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On application of Wavelet Packets Decomposition to glass breaks acoustic signal features extraction.

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Abstract- The main subject of authors' research are non-contact methods of glass breaks detection based on analysis of acoustic signal generated during phenomena. Problem has essential meaning for modern, cost effective alarm systems, particularly installed into big buildings. Signal has stochastic character and the main difficulty of the problem is variability of many parameters (e.g. size and thickness of glass pane, distance from window to detector) and big amount of false signals (mainly accidental glass hits without break). Authors developed detection algorithm which uses Wavelet Transformation and few selected measures for signal features extraction and classification. Obtained detection efficiency >90% is satisfactory, but resistance to false signals (near to 80%) does not fulfill assumed level. Because the Wavelet Packet Decomposition (WPD) allows more detailed analysis in frequency domain than WT, it is more suitable for extraction of time-frequency interdependencies in analyzed signals. This paper discuss some methods and results of WPD application and wavelet selection for improving system performance, and increasing the resistance to false signals.

I. Introduction

Many modern alarm systems use non-contact glass breaks detection methods based on acoustic signal analysis. The main advantages of those methods are lack of wires and free number of simultaneously monitored windows. Although those features make them cheap and flexible in application, but stochastic character of analyzed phenomena, its non-linearity, big amount of varied parameters and materials features make this problem very complicated. Moreover, solutions of the problem are restricted by strong standard requirements. For example German VdS standard [9] requires over 90% of breaks detection efficiency (detectability), and at the same time near 100% of resistance to strictly defined false signals. Note, that more important than detectability is the resistance to false signals. It is caused by costs of false alarms. Additionally false alarms can sleep watchfulness of a guard (it is one of sabotage methods). The main difficulty of the task, consist in a big amount of signals received by the detector, like: mechanically and thermally stimulated glass breaks (true signals), human voices, traffic sounds, environment sounds, sabotage sounds, and other false signals (often with frequency spectrum similar to true signals).

Typical glass break acoustic signal is about 2 seconds long, and has very wide bandwidth (from Hz to hundreds of kHz) [8], but most methods analyze only narrow band around 3-6 kHz. Presently many non-contact methods base on detection of a few acoustic frequencies [3], but these methods do not allow fulfill standards, because essential meaning have time-frequency relations of the signal [1], [8].

Authors proposed novel JTFA approach, based on Wavelet Transformation and some distinctive measures to analyze input signal [1]. The WT divides signal into few separate bands, and moves it into the orthogonal base of wavelet coefficients (details and approximations). During research authors have found few distinctive features of the signal allowing its effective classification, built detection algorithm optimized for embedded systems, and tested it in Matlab environment using real signals. Obtained detectability (over 90%) meets VdS standard, but 80% of resistance to false signals not. While research it has been found that more detailed analysis in frequency domain is required for improving performance of the system, and authors have decided to apply WPD for signal features extraction.

II. Wavelet Transformation versus Wavelet Packet Decomposition

WT is a mathematical tool for signal analysis. It is self-scaling and has good resolution in time and frequency domains, but most important it has small computation complexity. These advantages make it useful for on-line analysis of non-stationary signals. Its results can be seen as a correlation between analyzed signal and the set of functions called wavelets, generated by scaling and translating of given mother wavelet. The Continuous Wavelet Transformation (CWT) is expressed by the formula (1):

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

where: $\psi^*(t)$ is complex conjugate of wavelet $\psi(t)$, *a, b* dilatation and translation coefficients, and *s(t)* is analyzed signal. In the discrete time domain the Discrete Wavelet Transformation (DWT) is used:

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

Set of wavelets span some frequency range. From this point of view wavelets can bee seen as special filter bank. In practical applications usually only two filters created from mother wavelet and its scaling function consist on Wavelet Filter Bank, called quadrature mirror filters [2], [10]. By selecting the mother wavelet (filter) it is possible to get out different features of the signals [1], [4]-[7].

