AE SOURCE RECOGNITION BY NEURAL NETWORKS WITH OPTIMIZED SIGNAL PARAMETERS

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Abstract

AE source recognition procedures using artificial neural networks (ANN) were already applied successfully to AE data from numerical models and simple structures. One of the main problems in general data recognition is proper selection of extracted data features. Some of commonly used AE-signal parameters are redundant or lowly significant. Such parameters (data features) only complicate the recognition problem. Therefore, several modifications of the standard AE-signal parameterization are proposed in this paper to reduce data redundancy. The set of AE parameters is optimized by PCA (principal component analysis) and sensitivity analysis of trained neural networks used for pattern recognition. The optimization process is illustrated on recognition of various AE sources, detected during fatigue test of an aircraft structural part. Resulting optimized feature set of AE signals provides the maximal information with minimized number of selected parameters.

Introduction

Acoustic emission source identification represents one of the most difficult problems in AE analysis. The lack of exact knowledge about the influence of geometrical dispersion effects is one of the most important constraining factors in AE-source classification. In many practical applications, the complete inverse solution is not necessary for diagnostic decision, and simplified AE-source-identification procedure is sufficient. Example of such procedure is statistical pattern recognition of the source described by significant signal parameters. AE signals may be often generated not only by structural defects but also by undesirable acoustic interference. Reliable AE-source classification and following diagnostic decision should take into account only the emission sources related with damage processes in tested structure. Therefore, AE-source classifier using optimized number of signal parameters is described in following sections.

Experiments

Well-identifiable data set is a necessary condition for any AE-source-classifier design and testing. AE signals recorded during laboratory fatigue tests of a small aircraft part satisfy requirements on reliable data set as AE source localization revealed two dominant AE-activity regions.

Tested object was a steering actuator bracket (SAB), which is a part of the aircraft nose landing gear. The bracket was loaded under pulsating stress cycles (R = 0, frequency 0.5 Hz) on Instron-Schenck 100 kN uniaxial loading machine to the maximal load level of 43 kN causing the maximum stress of about of 870 MPa in the critical points. AE was monitored during the loading cycles by DAKEL XEDO AE system. All AE signals were stored, and after certain loading periods, the detailed AE event-location analysis using an “Expert AE localization procedure” was performed so as to detect crack initiation. Most AE events arose near “expected” crack formation area ("A" in Fig. 1).

Another AE accumulation was observed around one hole in the left part of SAB (area "B" in Fig. 1). The task of source-classifier design is to recognize signal types, "A" and "B", originating in both areas where the different source mechanisms are supposed.

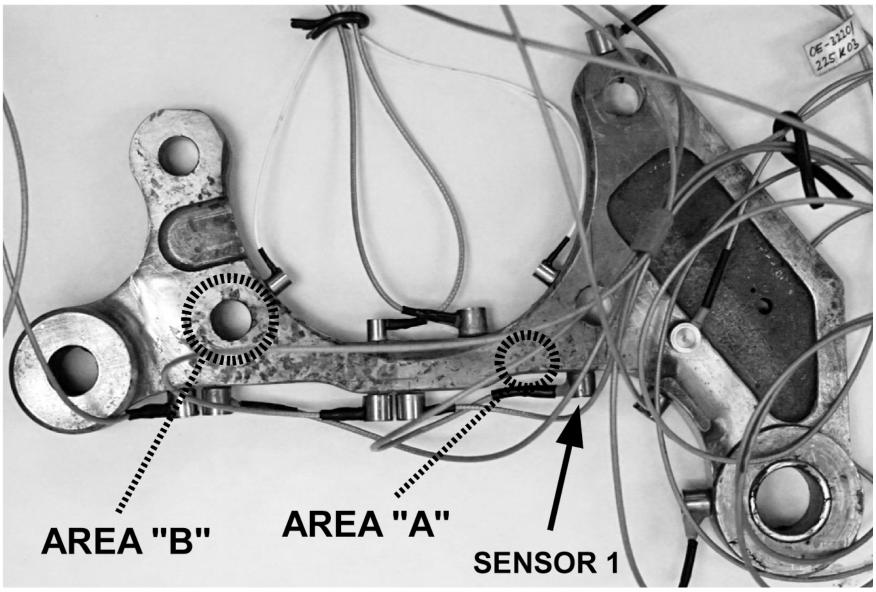


Fig. 1. Steering actuator bracket.

