THRESHOLD COUNTING IN WAVELET DOMAIN

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Abstract

Threshold counting of AE signal is the simplest and most frequently used type of AE signal parameterization. As the wavelet transform of AE signal appears to be useful tool for AE analysis, the threshold counting applied to the wavelet decomposition represents a logical extension of commonly used procedures. New AE signal parameters (wavelet counts) are introduced using a two-level threshold counting of wavelet coefficients. The application of wavelet counts is illustrated in three examples of both real and simulated AE data. The significance of various classical and newly introduced AE signal parameters used to AE source identification is tested using the neural network sensitivity and factor analyses. The wavelet counts, carrying the global information in both time and frequency domains, can replace ill-defined frequency spectrum parameters of AE signal in a more efficient way.

1. Threshold Counting

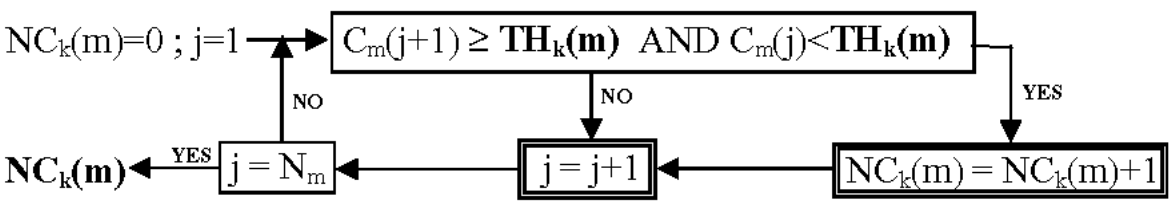
1.1 AE signal parameterization

Threshold counting (TC) of AE signal crossings of predetermined voltage levels is one of the oldest and most common parameterization methods in the AE analysis. The number of threshold counts Nc or count rate, dNc/dt, simply characterizes both the continuous and burst AE signals in time domain. TC substantially reduces information about AE signal, and saves good knowledge on the global AE activity. TC methods are very effective as simple devices and/or digital signal processing (DSP) procedures can be used for AE detection and quantitative evaluation. The most efficient seems to be the dual TC (low and high amplitude threshold level, [1]), as it allows distinguishing solitary high amplitude signal bursts in quasi-continuous AE. In the most cases, the time evolution of count rate closely correlates with, e.g. that of signal RMS value, as both quantities are related to the instantaneous signal energy. The main information differences between both signal energy measures consist in a constant noise level suppression at the TC, i.e., d.c. component of RMS curve is eliminated. Another difference deals with the signal transform linearity. Contrary to the RMS measure, TC represents a highly nonlinear signal transform, which may cause some difficulties (it is surprising that rigorous mathematical treatment of TC transform properties is still insufficient). On the other hand, due to its non-linearity, the TC allows often better recognition of some critical events (e.g. in leak detection) than linear signal treatments.

The purpose of AE signal parameterization is to reduce registered signal waveform data into the lowest possible number of signal features carrying maximum of important signal information in a simplest form. The number and type of signal features are chosen so as to conform to various criteria (diagnostic purpose, device capabilities, simple and effective DSP, etc.). Together with a number of signal parameters in time domain, parameters of frequency spectra (parameterization in frequency domain) are often used by AE source identification procedures. The time-frequency representation (windowed FFT, Wigner-Ville distribution, etc.) combines both aspects of AE signal processing [2]. The most advanced processing of AE signal in the wavelet domain [3] may be considered as an enhancement of the time-frequency representation. The governing wavelet transform (WT) is extremely useful in analyzing time series containing non-stationary power at many different frequencies. In addition to its main destination (signal de-noising and compression), the WT has shown to be very effective tool for AE signal processing (e.g. source location in plates [4], fracture mode classification in composites [5], etc.). Also from the computational point of view, the WT seems to be more effective than e.g. FFT used in real time DSP of AE signals. Nevertheless, for the purpose of AE signal classification, the WT signal representation should be parameterized to reduce the extent of input data to pattern recognition analysis (e.g. by artificial neural networks). The simplest way to extract general features from the AE signal decomposed by WT is threshold counting at various decomposition levels. This procedure may be introduced as an equivalent to the TC of AE signal in different frequency bands.

