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Application of Rock Solid Attributes for robust identification of glass breaks acoustic signals via Wavelet Transformation.

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Abstract – Nowadays, the most popular method of glass breaks detection in alarm systems, is analysis of acoustic signals (because of performances and costs). Often used method are based on detection of some characteristic frequencies, is insufficiently resistant to other (false) signals. As papers [5] and [6] show, signal decomposition by JTFA is more useful for this kind of signals. To develop a robust method of glass breaks detection the authors applied Wavelet Transformation. Presented in [1] and [2] early results did not meet strong requirements of VdS standard presented in [6]. In this paper a new approach based on Wavelet Transformation and Rock Solid Attributes (used in geology) is presented.

Keywords: RSA, Wavelet Transformation, glass breaks

1. INTRODUCTION

Presently, most of popular alarm systems are based on wireless glass breaks detection by acoustic signal analysis. Unfortunately, correct identification of signal is very difficult, due to stochastic character of process, its nonlinearity, a lot of variable parameters and strong requirements of standards (e.g. „VdS - Verband der Schadenverhütung“ [1] standard require over 90% of detection efficiency, and at the same time near 100% of resistance to false signals - when glass hasn't broken). Detection of a few specific acoustic frequencies is frequently used, but it does not allow detectors to meet requirements. Better results can be achieved when analysis of time dependences of particular frequencies is done simultaneously with detection of that signals, but this methods need a lot of heuristic in algorithms. The best results are achieved by Joint Time Frequency Analysis methods, e.g. based on Hilbert transformation [6], unfortunately JTFA methods are most computational consuming.

The authors propose to use a Wavelet Transformation, to solve the problem. Initial results has allowed them to develop a theory of the solution, but the early method [1] did not meet expected performance because of lack of enough distinctive measures of the signal [2]. In this paper modified method based on Wavelet Transformation and Rock Solid Attributes (RSA) as a distinctive measures of a glass breaks acoustic signals is presented. As accomplished results show, RSA approach can be useful for identification of glass breaks acoustic signals. In compare to methods presented in [1] and [2], estimated detection level rise above to 90%, and resistance to false signals over 90%.

2. THEORY OUTLINE

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 the attributes are showed below.
Trace Envelope and Time Derivative of Envelope:

$$E(t)=\sqrt{f^2(t)+g^2(t)};\quad d[E(t)]/dt=E(t)*diff(t). \tag{1}$$

Instantaneous Phase and Frequency:

$$Ph(t)=\arctan\left[\frac{g(t)}{f(t)}\right];\qquad F(t)=\frac{\partial Ph(t)}{\partial (t)}. \tag{2}$$

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:

$$S(t)=g(t)+if(t), \tag{3}$$

where: $f(t)=-Hilbert[g(t)],$

$g(t)$ is acoustic signal recived by geophone.

Wavelet Transformation (WT) is a mathematic tool for signal analysis. Its self-scaling and good resolution in time and frequency domains makes it ideal for nonstationary signals analysis. The WT can be seen as a correlation between a signal and the set of functions called wavelets. The wavelets are generated by scaling and translating mother wavelet. Equation of Continuous Wavelet Transformation is presented below.

$$CWT(a,b)=\frac{1}{\sqrt{a}}\int h*(\frac{t-b}{a})\cdot s(t)\quad dt, \tag{4}$$

where $h^*(t)$ denotes complex conjugate of the mother wavelet $h(t)$, $s(t)$ is the signal, and a and b are dilation and translation coefficients, respectively. The discrete version of Wavelet Transformation is described by next formula:

[1] http://www.vds.de

$$DWT_x^{\Psi}(m,s) = \frac{1}{\sqrt{s}} \sum x(n) \cdot \Psi_s^*(n-m). \qquad (5)$$

In practice, most frequently, a discrete version of WT called Fast Wavelet Transformation is used. It is based on iterative Mallat algorithm (Fig.1.), which does not fix the number of iterations, so in fact, it is possible to compute various number of approximations for the same signal. Convolution and decimation in Mallat processing can be described by the following algebraic expressions:

$$\begin{aligned} a_{j+1}[n] &= \downarrow_2 \left[a_j[n] * h[k]\right] = \sum_k a_j[2n-k]h[k] \\ d_{j+1}[n] &= \downarrow_2 \left[a_j[n] * g[k]\right] = \sum_k a_j[2n-k]g[k], \end{aligned} \qquad (6)$$

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]. By selecting wavelet filters (mother wavelet) it is possible to get out different features of signals [4].

