.6
Inst. Envelope	amplitude	low (<30%)	Bior.1.3, 1.5, 2.6
Inst. Phase of amplitude	amplitude	very low (~0%)	unknown

Table I. contains selected attributes, and their ability to distinct long time true and false signals. Level of distinct is estimated as percentage count of true signals in signals exceed fixed value of given parameter. Generally, amplitude dependent parameters are more distinctive when long signals are analysed. Amplitude independent attributes have very stochastic character, and must to be analysed sample by sample. Authors concluded that this kind of attributes are more suitable for short signals analysis, and the differences in true and false signals occupy only few samples (typically in interval 0.1 – 0.5ms). Additionally, amplitude form of signals is worse than energy form [2], therefore in the next stage of investigation only energy representation of signal will be analysed in details. The amplitude and power forms will be used for comparison only.

Due to results presented above the signals were shorted down to 2,5 ms (250 samples). Because of unknown amplitudes of input signals, only amplitude insensitive attributes were analysed. As presented in [1] and [2] most useful form of signal is Energy. Analysis of RSA with different forms of signal confirm this thesis. Due to this property, only results for energy form are presented. Below a few RSA (in combination with wavelets) and most significant differenced are described.

The simplest amplitude independent attribute is Instantaneous Phase (formula 8). After summing the results of every 8 samples the diagrams are more smooth. In Fig. 5 Instantaneous Phase on tree levels is shown, Sym5 (left) and Bior1.3 (right graph) wavelets. As the figure shows, true signals (dark) have bigger values than false signals (light), and differences occupy about 0.4ms from hit on level 1 and 2 (different time scales).

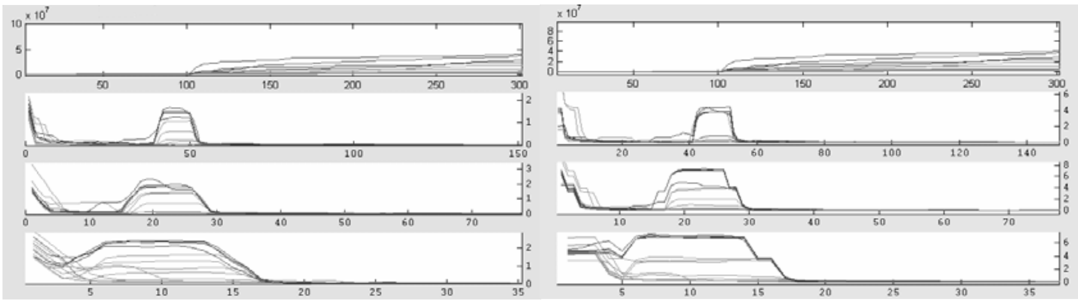

Fig.5. Instantaneous Phase of Energy form of signals; wavelet Sym5 (left); wavelet Bior1.3 (right);

In analysed set, when Bior.1.3 wavelet was used, only 20% of false signals have values comparable to true signals. Similarly some true signals (not more than 10%) have much lower values than other ones. This observation is compatible witch results described in [6].

Second simple, amplitude insensitive attribute is Instantaneous Frequency. It is usually computed as time derivative of arc tangent function, to avoid discontinuities of 2π jumps of Instantaneous Frequency. Figure 6 shows this attribute on three levels Bior1.3 (left) and Sym 5 (right) wavelet. There is no clear difference between values for true and false signals. Although most of true signals have amplitudes about 0.1, as much as 30% of false signals have comparable values. In this case period of first wave (after hit) is better feature of true signals. Differences are clearer for wavelet Bior1.3 than Sym 5. First wave period (zero cross) on first level of approximation of true signals (80%), is no shorter than 0.2ms. False signals have this time about half shorter.

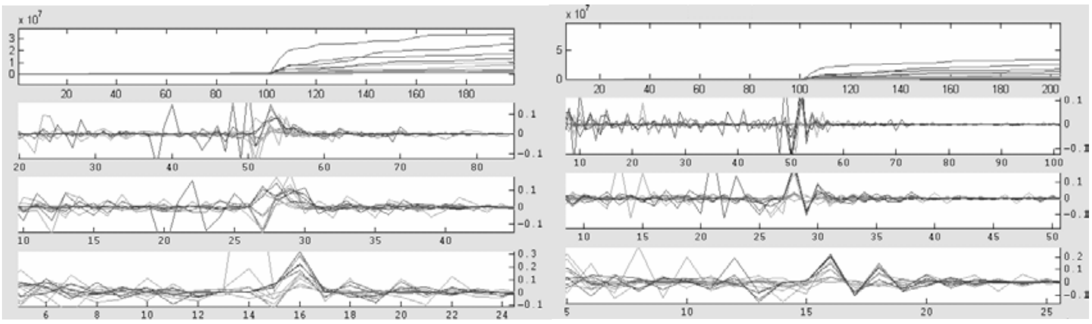

Fig.6. Instantaneous Frequency of Energy form of signals; wavelet Bior1.3; wavelet Sym5

Authors mean, that to improve detectability of this attribute, both parameters - amplitude, and first wave period should be calculated. Interesting observation is that true signals with time of first wave shorter than 0,2 ms, have a few oscillations instead of single wave.