1.2. Definition of new AE parameters

Let us suppose, that we have a discrete, multi-level one-dimensional wavelet decomposition of a sampled signal s(i). Let $C_m(j)$, j=1…N_m be the approximation coefficients (m=1) or detail wavelet coefficients at specific level m (m=2,...,L+1, where L is a number of decomposition levels). The three new parameters $NC_1(m)$, $NC_2(m)$ and RCG_m of each detail level and/or approximation are computed as follows:



where $TH_k(m)$ (k=1,2) are counting two threshold levels. They differ with each wavelet decomposition level. The value $TH_1(m)$ is usually set just under the level of noisy coefficients and $TH_2(m)$ around the first quarter between the noise magnitude and maximum coefficient of corresponding wavelet decomposition level. Parameter RCG_m is relative gravity center of wavelet coefficients in analyzed signal sample:

$$RCG_m = \frac{\sum_{j=1}^{N_m} j \cdot |C_m(j)|}{N_m \cdot \sum_{j=1}^{N_m} |C_m(j)|}$$

By the computation above, we obtain 3(L+1) new parameters, which are then compared with the following classical AE parameters (signal features) [6] in time and frequency (spectral) domain:

- *Time domain:* (1) Amplitude, (2) Rise time, (3) RMS, (4) Energy moment, (5) Relative center of gravity, (6) ASL, (7-9) Second-order statistical moments.
- *Frequency spectrum parameters:* parameters of power spectral density function f(ω)

$$P_X = 100 \cdot \int_X f(\omega)d\omega \Big/ \int_G f(\omega)d\omega \ , \ X \in \{A,B,C,D,E,F\}$$

where arbitrarily chosen six frequency bands *X* are related to the Nyquist frequency, ω_N. A: (0 - 0.12)*ω_N; B: (0.12 - 0.24)*ω_N; C: (0.24 - 0.36)*ω_N; D:(0.36 - 0.48)*ω_N; E: (0.48 - 0.6)*ω_N; F:(0.6 - 1)*ω_N.

2. Analysis of AE Signal Parametrization

The main goal of any parameterization is to extract maximum of useful information on given data. On the other hand, the redundancy of computed parameters should be minimized. Two methods, the factor analysis and the neural network sensitivity analysis are helpful tools as to reduce the number of extracted parameters. Both methods show us which features support the most important information about existing problem and whether the newly developed parameters are independent with one another.

2.1 Factor analysis (FA)

FA is a method frequently used to find linear relations among parameters and to compute new, hypothetical variables (factors) explaining variance of parameters. FA is based on principal component analysis (PCA). PCA has three effects:

1. orthogonalizes components of transformed input vectors so that they become uncorrelated;
2. organizes resulting orthogonal components (principal components) so that the component with the largest variance is the first; and
3. eliminates components that contribute only little to the variance of data set.

The loss of information is minimized, and corresponds to the difference between the original and transformed data. PCA represents linear data transform (orthogonal rotation followed by scaling). It can be expressed as a matrix-multiplication $Z = AP$, where the original data are stored in matrix Z, new hypothetical variables (factors) in matrix P and the *factor scheme* A represents regression coefficients of factors to the original variables.

2.2 Sensitivity analysis of neural networks

One of the most important problems in NN-based classification systems [7] is the appropriate choice of input pattern parameters called features. The problem of optimal feature selection consists in identification of significant parameters and deletion of remaining ones from the initially large, redundant set of features. Some pattern features can be redundant for making the correct decision. When the number of features is relatively small, exhaustive or quasi-exhaustive search may be used to select the best feature subset. But increasing number of attributes results in rapid growth of the number of possible combinations. Therefore, Fidalgo [8] suggested an alternative approach to the feature subset selection, comprising of the following steps:

1. Train the BP (back propagation)-network with outputs y_j ($j = 1 \ldots m$) using all possible candidate features.
2. For all training patterns, compute $\partial y_j / \partial x_i$, which is the derivative of the network outputs y_j with respect to its inputs x_i ($i = 1 \ldots n$).
3. Compute the mean absolute value of the above derivatives for each input x_i to define the sensitivity coefficient s_{ij} as:

$$s_{ij} = \frac{1}{P} \sum_{p=1}^{P} \left| \frac{\partial y_{pj}}{\partial x_{pi}} \right|$$

where p represents the pattern index.

High values of sensitivity coefficients s_{ij} indicate “important“ features for the trained BP-networks. The differences of s_{ij} values among significant and dummy features become smaller with increasing amount of noise. If dummy features are eliminated and BP NN training is repeated using only the remaining ones, the performance error becomes lower. This confirms the advantage of eliminating dummy variables that just introduce noise. Sensitivity coefficients of the trained BP-networks can also be calculated by BP technique algorithm. These coefficients express the network sensitivity to the considered set of input patterns.

3. Comparison of Parametrized AE Data

Performance of various AE signal parameterization and classification procedures including parameterization in wavelet domain has been tested on examples of both experimental and simulated AE data obtained by different ways.