Computation is based on iterative Mallat's algorithm (Fig.1a.) with dyadic scaling, usually applied for MRA. Signal is convolved with low-pass and high-pass filters and the results represent low- and high-frequency parts of the analyzed data (approximations and details). Formula (3) describes the processing. This computation process is known as Fast Wavelet Transformation (FWT) [2], [10].

$$\begin{aligned} a_{j+1}[n] &= \downarrow_2 \left[a_j[n] * h[k] \right] = \sum_k a_j[2n-k] h[k], \\ d_{j+1}[n] &= \downarrow_2 \left[a_j[n] * g[k] \right] = \sum_k a_j[2n-k] g[k], \end{aligned} \tag{3}$$

where $a_{j+1}[n]$ represent the approximations, and $d_{j+1}[n]$ the details of the input signal $a_j[n]$ convolved with filters h[k] and g[k]. In consequence octave band filter bank is created, with time-frequency resolution schematically presented in Fig. 1b. Note, that while time resolution grows the frequency resolution becomes smaller.

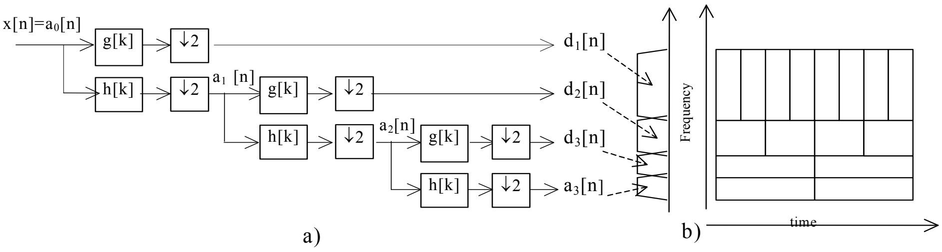

Fig. 1. Iterative FWT Mallat's algorithm (a) and its time-frequency resolution (b).

For more detailed analysis in frequency domain Wavelet Packet Decomposition can be used. WPD is the generalization of the WT and allows more precise selection of analyzed frequency band. Formula (4) shows the method to obtain Wavelet Packet Filters on successive levels, starting from h[k] and g[k].

$$\begin{aligned} W_{2n}[t] &= \sqrt{2} \sum_{k=0}^{2N-1} h[k] W_n[2t-k] \\ W_{2n+1}[t] &= \sqrt{2} \sum_{k=0}^{2N-1} g[k] W_n[2t-k] \end{aligned} \tag{4}$$

While WPD not only approximations but also details on every level are decomposed. Full tree of the process (3 levels) is presented in Fig 2. It is important that natural order of filters is different than order of frequency bands - this is consequence of WT filters properties. In most cases (for signal recognition, compression and denoising) it is not necessary to order the results of WPD in monotonically increased frequency scale, but it can be useful for observation of signal spectrum.

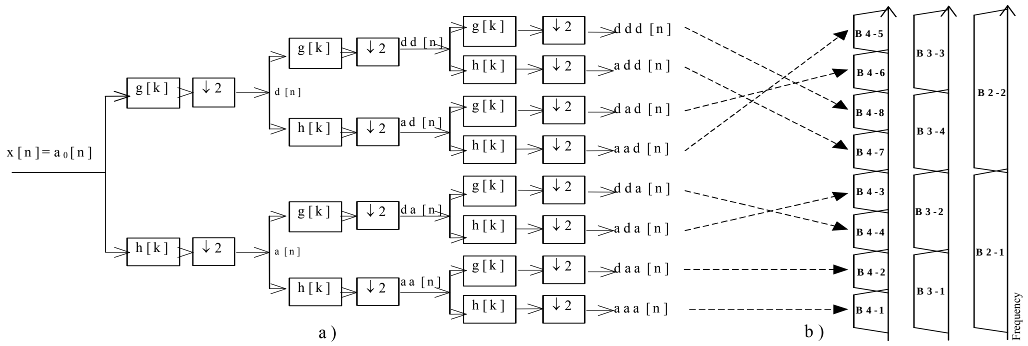

Fig. 2. WPD full tree algorithm (a) and corresponding frequency bands (b).