Definition of Signal Parameters

The main purpose of AE-signal parameterization is to reduce large waveform data to the lowest number of signal features carrying maximum of important information. The number and type of signal features are selected so as to comply with various criteria (diagnostic purpose, device capabilities, simple and effective processing, etc.). AE source-identification procedures are mostly based on signal parameters in both time and frequency domain. Due to some inadequacies of standard AE signal parameters (e.g., phase sensitivity of peak amplitude and rise time), we propose several new signal characteristics derived from the auxiliary local gravity-center vector, g, used in the expert signal-arrival-detection procedure [1]. It is the i-th element in the magnitude of gravity center $GC_Y(|s_i|)$ around the i-th sample in signal segment s_i:

$$g(i) = GC_Y(|s_i|) = \frac{\sum_{j=1}^{k_i} (k_i+1-j)|s_i(j)|}{\frac{1}{2}(k_i^2+k_i)}$$

where existing signal part s_i and "measuring window length" k are considered as:

$$s_i = \{ s(j) \mid j=max\{i-k,1\},\dots, min\{i+k,N\}\}$$
$$k = c_k \cdot max(diff(z))$$
$$diff(x) = \{ x(j+1)-x(j) \mid j=1,\dots,N-1 \}$$

Vector $z = \{z(i) \mid i = 1 \dots N\}$ consists of logical values 0 and 1, determining whether the sample record is less than one-third of the peak amplitude:

$$z(i) = \begin{cases} 1 & if \;\; s(i) < amplitude/3 \\ 0 & otherwise \end{cases}$$

The following AE parameters (numbered 1-19) in time and frequency (spectral) domains were also computed:

Time domain: **(1)** signal amplitude, **(2)** vector g amplitude, **(3)** signal rise time, **(4)** vector g rise time, **(5)** signal RMS, **(6)** signal energy moment, **(7-10)** 1st to 4th central moments of vector g in terms of probability density function.

Frequency spectrum parameters: **(11-15)** parameters of signal power spectral density function $f(\omega)$:

$$P_X - 100 . \int_X f(\omega)\, d\omega / \int_G f(\omega)\, d\omega \;, \quad X \in \{A, B, C, D, E\}$$

where G is overall frequency range and arbitrarily chosen five frequency bands X are related to the Nyquist frequency ω_N as follow:

A:(0-0.05)* ω_N; B:(0.05-0.1)* ω_N; C:(0.1-0.15)* ω_N; D:(0.15-0.3)* ω_N; E:(0.3-0.5)* ω_N.

(16-19) 1st - 4th central moments of $f(\omega)$ in terms of probability density function.

Analysis of AE Signal Parametrization

The main goal of any parameterization is to extract maximum of useful information on given data whereas the redundancy of computed parameters should be minimized. The factor analysis (FA) [2] and the neural-network sensitivity analysis are helpful tools to reduce the number of extracted parameters. Both methods show us the features that carry the most important information about existing problem and whether the parameters are independent among each other.

Factor analysis: 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), which has three effects:

1. Orthogonalizing transformed input-vector components as they become uncorrelated;
2. Organizing orthogonalized (principal) components with the component having the largest variance as the first;
3. Eliminating components that contribute only little to the data set variance.

The loss of information is minimized, corresponding to the difference between original and transformed data. In most cases, PCA and FA usually yield similar results. However, PCA is preferred in data reduction, while FA is better for the recognition of data structure. FA 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 the regression coefficients of factors to original variables. Interpretation of factors is somewhat difficult since the problem solution may be any rotation of the factor scheme. The goal of all rotational strategies (e.g. VARIMAX) is to obtain a clear pattern of factor loadings (the simplest structure).