3.1 Continuous AE data

The first example is related to relatively long records of quasi-continuous AE. AE signals were recorded during the metal-sheet punching process described in [9]. Punching is usually accompanied by AE of high intensity, and AE monitoring can be used to identify occurrence of defects on cutting tools. Computer-controlled hydraulic press has been used to cutout circle and square pieces from 1-mm-thick carbon steel sheets (both the diameter of circle and side of the square were 160 mm). Punching tests were performed using intact and damaged cutting tools. The artificial damage was produced by grinding small parts of cutting tool edge (1% of circumference). Four AE transducers were placed at various positions on cutting tool (matrix). Signals from AE transducers were filtered (high-pass 100 kHz), pre-amplified (40 dB), and recorded by a transient recorder YOKOGAWA DL708 (10 MS/s at 12 bits). The length of stored AE signals was up to 0.5 s, so very large data were treated. Scheme of punching process accompanied by AE signals from four transducers (A to D) is shown in Fig. 1. Localization ANN has been trained on Pen - test data. Hundreds of AE events superimposed on continuous AE background were extracted from each record, and were localized using fuzzy neural networks.

The initial idea of these tests was to identify process changes and small cutting tool defects directly according to the changes of some typical (spectral) AE signal features. Hundreds of punching tests have been performed and analyzed by using classical AE signal parameterization mentioned above. Neither FA nor NN sensitivity analysis showed any important differences between tests with intact and damaged tools (the energy weighted probability summations of the fuzzy located events were finally used to recognize and localize cutting tool defects, which is discussed elsewhere [9]). Recently, the stored signals were re-analyzed using the TC parameterization in wavelet domain. Figure 2 illustrates the time evolution of resulting wavelet domain counts $NC_1(m)$ derived from one AE signal recorded during the test #V005. The whole record

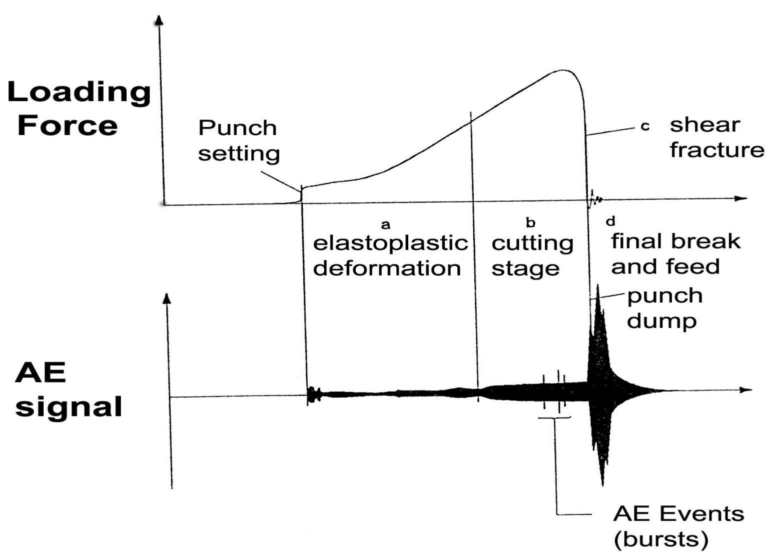


Fig. 1a. Scheme of metal punching process.

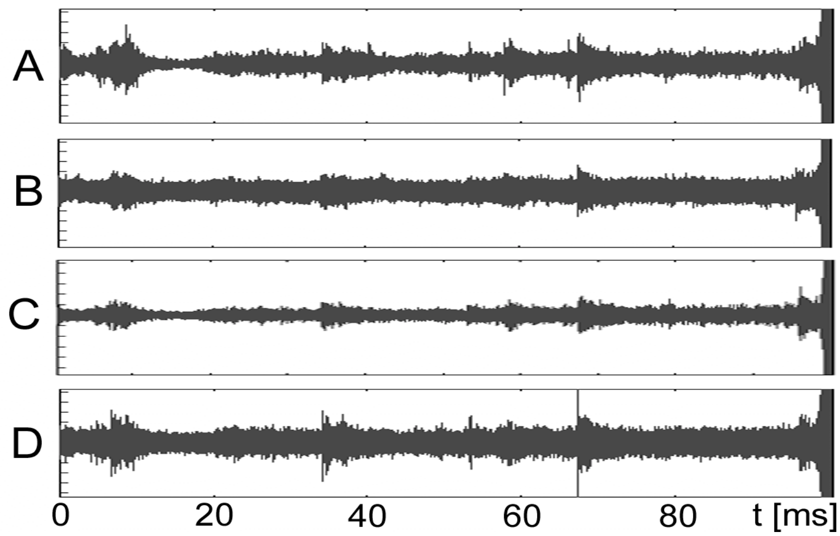


Fig. 1b. AE signals of metal punching process, recorded by four AE transducers (zoomed part b of the process in Fig. 1a) placed on cutting tool [9].