The more detailed signal analysis increases computation complexity. In most practical applications it is not necessary to analyse all bands or their interdependencies [5], [6]. Therefore one of the main matters in WPD is selection of most interested bands – Best Tree. For example Coifman-Wickerhauser method based on minimum entropy criterion is commonly used for signal compression. In paper [6] a simple algorithm using WPD Best Tree selection is proposed as a method for classification of the signals with similar to glass breaks character. Unnormalized Shanon entropy is defined by formula:

$$E = -\sum_n x[n]^2 \log(x[n]^2) \quad . \tag{5}$$

This criterion was also used by authors while research on WPD application for Glass Break Acoustic Signals (GBAS) classification. Obviously other selection criteria are known and can be used. Generally the criterion should be fit to the purpose.

III. Methods of the research

During research a set of signals obtained while real tests in Alarmtech[1] laboratory was used. Signals were recorded with sample rate 100kS/s with 2 meters distance from glass pane being broken. Because the most difficult for classification are acoustic signals generated when glass was hit but not broken, only this kind of false signals had been taken for consideration while research.

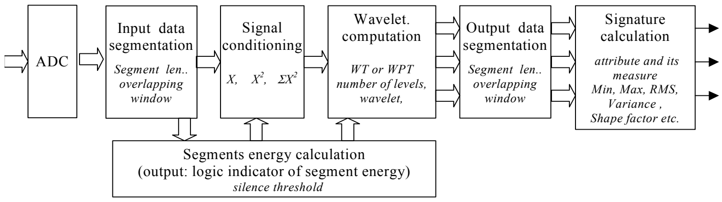

Fig. 3. Structure of basics analysis algorithm

Acoustic signals were analysed using algorithm presented in figure 3. After A/D conversion they are formed into short (2.5 – 5ms) overlapped frames and their energy is calculated. Every segment with energy over some fixed value is marked as "useful", conditioned and processed by WT (or WPD) algorithm. To increase time resolution of selected measures [1], output data segmentation (called post-segmentation) is used. Usually 16-32 samples length post-segments gives best results. Finally some measure of segments is calculated and collected creating signal signature. The quality of measurement is estimated using the following equation (5)

$$H = \left| \frac{Pp}{Lp} - \frac{Bf}{Lf} \right| \cdot 100\% \quad , \tag{5}$$

where Pp is the number of correctly classified true signals, Bf is the number of incorrectly classified false signals, Lp and Lf are the numbers of all true and false signals.

Research has been managed in two main aspects. First - analysis of WPD usefulness for identification of GBAS using algorithm showed in Fig.3, and methods presented in [1]. The second aspect was possibility of common Best Tree construction for limitation of computation complexity and possibility of Coifman-Wickerhauser method application for this task.

Authors used MatLab® environment for computation the results. There were analyzed over 900 combinations of Wavelet-Attribute-Measure sets called aggregates, with different post-segmentation length, while research. According to results obtained for WT, only first four levels of approximations (15 bands) was used - such number of bands was enough to obtain 90% of detectability using WT, and authors expected increasing of method performance.

IV. Results

As it was mentioned, the main problem analyzed by authors was possibility of improvement of the early method [1] by application of WPD. Table 1 presents the final detectability obtained on first 3 levels for Bior1.3 and Bior1.5 wavelets. Most of the cells have value under 30%, and authors decided to leave them unfilled for clearance. Because WT algorithm presented in [1] covers bands L1-1, L2-1 and L3-1 of WPD, such columns are not interesting from this point of view, while meaningful values in columns L2-2 and L3-2 to L3-4 indicate that WPD improves particular aggregate. It is easy to see that for example aggregate Bior1.3-EnvelopeModulatedPhase-Maximum gives very well results in band L3-4 for all

[1] Alarmtech Polska, www.alarmtech.pl

lengths of post-segments, and moreover its detectability is improved in relation to the results obtained for WT (L1-1, L2-1, L3-1). Bior1.5-Envelope-RMS L3-4, Bior1.5-Frequency-Mean L3-3, Bior1.5-Imaginary-Peak L3-2 are also better than presented in [1]. Similarly, Bior1.3-Phase-ShapeFactor allows good classification of signal using band L2-2 only. Due to lack of space, authors do not attach tables for other wavelets, but their analysis gives the evidence that WPD makes classification of GBAS easier and more unequivocal. From other hand it is worth to note that detectability of some very useful aggregates (e.g. Bior1.5-Phase) remains unimproved. According to the results presented in [1] it was expected that phase aggregates which gave best detectability for WT, still have very good detectability in bands L1-1, L2-1, and L3-1 of WPD. This result proves that WPD method constitutes deployment of WT and can extracts features from bigger number of narrower bands.