Important property of Wavelet Transformation is orthogonality of 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.

3. DESCRIPTION AND INVESTIGATION OF THE METHOD

Discontinuity and nonstationarity of geological signals make them similar to glass breaks signals. Therefore, in authors' opinion, 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.

The main idea of calculation is presented on figure 1.

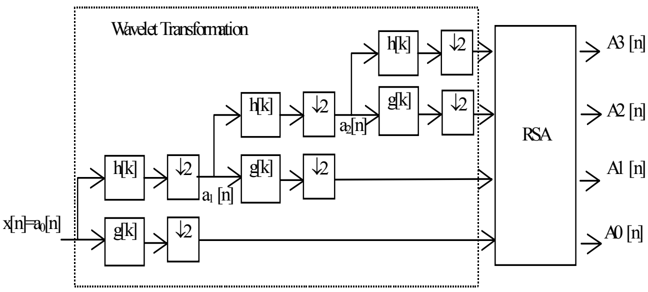

Fig. 1. Main idea of computation process based on Mallat algorithm

Analytical signal can be constructed in several ways. Authors propose to calculate RSA as a result of computation of signal composed of approximations and details on particular levels of Mallat algorithm:

$$S[n] = a_j[n] + id_j[n], \qquad (7)$$

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

In order to compare the usefulness of individual attributes for glass breaks detection, the authors have used the same criterion as for simply measures (e.g. energy and derivatives of wavelet coefficients) presented in [1] and [2]. General idea is to compare values of RSA of true (when glass has broken) and false (when glass hasn't broken) acoustic signals for different scales and wavelets. In practice, authors searched that attributes (in combinations with wavelets), which had different features for true and false signals, or in some parts of these signals (Fig 2). As the result of specific character of every attribute it is impossible to compare the same parameter for all RSA.

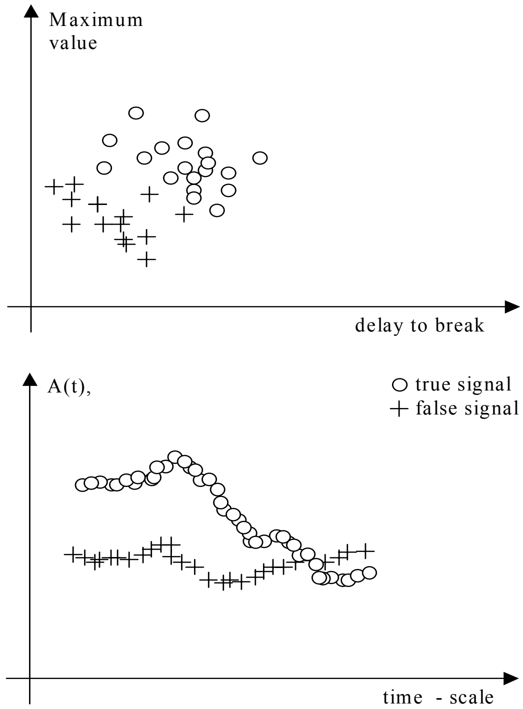

Fig. 2. Ideas of comparison of false and true signals using different kinds of RSA

Proposed method is helpfull for designing parameters and time points of signal for practical identyfication method, additionaly clearly shows distinctivity of RSA for false and true signals.

Due to a number of RSA parameters, authors choose some instantaneous attributes as a subject of work (wavelet and geometrical attributes will be analyzed n the future). Next selected a group which values depend on amplitude of analytical signal: Real and Imaginary part, Instantaneous Envelope, Time Derivatives of Envelope; and group of attributes of values independent on input signal amplitude: Instantaneous Phase, Instantaneous Frequency, Band Width and Instantaneous Q factor. Note that Real and Imaginary Part of signals are simply approximations and details of signals, and were analyzed in paper [1].

The authors had analyzed 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.