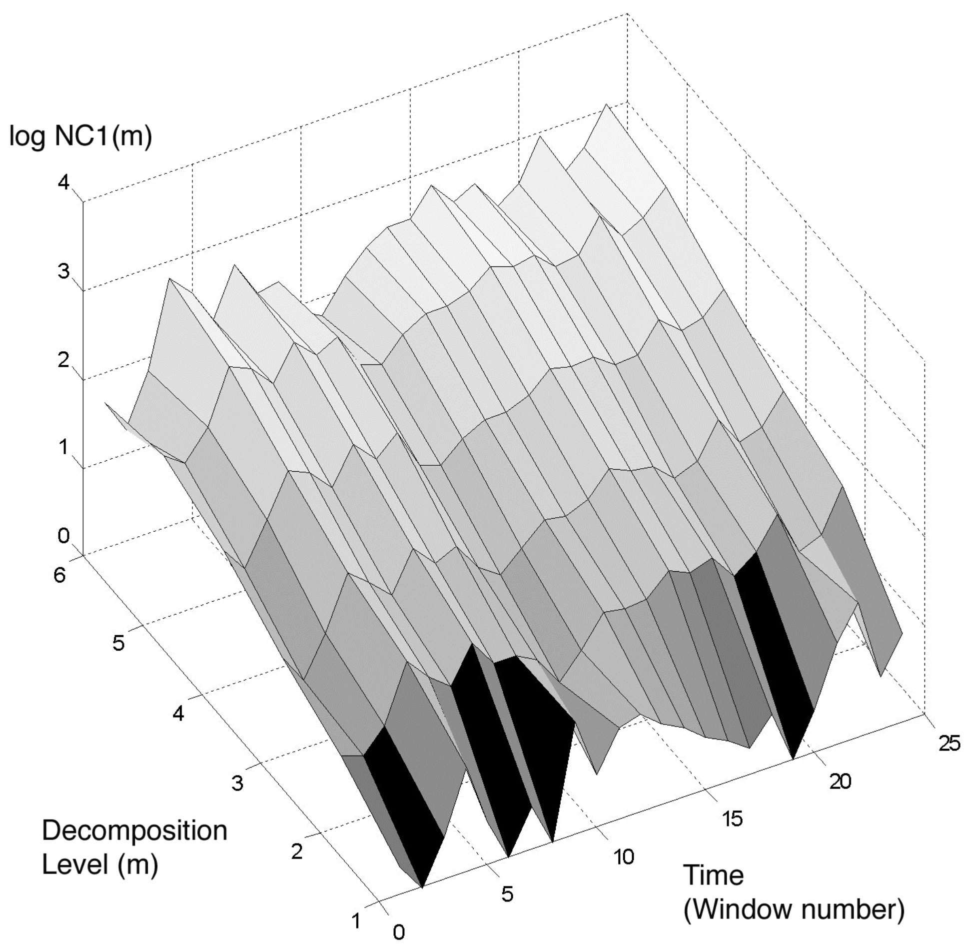


Fig. 2. Time development of AE signal parameters NC_1 (m = 1 to 6) during the metal sheet punching ($NC_i(m)$ are plotted in logarithmic scale).

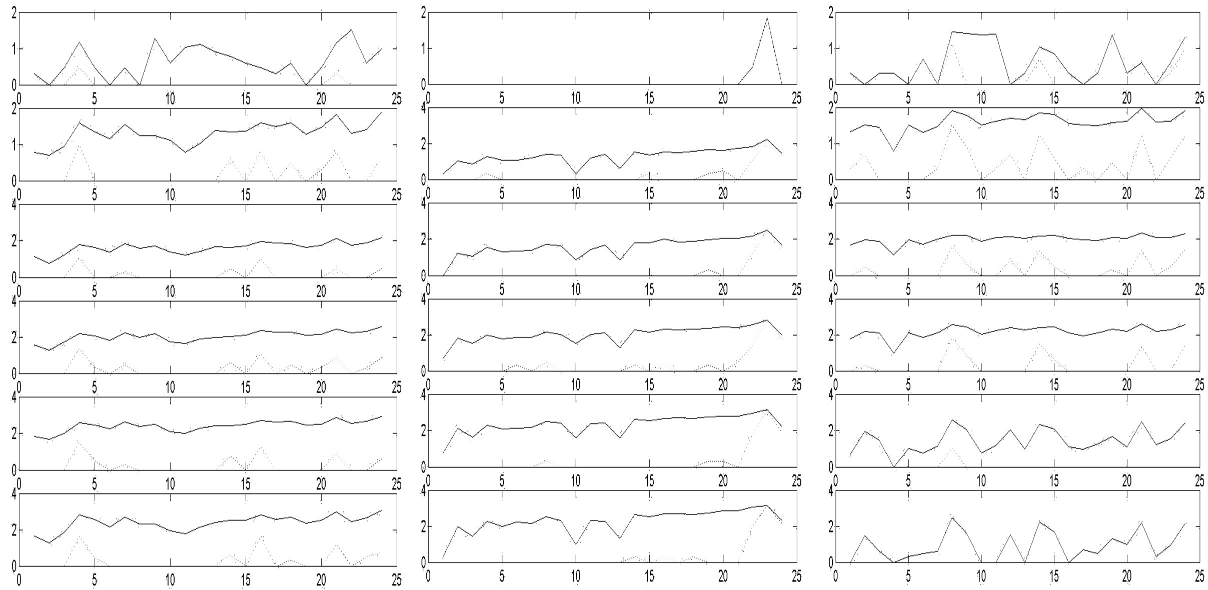


Fig. 3. Logarithmic NC_1 and NC_2 curves (solid and dashed lines, respectively) during the tests #V005 (left), #V007 (middle), and #V010 (right). Counts of the wavelet approximations are at the top, and counts of wavelet details m = 2 to 6 are below.