Sensitivity analysis of artificial neural networks (ANN): Proper selection of input data is very important when the ANN is used for AE-source classification [3]. It is important also to recognize significant pattern features within initially large, redundant feature set, and discard insignificant features for the correct ANN decision. In many real cases, the input features may be interdependent and the system output is then influenced by relationships between inputs rather than by the separate input values. When the number of input features is small, a quasi-exhaustive search may be used to select the best feature subset. However, the number of possible combinations grows rapidly with the number of attributes. An alternative, sensitivity-analysis approach to feature selection (called FSS) is proposed in [4]. It comprises following steps:

- Back-propagation (BP)-network training by all possible feature candidates;
- For all training patterns p with corresponding network outputs $y_{p,j}$ and inputs $x_{p,i}$, are computed sensitivity coefficients $s_{j,i}$, defined as:

$$s_{j,i} = \frac{1}{P}\sum_{p=1}^{P}\left|\frac{\partial y_{p,j}}{\partial x_{p,i}}\right|$$

- Elimination of "dummy" features with small values of $s_{j,i}$ coefficients. High values of the sensitivity coefficients indicate "important" features for the trained BP-networks.

AE Source Classifier

Factor scores calculation: We used the *factor scores* (i.e. the values of new hypothetical features given by FA) as classifier-input parameters. PCA showed that only 6 factors can interpret 96% of total data variance. Table 1 represents rotated factor scheme for all 19 original parameters. Factor loadings are shadowed by values. It is evident that the first factor is saturated by signal-shape features, such as the amplitude, RMS and central moments of vector g. Next, well-interpretable factors are clearly determined by lower spectral band parameters, Nos. 11-13 (factor 2), and the shape of power spectral density function (factor 4). The application of factor analysis has proven that the proposed features of power spectral density shape (parameters Nos. 16 to 19) represent new, linearly independent information. Desirable factor scores (new uncorrelated signal features) were computed as $P = A'\cdot R^{-1}\cdot Z'$, where R is correlation matrix of standardized data Z [2].

Table 1. Factor analysis.

ROTATED FACTOR SCHEME (absolute values)

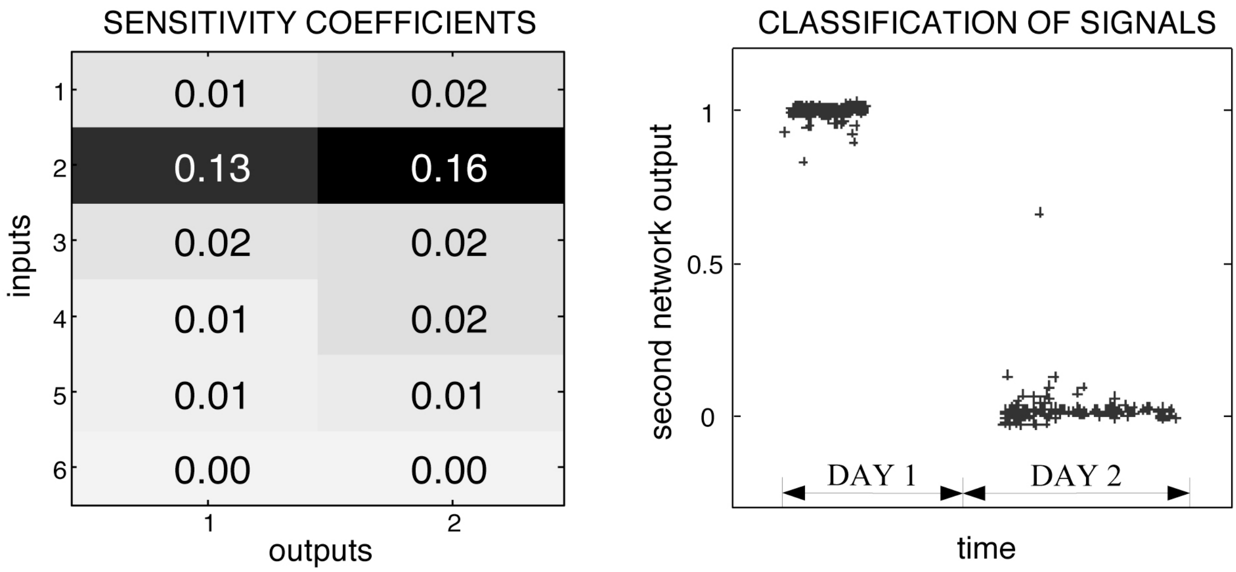
parameters \ factors	1	2	3	4	5	6
1	0.71	0.40	0.11	0.11	0.18	0.49
2	0.78	0.35	0.11	0.14	0.00	0.43
3	0.15	0.10	0.97	0.03	0.02	0.09
4	0.07	0.13	0.95	0.01	0.02	0.15
5	0.91	0.07	0.23	0.25	0.00	0.18
6	0.06	0.09	0.96	0.17	0.03	0.12
7	0.93	0.04	0.14	0.00	0.17	0.12
8	0.90	0.04	0.04	0.36	0.04	0.00
9	0.97	0.02	0.16	0.08	0.12	0.10
10	0.94	0.03	0.00	0.28	0.03	0.02
11	0.13	0.92	0.11	0.21	0.17	0.13
12	0.07	0.97	0.08	0.05	0.03	0.02
13	0.07	0.97	0.08	0.18	0.06	0.04
14	0.14	0.85	0.20	0.44	0.11	0.00
15	0.26	0.81	0.12	0.40	0.14	0.00
16	0.37	0.25	0.06	0.59	0.65	0.07
17	0.15	0.24	0.42	0.82	0.03	0.05
18	0.36	0.15	0.15	0.87	0.20	0.04
19	0.22	0.22	0.07	0.92	0.05	0.05