Table 1. Detectability of selected aggregates of Bior1.3 and 1.5 wavelets (empty cells have values less than 30)

Attribute	***Measure***	***L1-1***	***L2-1***	***L2-2***	***L3-1***	***L3-2***	***L3-3***	***L3-4***
Bior1.3 Phase	SHAPE -	70-90						
	SHAPE 8	p50	p50	45-60				
	SHAPE 16			50-75				
	SHAPE 32			50-60	50-70			
	MEAN -,8,16	50-70			50-70			
	MEAN 32	50-85	~40		50-70	p50		
Bior1.3 ABS(Phase)	MEAN -	~75						
	MEAN 32				50-70			
	VAR 16	~ 50			50-75			
	MIN 16,32	50-60	~ 50					
Bior1.3 Envelope Modulated Phase	RMS – ALL							50-70
	MAX -	~50		~50			~50	50-70
	MAX 8	~50	~50	~50			~50	50-70
	MAX 16	~50		~50			~50	50-70
	MAX 32	~50		~50			~50	50-70
	SHAPE 8	50-70	~45	~45				
	SHAPE 16	50-70						
Bior1.3 Frequency	SHAPE -	50-85	50-75					
	PEAK -		~50	~50				
Bior1.3 Imaginary part	SHAPE 8			50-75				
	VAR -				~50	~50 p75	~40, p50	
Bior1.5 Phase	SHAPE 8					40-50	~40	~50 p80
	SHAPE 16		40-65	40 p50	~50			p50
	RMS -	~50	~50 p60	~25				~40 p65
	RMS 8	~50	~40	~45	~40 p50			40-50
	RMS 16	~50	75	50	40-p50	40 p50		
	RMS 32	~50	>65 pp90					40 p60
	MEAN -	50-75	70-85					
	MEAN 8	50-55	~40 p50		~40 p50			~40 p55
	MEAN 16	50-55	80-100		~40 p75			50 p55
	MEAN 32	65-75	85-100					
	VAR -	50-70	50-75					
	VAR 8	~50						
	VAR 16	~50	80-95					pp45
	VAR 32	65-75	90-95					
Bior1.5 ABS(Phase)	MIN 8		65-75		~40-45			
	MIN 16	~40-45	85-95					
Bior1.5, Envelope	SHAPE -	~50 p70	~50					
	SHAPE 16		~30 p55		70 p75	~40	~40	~40
	SHAPE 32	~50 p55	~45 p55					~50
	RMS -							~50 p55
	RMS 8							~50 p70
	RMS 16,32							~45 p60
Bior1.5 Frequency	MEAN -				~40 p50		50-75	
	MEAN 8, 16				50-55	50-55	60-85	
	MEAN 32				~40 p55		50-70	
Bior1.5 Imaginary part	PEAK 16					60-75		
	PEAK 32					60-90		

Table 2 presents few improved amplitude sensitive and insensitive aggregates which gives the best identification using WPD characteristic bands only. As it can bee seen, amplitude insensitive parameters (like phase and frequency) usually have one meaningful band, while amplitude sensitive parameters (like envelope, real and imaginary part) has few bands with big detectability. Analysing certain position of pointed bands on frequency scale (see figure 2) it is easy to see that bands 3-1 and 3-2 are parts of band 2-1, and 3-3 , 3-4 of band 2-2. Basing of this feature it is clear why particular bands occur together.

Table 2. Detectability of best WPD aggregates.