of about 400 ms was first eight-times down-sampled, which resulted in 500,000 signal samples. Down-sampled signal was then divided into 24 equidistant time intervals (windows), and the wavelet decomposition was applied to each interval (mother wavelet db1, L=5 detail levels). Subsequently, two-level threshold counting was performed on the wavelet coefficients of five details and low frequency approximation, which resulted in 2(L+1) parameters in each time interval (144 data in sum). This procedure represents ca. 3500 times data reduction, saving a global information on time and frequency changes of the whole process. The detailed $NC_{1,2}(m)$ curves are shown in Fig. 3: The wavelet parameters $NC_1(m)$ and $NC_2(m)$, evaluated in 24 time windows, are plotted so that counts of the wavelet approximation (m=1) are on the top, and below are counts of wavelet decomposition details of m = 2 to 6 (down from low to high frequency details). Low-amplitude level counts NC_1 are plotted as solid lines, and high-level NC_2 curves as dashed lines. NC_i curves, evaluated at all three tests in the same manner, can be compared. Threshold counting levels and other parameters of all tests were the same. Punching tests were performed using the cutting tool with very small damage. The only difference was the quality of punched metal sheets (degree of surface corrosion), which is pronounced mainly at the wavelet approximation level (no visible corrosion was at the sheet #V007 in the middle of Fig. 3). At all three parts of Fig. 3 we can see that NC_i curves have very similar form at all wavelet decomposition levels. This means that no remarkable changes in signal spectrum are observed during the running process, and an attempt to recognize different process stages by using spectral parameters has no sense.

3.2 Classification of simulated AE data

In this section, the use of new wavelet-domain parameters is demonstrated also on a simulated AE data, generated for the testing of NN-based AE source classification procedure [10]. Different time functions of AE sources were assumed to simulate and classify various emitting defects. At first, it was necessary to train a BP-NN, to classify the original source functions, and finally, the most significant AE parameters of generated waveforms were tested.

The training AE waveforms (input data) were generated as a convolution of the source function (having different forms) with a Green's function. The Green's function has been obtained experimentally as a transfer function between the AE source and sensor measured during the pulse laser excitation of a steel plate (representing the impulse source of propagating elastic waves) at a distance 140 mm from the source [10]. Its graph is shown at the top of Fig. 4. Input patterns for the classification BP-network are composed of the following 14 parameters extracted from the “input signal“ z(t): amplitude, rise time, RMS value, energy moment, ASL, gravity center of signal, second to fourth statistical moments, six spectral parameters, and above defined parameters in wavelet domain.

Different AE signal sources S_p (p indicates the pattern index) were simulated as a linear combination of three source functions ("waves"): $wave_1$, $wave_2$, $wave_3$, weighted by randomly generated coefficients a_p, b_p, c_p:

$$S_p = a_p \,.\, wave_1 + b_p \,.\, wave_2 + c_p \,.\, wave_3$$

In order to obtain more comparable results, these coefficients are normalized so that their sum equals to one. The graphs of the source "waves" and their combination are also shown in Fig. 4, along with the “input signal“ $z_p(t)$ computed as a convolution of the AE source function S_p with the Green function G:

$$z_p(t) = conv(S_p, G).$$

500 training patterns were generated for the training of 50 neural networks of the same architecture (topology 45-19-3, resulting error < 0.01). Only initial weights were set differently among the trained NN's. The averages of sensitivity coefficients calculated for all tested networks are presented in Table 1 (shaded by values).

Each of the three columns in Table 1 contains 24 values corresponding to input signal features. Only 9 wavelet parameters at 3 highest frequency detail levels were considered in this analysis, as the low frequency wavelet coefficients differ little for various model sources. From Table 1 we can see that the most important are pattern features number 6, 11, 14, 15 and 24. It means that the generated signal waveforms differ mostly at higher frequencies and a linear combination of different source "waves" can be estimated ("source classification") using the relative signal gravity centers in time domain and gravity centers of wavelet decompositions.

The application of PCA has proven (see Table 2) that the new “wavelet counting parameters“ (parameters number 16 to 24) represent new, linearly independent information. Nevertheless, this information seems to be unimportant for the estimation of the composed signal "weights" as expected, while the linearly dependent classical parameters appear to be more important in this case.