At the beginning, time interval had been fixed to 100ms, and finally shorted to 2,5ms. Due to limited time interval of signals, the number of approximation levels has been limited. Signals with sample rate of 25kS/s were computed on three levels, and signals of 100kS/s on four levels; when the maximum sample rate is 100kHz, four levels are enough to achieve bandwidth of the last approximation of less than 3,25kHz. Presented procedure shortens sample counts and decreases number of calculations. To check if other wavelets apart from selected in [1] and [2] (dmey, symlet, bior) gets good results, initial research has been done for nearly 40 wavelets.

4. RESULTS

Due to limitations described in previous chapter (time interval, number of levels, wavelets), analysis of results has been divided into two parts. Research started with checking of character of particular attributes on long term signals (time period 100ms), and on second stage on searching of distinctive differences on short signals (2,5ms) had been done.

4.1 Analysis of long term signals

Input data started about 10 ms before hit, and lasts 100ms. False and true signals had similar time-scale spectrum, and additionally big number of samples (10000), what does not allow the user to directly compare results. Like it was presented in papers [1] and [2], character of true and false signals envelopes are similar. Only amplitudes of signals are different, but it is poor feature, because of unknown distance from source (glass pane) to detector, so in fact both true and false signals can have the same amplitudes. Fig. 3 shows comparison of true (dark) and false signals (light) amplitudes (a), and their Instantaneous Envelopes on three levels of approximations (b, c, d). Different counts of samples on every level is a result of decimation in Mallat algorithm. As we can see differences between amplitudes are not distinctive. Power form of signal enhance this features, but results still do not meet assumed level of difference, and additionally they are to long for analyze.

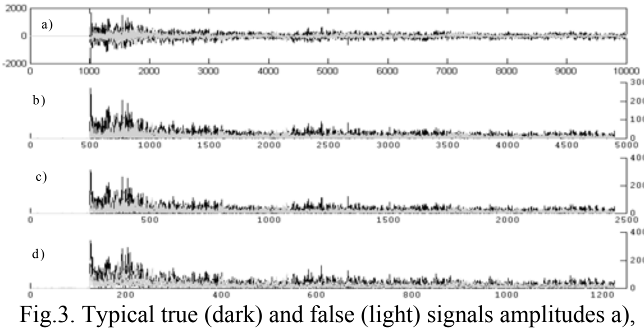

Fig.3. Typical true (dark) and false (light) signals amplitudes a), and Instantaneous Envelopes on different levels of approximation b), c), d); signal interval 100ms; wavelet Bior2.6

Figure 4. shows results when signal period is 10ms, here we can see that significant differences between signals occur about 2-4 ms near to hit. Similar results has been achieved for other attributes depend on signal amplitudes. Note that most of this amplitude sensitive attributes, are similar to subject of research presented in [1] and [2].

Results obtained for attributes with values independent of signal amplitudes were not very distinctive or were difficult to interpretation. As an example Fig. 5 shows Instantaneous Phase of signals on three levels, for wavelet Bior 1.5. As we can see, true and false signals has similar values of this parameter.

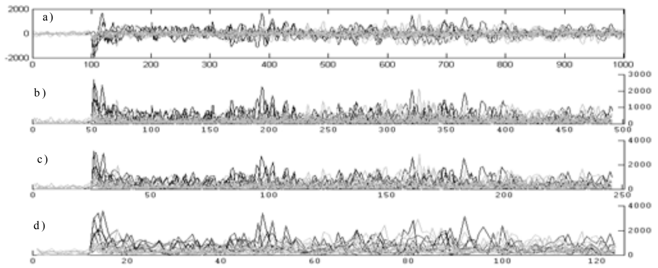

Fig.4. Typical true (dark) and false (light) signals amplitudes a), and Instantaneous Envelopes on different levels of approximation b), c), d); signal interval 10ms

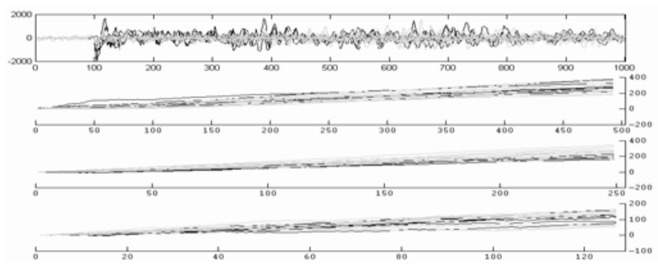

Fig.5. Instantaneous Phase of first 10ms of true (dark) and false (light) signals on three levels of approximations; wavelet: Bior1.5

To show that the detection of hit, and synchronization of signals were correct (software synchronization), in Fig. 6. Normalized Amplitude of signals for wavelet Bior1.3 is presented; time interval is limited to 0,6ms. As we can see, all signals has similar shape between 50th and 60th sample on first level of approximation, and significant differences in amplitudes on top graph. Second difference (but not very distinctive) between signals is time of first wave – for true signals about 0.1ms and for false 0.15ms.