Other interesting attribute is Instantaneous Q Factor. It is calculated as a ratio of Instantaneous Frequency to decay of Instantaneous Envelope, with $-\pi$ factor, and can be interpreted as leakage of energy from signal (probably energy is absorbed by glass pane). Fig. 7 shows values of Q Factor for Haar wavelet (left – for comparision) , and Bior1.5 wavelet (right). As we can see almost all of true signals have values of this attribute near to zero on the hit moment, and at least 0.1ms after hit. Note, that none of false signals has such a low value for more than 0.04ms Low values of Q Factor for true signals can be seen on all three levels. Note, that this attribute is almost insensitive on wavelet selection, but best result are achieved for Bior1.3 and Bior1.5 wavelets again.

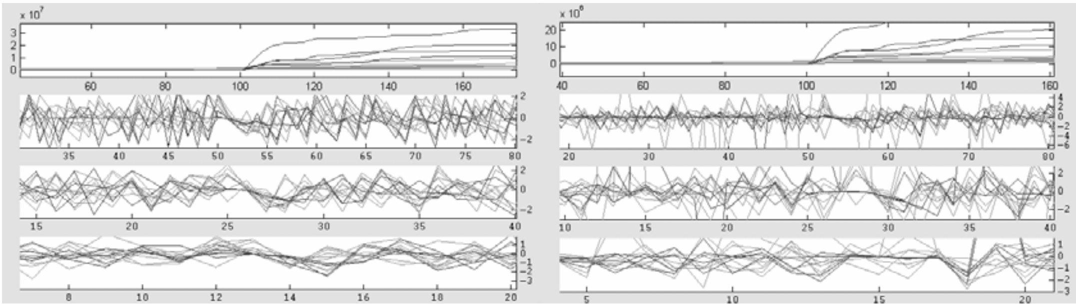

Fig.7. Instantaneous Q factor of Energy form of signals; wavelet Haar; wavelet Bior.1.5;

Table II presents described above attributes and their estimated ability to distinct short true and false signals. Additionally wavelets which are best for particular parameters are indicated. Results were obtained for 30 signals (20 false, 10 true) with sample rate 100kS/s. Results for signals with lower sample rates have been much worse.

TABLE II. Selected amplitude insensitive RSA, short signals analysis

Attribute	parameter	level of distinct	best wavelets
Inst. Phase of energy	amplitude	high (>70%)	Bior.1.3, 1.5, Sym. 5
Inst. Frequency of energy	amplitude	low (<20%)	Bior.1.3, Sym. 5
Inst. Frequency of energy	period of first wave	medium (>50%)	Bior.1.3, Sym. 5
Inst. Q factor of energy	amplitude	high (>70%)	Bior 1.3, 1.5

IV. Conclusions

Presented results show that Rock Solid Attributes are more distinctive measures of true and false glass breaks acoustic signals than presented in [1] and [2]. They can improve detectability of identification algorithm, and its resistance to false signals. Important result of investigation is the selection of attributes and estimation of their detectability. The results show that most distinctive part of signals is placed near of the hit, and amplitude sensitive parameters are more suitable to find this point, but amplitude insensitive attributes are more suitable to distinguish true and false signals. Moreover not only amplitudes of RSA, but time dependences of particular attributes may be equally important.

Research confirmed that short and smooth wavelets are much more suitable for analysis than long ones. Best results are obtained for Bior1.3 and Bior1.5. independently what kind of attribute is calculated. Results also confirmed that energy form of input signal is much more useful for identification than amplitude, and power of acoustic signal.

After analysis of estimation of level of distinct of true and false signal it is easy to see that RSA can be very useful for identification of true and false signals. Additionally, characteristic parameters and their values of particular attributes were indicated, what is helpful for practical detection algorithm designing.

Initial results of application of this method for glass breaks detection will be presented on the conference.

References

[1] Bemke I. Zielonko R.: *„Application of Wavelet Transformation in construction of glass pane breaks detector."* 3rd International Congress of Technical Diagnostic 2004, Poznań, Poland.

[2] Bemke I. Zielonko R.: *„Badania nad odporną detekcją pęknięcia szyby z zastosowaniem transformacji falkowej."*, Krajowy Kongres Metrologii , Wrocław 2004.

[3] Białasiewicz J.T.: *„Falki i aproksymacje"*, WNT Warszawa 2000.

[4] Horodko L.: *„Wpływ typu falki na własności czasowo – częstotliwościowej reprezentacji niestacjonarnego sygnału"*, Zeszyty Naukowe Politechniki Łódzkiej, Nr 886, 2001.

[5] Radkowski S.: *„Wibroakustyczna diagnostyka uszkodzeń niskoenergetycznych"*, Wyd. ITE, Warszawa-Radom 2002.

[6] Tlaga J., Tlaga W.: *„Zdalna diagnostyka tafli szklanej z zastosowaniem elementów analizy sygnałów Hilberta"* 3rd International Congress of Technical Diagnostic 2004, Poznań, Poland.

[7] Wojtaszczyk P.: *„Teoria falek"*, PWN, Warszawa 2000.

[8] Zieliński T. P. *„Wavelet Transform Applications in Instrumentation and Measurement: Tutorial & Literature Survey"*, Metrology and Measurement 1/2004.