Finally, numerical experiment with NN training has proven that for successful learning it is possible to use only the spectral parameters (features number 10 - 15) or just wavelet decomposition parameters (features number 16 - 24) giving very similar results.

3.3. Recognition of AE sources in polymer composite samples

The last example demonstrates importance of various AE parameters in recognition of AE signals coming from three types of model GFRP composite specimens. Unidirectional reinforced composite samples of three special forms were prepared and tested in [11] so that the three different damage mechanisms prevailed during the specimen loading (delamination, fiber breaks,

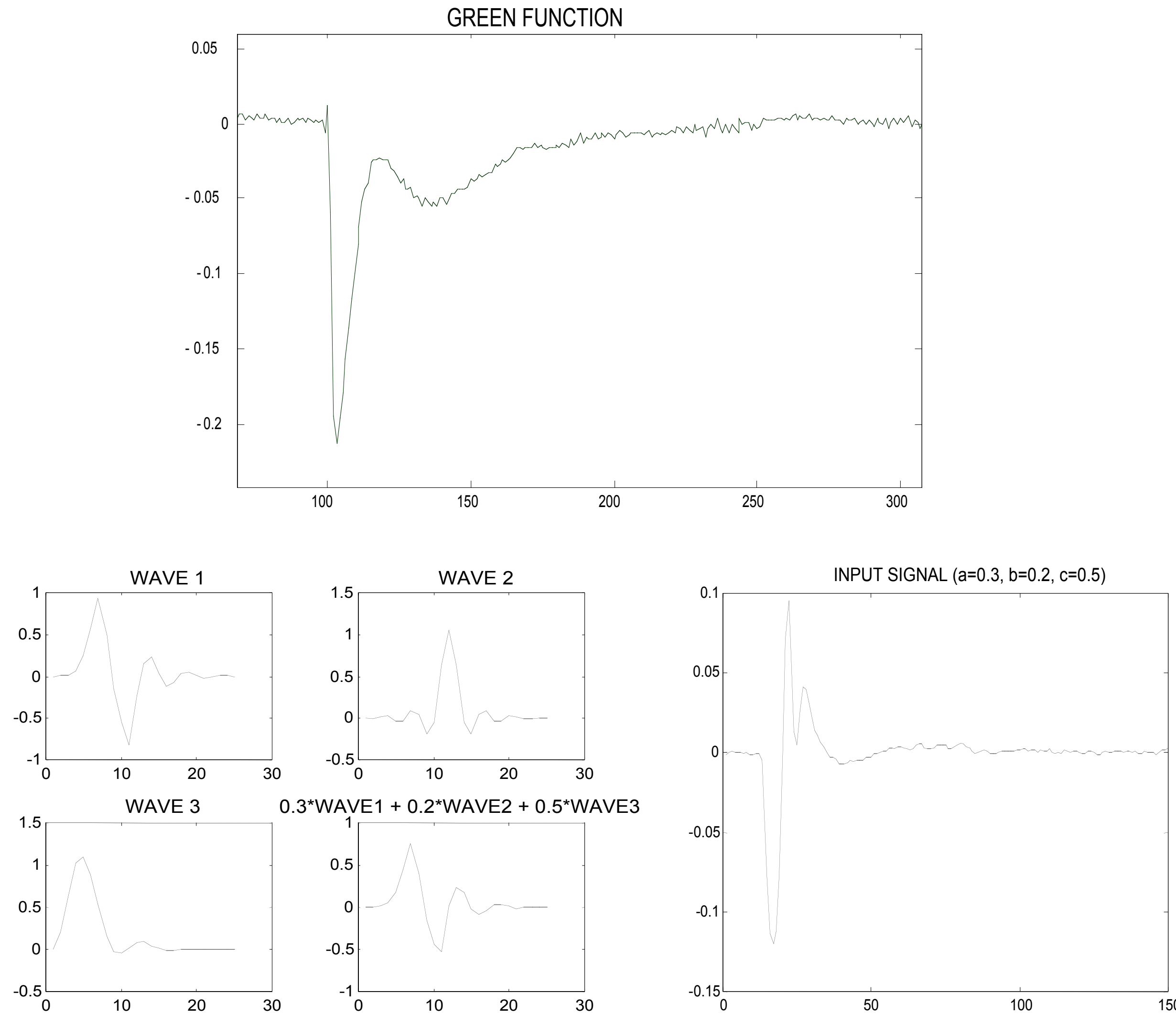


Fig. 4. Graphs of the source model functions ("waves" 1,2,3, and their linear combination) and the input signal resulting from the convolution of the source and Green's function.

and matrix cracks). The data (AE signal parameters) from specimens of different forms are used to see the significance of various AE parameters for the recognition of the three different AE source mechanisms. The NN with AE parameter inputs was trained to indicate the highest value on particular output corresponding to each specimen form (AE source mechanism). In Table 3 we can see that resulting NN sensitivity coefficients show similar picture as in Table 1 for simulated signals. Again, as the most important features (all five wavelet decomposition levels were considered in this case) seem to be the centers of gravity of spectral or wavelet parameters.