Simultaneously wavelets selection had been done. Authors preferred wavelets selected in [1] and [2], but initial analysis for other wavelets had been done too. As it was expected, short and smooth wavelets were better than long. After all, the authors selected 5 wavelets used for next calculations: Bior 1.3, Bior 1.5, Bior 2.6, Symlet 5 and Haar.

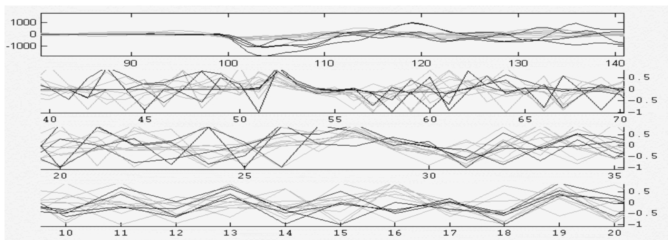

Fig.6. Real amplitude (a), and Normalized amplitude (b, c, d) of signals on different levels of approximation; signal interval 0,6ms

4.2 *Analysis of short signals.*

As it was described, the authors searched differences between values of RSA for true and false signals. This features occupy only few samples of signals (typically in interval 0.1 – 0.5ms). Because of unknown amplitudes of input signals, only amplitude insensitive attributes were analyzed. 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 insensitive attribute is Instantaneous Phase (formula 2). To get more smooth diagrams, a sum of 8 samples is calculated. Fig. 7 shows graphs of Instantaneous Phase on tree levels, for Haar wavelet. It's simply to see that usually true signals (dark) gets bigger values than false signals (light). As it was described difference occupy about 0.4ms from hit on level 1 and 2 (different time scales).

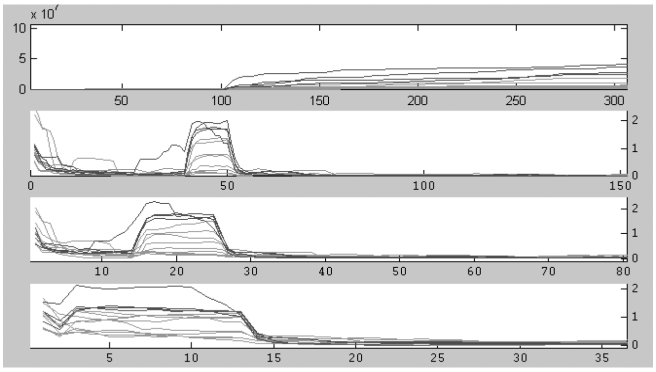

Fig.7. Instantaneous Phase of Energy form of signals; wavelet Haar

Better results can be achieved if wavelet Sym5 (Fig. 8.) or Bior1.3 (Fig. 9.) is used. As we can see on Fig. 8 values for true signals (dark) are over twice bigger than for false signals. Note, that some false signals get values as big as true signals. In analyzed set, 20% of false records have values comparable to true records. Similarly some true signals (depend on wavelet, but not more than 10%) have lower values. This observation is compatible witch results described in [6] – one parameter has no more than 30% of detectability.