Attribute - Measure	***L1-1***	***L2-1***	***L2-2***	***L3-1***	***L3-2***	***L3-3***	***L3-4***
Bior1.3 Phase - Shape Factor 16			50-75				
Bior1.3 Env. Mod. Phase – Max 16	~50	~50	~50			~50	50-70
Bior1.5 Frequency - Mean 8				50-55	50-55	60-85	
Coiflet1 ABS(Phase) - Std. Deviation -			55-65	50-65		50-65	
Bior1.3 Imaginary –Shape Factor 8			50-75				
Coiflet1 Real RMS 32						50-55	50-65
Coiflet1 Envelope RMS 32			45-60		45-50		50-70
Coiflet1 Envelope Variance 32			50-70		45-55	<45	50-60

For contrast Table 3 presents detectability of the best Bior1.5 aggregates on 4-th level. As it can be seen there are no interesting bands, and almost all results are smaller than 50%. Other wavelets gave similar weak results on this level. Authors concluded that first 3 iterations of WPD are enough to GBAS identification, and has limited further analysis for 3 levels only (7 bands presented in Table 1).

Table 3. Detectability of some single element Bior 1.5 signatures on level 4.

	L 4-1	L4-2	L4-3	L4-4	L4-5	L4-6	L4-7	L4-8
Variance of Phase	40-50	~40, p 65,	<25, p 40	<25, p 50	~25, p50	~25,	25-30	<25
Std. Dev. of Phase	45, p 60	p 70	~25, p 50	~25, p 50	<25	30-50	25-40	<25
RMS of Phase	45, p 60	p 60	<25	<25	<25, p30	25-50	<25	<25

Other very important aspect is possibility of extracting Time-Frequency interdependences using WPD in place of WT. The only method to show these interdependences is graphical presentation. Figure 4 shows typical time charts of true and false signals in different bands (time scale shows number of segments not direct time). First two left columns show examples of phase aggregates. However global shape of these charts is characteristic, it is difficult to find clear differences between true and false signals. The only difference is magnitude of data, what explains obtained detectability of single element signatures for phase aggregates (Table. 1). Two right columns show typical amplitude dependent aggregates – imaginary part and envelope. There are many clear differences between charts of true and false signals. Using theses features, it is easy to construct multi-element true or false time signatures of particular bands for selected aggregate. It is worth to note that significant differences can be observed in all bands of WPD.

The main disadvantage of time signatures is need of remembering and comparing 10-20ms records. Authors use post-segmentation to decrease number of samples need to be stored. Depend of length of post-segments, 10ms signature consist of 32 to 128 samples. In addition amplitude aggregates are very sensitive for environment parameter (e.g. distance from broken pane, existence of silencing materials in the room) what can be the reason of improper classification.

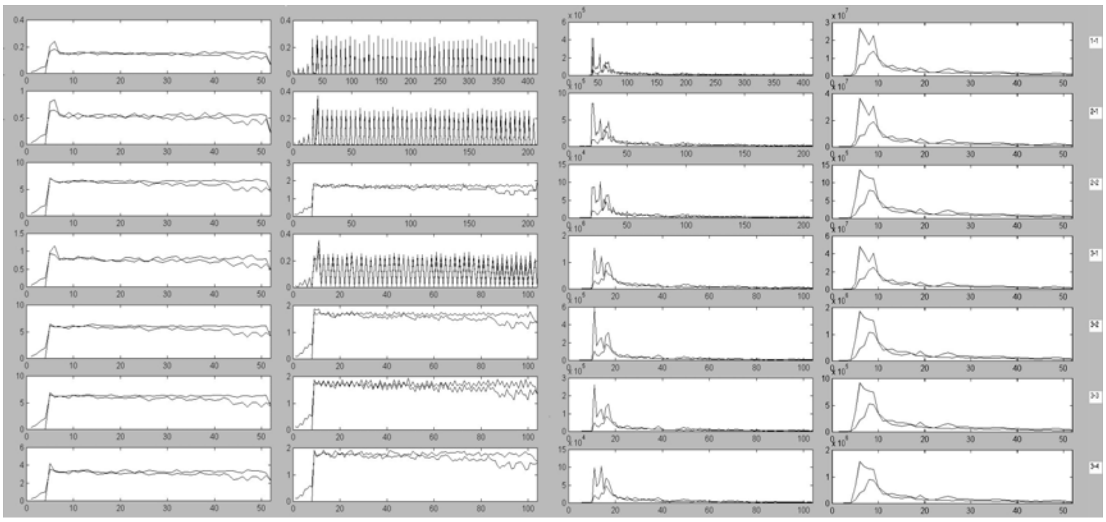

Fig. 4. Typical time charts of averaged true and false signals aggregates (100ms) – bands 1-1 to 3-4 (from left - phase, phase with post-segmentation, imaginary part with post-segmentation, envelope)