Neural network learning: Following the previous good experience with AE source-model recognition [5], we used the BP-networks with two hidden layers as a classifier basis. Only the signals from one sensor (sensor #1) were considered in the classifier. The number of factors determines the number of input neurons. The optimal architecture of the applied network versions was about 9 neurons in the first and 7 neurons in the second hidden layer with sigmoidal transfer functions. The third layer has two neurons with linear transfer function computing an estimate of classification weights. During the ANN learning process, weights and biases of the network were iteratively adjusted by fast resilient back-propagation training algorithm with momentum and generalization-improvement regularization. For given factor scores, corresponding to AE sources of A and B types, the trained network outputs should be close to vectors [1,0] and [0,1], respectively. As the training data set, one half of all 900 processed signals have been used, while the rest of them served for testing. Initial weights and biases considerably affect the ANN learning process along with its sensitivity to input-data variance. The starting neuron potentials should lie in interval of the highest slope of sigmoidal transfer function, i.e., in a symmetric interval with zero midpoint. For that reason, the initial weights were adjusted by statistical optimization of starting neuron potentials.

After approximately 100 cycles of training algorithm, the value of MSE_{TRAIN} (mean of square errors of training data with normalized means and standard deviations) was 0.000187, while the generalization error MSE_{TEST} (i.e., MSE considered for all data with normalized means and standard deviations) was 0.0034. The table in Fig. 2 represents sensitivity coefficients shadowed by values. Each of two columns contains six values for respective network inputs. We can see that the most important input corresponds to the second factor saturated by the original lower frequency spectral band parameters. This result reflects the fact that two AE signal types are almost linearly separable with some spectral parameters and, theoretically, one perceptron should be sufficient to distinguish the AE source types. However, this preliminary information served only for methodology verification, and was not used in the classifier design.

The right part of Fig. 2 illustrates results of recognition for the whole testing data set. Nearly all signals were successfully assigned to correct location areas. Second ANN output of 1 or 0 allocates the AE origin to area "B" or "A", respectively.

Fig. 2. Classifier results.



Conclusions

A simple AE-source classifier and optimization of AE signal parameters is proposed in the paper. The aim of the ANN-based recognition method is to reliably eliminate undesirable AE signals. Due to some inadequacies of standard AE parameters, new signal characteristics were introduced. The original data structure was interpreted and simplified by factor analysis, where six extracted factors clarified 96% of total data variance. Only these six new uncorrelated signal features were used as ANN-classifier inputs. Sensitivity analysis of the trained ANNs indicated the second extracted factor as the most significant new AE signal feature suitable for AE source identification. This enclosure corresponds well with the prior information about data structure and can be easily interpreted in a frame of elastic wave-propagation theory. The advantages of proposed methodology were demonstrated on an AE-data example recorded during the fatigue testing of an aircraft structural part. Results of proposed classification method are promising for further use on complex AE data.

Acknowledgements

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