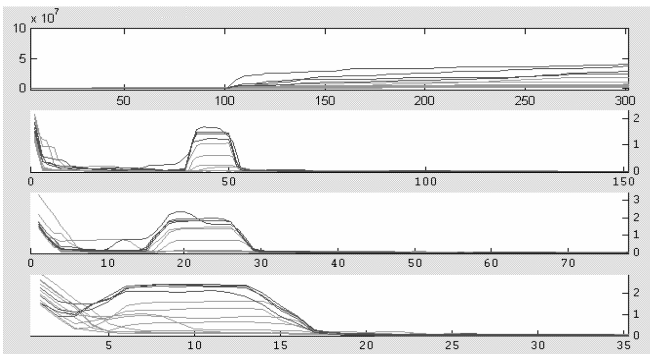

Fig.8. Instantaneous Phase of Energy form of signals; wavelet Sym5

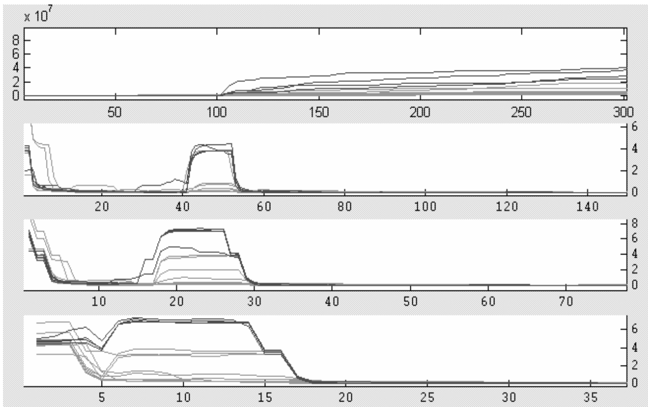

Fig.9. Instantaneous Phase of Energy form of signals; wavelet Bior1.3

Other simple and amplitude insensitive attribute is Instantaneous Frequency (formula 2). Due to 2π jumps of Phase, usually Instantaneous Frequency is calculated as time derivative of arc tangent function, to avoid discontinuities.

Fig 10. shows Instantaneous Frequency on three levels for Haar wavelet. There is no clear difference between values for true and false signals. Although most of true signals has amplitudes about 0.1, 30% of false signals has comparable values. Time of first wave (from hit) is better feature of true signals, in this case. Differences are clearer for wavelet Bior 1.3 (Fig. 11). First wave period (zero cross) on first level of approximation of true signals (80%), is no shorter than 0.2ms. False signals has this time about half shorter. For comparison Fig 12 shows Instantaneous Frequency for wavelet Sym 5.