4. Conclusions

The wavelet transform of AE signal is now broadly used as very useful tool for AE signal analysis in time-frequency domain. New AE signal parameters based on wavelet transform (wavelet counts) were introduced here as a logical extension of commonly used AE signal

Table 1. Sensitivity analysis of trained BP-networks.

SENSITIVITY COEFFICIENTS

INPUTS \ OUTPUTS	1	2	3
1	0.14	0.12	0.08
2	0.06	0.07	0.05
3	0.11	0.12	0.08
4	0.11	0.10	0.08
5	0.12	0.11	0.14
6	0.20	0.09	0.16
7	0.12	0.12	0.09
8	0.11	0.11	0.08
9	0.09	0.09	0.07
10	0.14	0.09	0.13
11	0.17	0.13	0.11
12	0.10	0.09	0.08
13	0.12	0.14	0.13
14	0.21	0.22	0.09
15	0.30	0.19	0.12
16	0.03	0.03	0.03
17	0.02	0.01	0.01
18	0.08	0.08	0.06
19	0.03	0.03	0.03
20	0.05	0.05	0.05
21	0.07	0.10	0.07
22	0.05	0.04	0.05
23	0.06	0.05	0.05
24	0.18	0.10	0.12

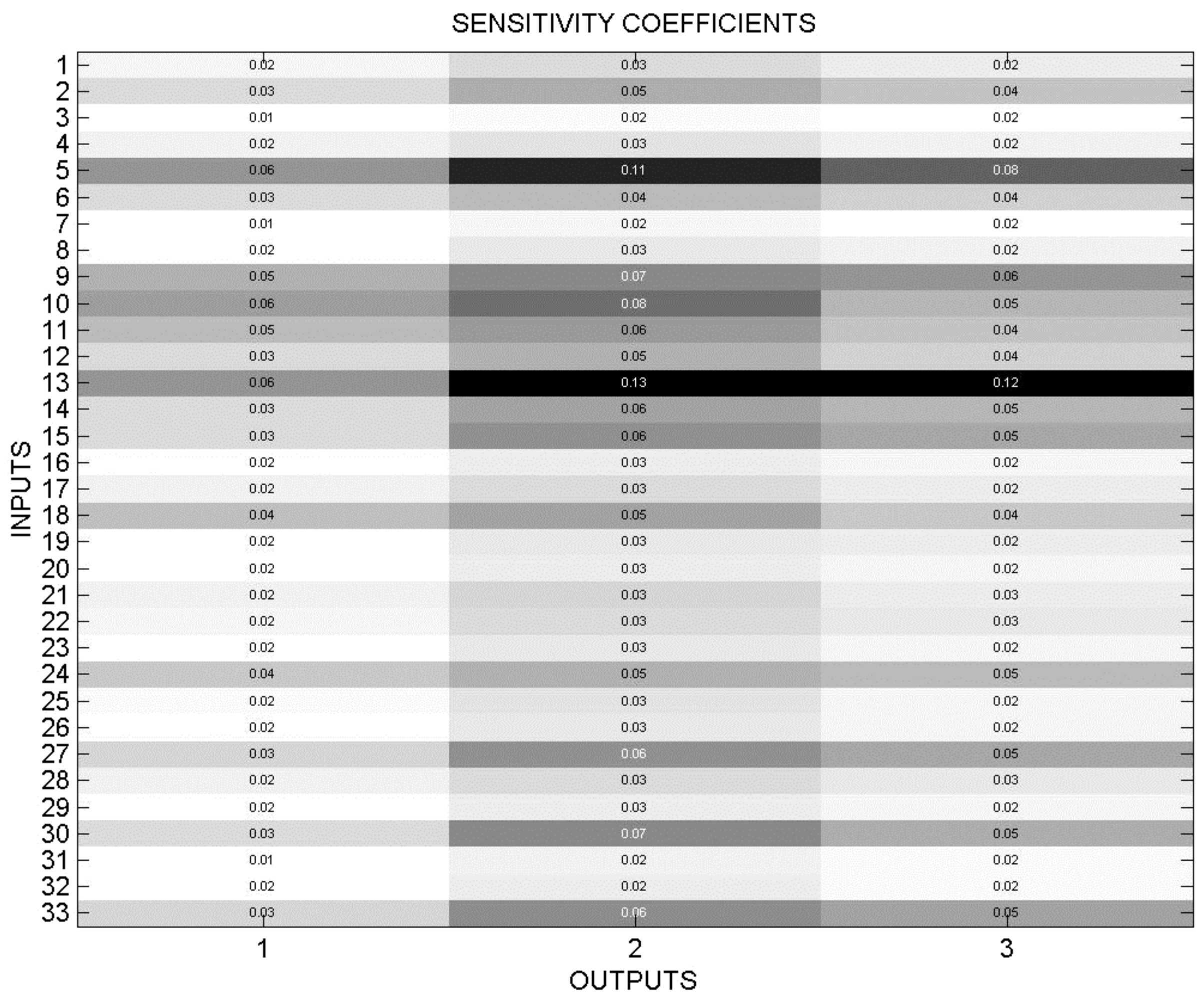
Table 2. Factor scheme (PCA) of tested signal parameters.