As it was mentioned in theoretical introduction, application of WPD dramatically increases computation complexity, so it is essential to find some method for automatic selection of bands being used for identification. Authors tried to use minimum entropy criterion to select common Best Tree. The probabilities of nodes occurrence for debauches, symlet, coiflet and biorthogonal wavelets had been calculated. Table 4 shows results for biorthogonal wavelets. To shorten the table, probabilities of 4-th level nodes are presented only. Biorthogonal family of wavelets had been selected as most suited for GBAS analysis, and while this experiment also gave most characteristic tree.

It is easy to see, that highest probability has nodes 3 and 4 (enclosed in band 3-1) but also other low band nodes have probabilities over 0.5 and this feature is almost independent on wavelet. Highest frequency nodes have much lower probability, what suggests that upper bands do not contain any important information about the signals, or its energy is very low in relation to other bands (with biorthogonal wavelets analysis).

Table 4. Probability of node presence in Best Tree with bior. wavelelets for min. entropy criterion

Wavelet	***N 1-2***	***N 3-4***	***N 5-6***	***N 7-8***	***N 9-10***	***N 11-12***	***N 13-14***	***N 15-16***
Bior1.3	0.43	1	0.71	0.43	0.29	0.14	0.29	0
	0.87	1	0.87	0.75	0.5	0.5	0.5	0.31
Bior 1.5	0.57	1	0.86	0.71	0	0	0	0
	0.86	1	0.6	0.6	0	0	0	0
Bior 2.6	0.57	1	0.71	0.71	0.23	0	0.23	0
	0.69	1	0.69	0.12	0.06	0	0	0

Presented results matches with STFT spectrum of the phenomena [8]. Basing upon these results, initial tree for further research was created - Fig 5a. For comparision WT decomposition tree is also presented. It is clear that new tree can be seen as extension of basic WT tree.

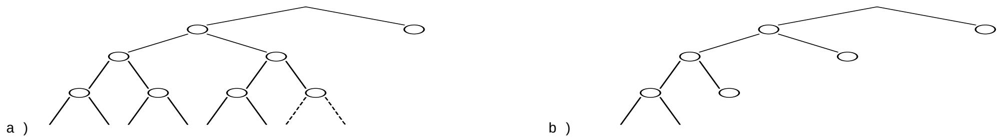

Fig. 5. WPT Best Tree created on the ground of Table 1. (a) and basic WT tree (b)

After analysis of detectability for different aggregates authors found that there are no single characteristic tree or set of bands which guarantee proper identification, and moreover high frequency bands are very useful. Finally authors considered that application of minimum entropy criterion for BT selection is not suitable for this task. What important, tables of probabilities were not such characteristic for other wavelets like for biorhogonal. Analysis of high frequency bands of differ wavelets, shows that they can be very useful for signal classification. Note, that main problem of GBAS identification lays not in lossless compression but in extraction of its most distinctive features. Authors propose new criterion which uses between-class correlation function as determinant for distinctive nodes selection. Such method requires assuming the set of true and false signals, what is quite difficult due to character of phenomena and number of possible false signals.

V.*Conclusions*

Presented matter shows that WPD can improve detectability of aggregates which give weak results for WT, in addition indicates that wavelets selected in [1] as the most useful are still the best. However WPD makes more aggregates valuable, the best results are still in bands covered by WT.

Second important advantage of WPD is possibility of construction more characteristic time signatures than WT does, what makes classification of signals easier. Authors estimate that application of 32 element time signature can improve breaks detectability and resistance to false signals to fulfill VDS standard requirements.

WPD increases computation complexity, so some node selection criteria is required for automatic tuning of the system. It was showed that Coifman-Wickerhauser method is not suitable. Analysing the goal of the task, authors has proposed new criterion based on signals correlation. This method allows select correlated and uncorrelated bands between true and false GBAS and build most distinctive tree. Initial research demonstrates that this criterion actually gives better nodes selection than entropy does.

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