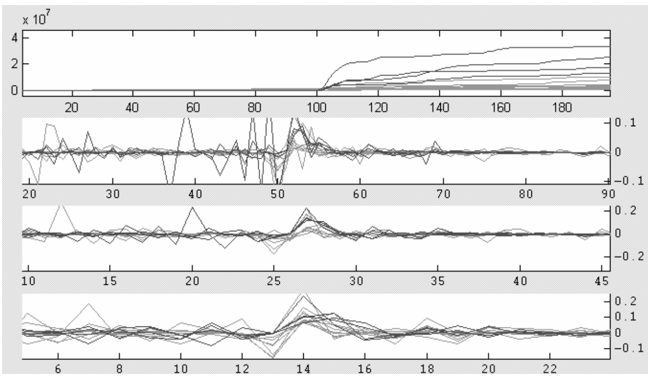

Fig.10. Instantaneous Frequency of Energy form of signals; wavelet Haar

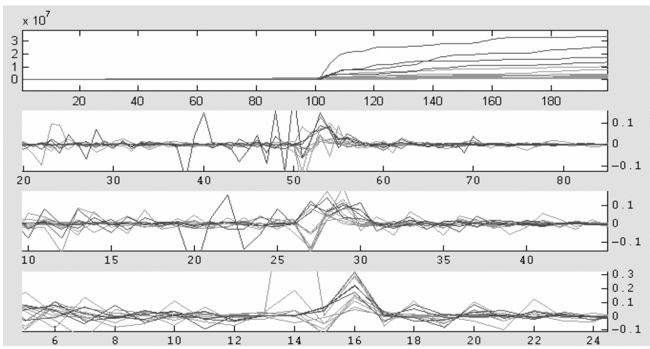

Fig.11. Instantaneous Frequency of Energy form of signals; wavelet Bior1.3

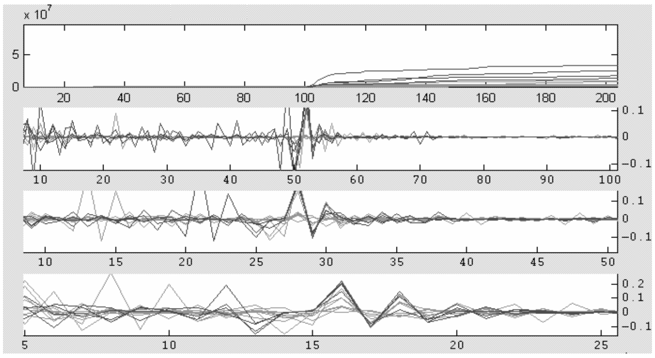

Fig.12. Instantaneous Frequency of Energy form of signals; wavelet Sym5

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

Other distinctive attribute is Instantaneous Q Factor. This attribute is similar to quality parameter of resonant circuit. Q Factor is calculated as a ratio of Instantaneous Frequency to decay of Instantaneous Envelope, with $-\pi$ factor. It can be interpreted as leakage of energy from signal (probably energy is absorbed by glass pane).

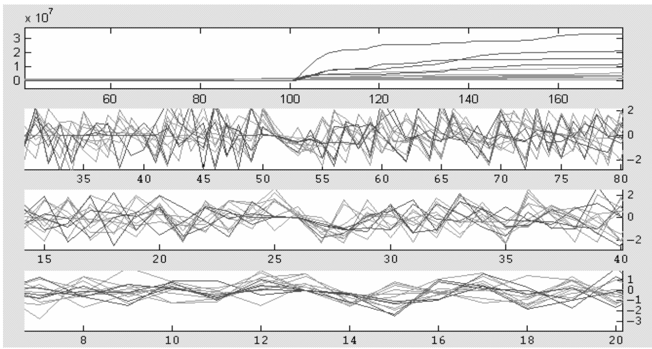

Fig.13. Instantaneous Q factor of Energy form of signals; wavelet Haar

Fig. 13 shows values of Q Factor for Haar wavelet, and Fig. 14 for Bior1.5 wavelet. 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.

TABLE I. Selected RSA, and estimated number of signals fulfilled found parameters

	Instantaneous Phase Value >3	Instantaneous Frequency Period > 0,1ms	Instantaneous Q Fator Value ≈ 0
True signals	90%	80%	90%
False signals	20%	30%	0%

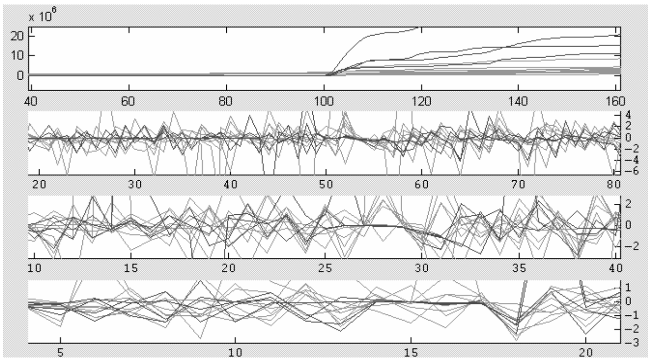

Fig.14. Instantaneous Q factor of Energy form of signals; wavelet Bior.1.5

Table I presents described above attributes and estimated number of signals fulfilled found parameters. Results were obtained for 30 signals (20 false, 10 true) with sample rate 100kS/s. Results for signals with lower sample rates has been much worse.

5. CONCLUSIONS

Important result of research is the selection of three instantaneous attributes and their parameters as a distinctive measures of true and false glass breaks acoustic signals. What is important, these attributes are insensitive to signal amplitude. As paper shows, time dependences of attributes may be equally important as their amplitudes, and differences are visible only near of the hit.

Research confirmed that short and smooth wavelets are much more suitable for analysis than long ones. Best results are obtained for Bior1.3 and Bior 1.5. It was also confirmed that energy form of input signal is much more useful for identification than amplitude, and power of acoustic signal.

Main conclusion of analysis is that identification of signal must be done step by step and simultaneous computation of a few scales and attributes is necessary for effective signal identification. First it is necessary to compute some envelope attribute to find a hit moment, next steps depends on results of pervious, and identification by elimination may be helpful.

Summing up Table 1, authors estimate detectability of true signals above 90%, (using all 3 attributes), and probability of mistake (when false signal is identified as true) no more than 10%. This estimation shows big improvements in comparison to results presented in paper [1], but still does not meet one of VdS requirements. Obtained results suggest that more attributes should be analyzed.

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

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