FACTOR SCHEME

PARAMETERS \ FACTORS	1	2	3	4	5	6	7
1	0.95	0.12	0.00	0.03	0.00	0.06	0.01
2	0.07	0.44	0.77	0.01	0.22	0.08	0.05
3	0.90	0.27	0.23	0.01	0.03	0.13	0.11
4	0.96	0.15	0.03	0.01	0.01	0.11	0.09
5	0.26	0.84	0.36	0.03	0.12	0.21	0.04
6	0.32	0.89	0.25	0.01	0.09	0.00	0.00
7	0.91	0.25	0.24	0.01	0.03	0.14	0.11
8	0.95	0.16	0.18	0.00	0.03	0.08	0.10
9	0.95	0.12	0.11	0.00	0.05	0.01	0.08
10	0.14	0.93	0.25	0.02	0.07	0.06	0.04
11	0.74	0.01	0.39	0.06	0.00	0.44	0.13
12	0.55	0.71	0.23	0.03	0.01	0.28	0.00
13	0.48	0.50	0.54	0.07	0.12	0.32	0.10
14	0.36	0.03	0.84	0.04	0.08	0.30	0.11
15	0.01	0.92	0.33	0.01	0.02	0.04	0.09
16	0.42	0.19	0.07	0.03	0.04	0.13	0.86
17	0.03	0.03	0.03	0.99	0.00	0.01	0.01
18	0.47	0.57	0.26	0.13	0.27	0.41	0.01
19	0.22	0.51	0.56	0.00	0.12	0.18	0.02
20	0.05	0.07	0.26	0.00	0.91	0.13	0.03
21	0.40	0.42	0.68	0.02	0.12	0.31	0.02
22	0.03	0.82	0.20	0.02	0.15	0.16	0.11
23	0.14	0.09	0.21	0.00	0.15	0.85	0.09
24	0.26	0.90	0.18	0.00	0.07	0.19	0.01

threshold counting procedures. These new AE signal parameters are defined as numbers of threshold crossing counts of wavelet coefficient amplitudes at various wavelet decomposition levels. Two predetermined threshold values are used in a simplest case, which can differ at various wavelet decomposition levels. Thresholds should be selected in a similar way as recommended in standard threshold counting of original AE signal. The applications of wavelet counts have been illustrated on three examples of both real and simulated AE data. Numerical tests have been performed using the neural-network sensitivity and factor analyses. Test results show which of various classical and newly introduced AE signal features are significant for AE source identification procedures. As the most important features seem to be the centers of gravity of spectral or wavelet parameters. The wavelet counts, carrying the global information in both time and frequency domains, can replace ill-defined frequency spectrum parameters of AE signal in a more efficient way. The strategy of neural network sensitivity analysis seems to be very useful to reveal the most significant AE signal features in various applications.

Table 3. NN sensitivity analysis results of tested AE parameters significance for the recognition of three different AE source mechanisms acting in loaded composite samples.



SENSITIVITY COEFFICIENTS

INPUTS	OUTPUTS 1	OUTPUTS 2	OUTPUTS 3
1	0.02	0.03	0.02
2	0.03	0.05	0.04
3	0.01	0.02	0.02
4	0.02	0.03	0.02
5	0.06	0.11	0.08
6	0.03	0.04	0.04
7	0.01	0.02	0.02
8	0.02	0.03	0.02
9	0.05	0.07	0.06
10	0.06	0.08	0.05
11	0.05	0.06	0.04
12	0.03	0.05	0.04
13	0.06	0.13	0.12
14	0.03	0.06	0.05
15	0.03	0.06	0.05
16	0.02	0.03	0.02
17	0.02	0.03	0.02
18	0.04	0.05	0.04
19	0.02	0.03	0.02
20	0.02	0.03	0.02
21	0.02	0.03	0.03
22	0.02	0.03	0.03
23	0.02	0.03	0.02
24	0.04	0.05	0.05
25	0.02	0.03	0.02
26	0.02	0.03	0.02
27	0.03	0.06	0.05
28	0.02	0.03	0.03
29	0.02	0.03	0.02
30	0.03	0.07	0.05
31	0.01	0.02	0.02
32	0.02	0.02	0.02
33	0.03	0.06	0.05

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