NEURAL NETWORK AE SOURCE LOCATION APART FROM STRUCTURE SIZE AND MATERIAL

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Abstract

AE localization procedures using artificial neural networks (ANN) represent extremely effective alternative to classical triangulation methods. Nevertheless, their application always requires full-scale, time consuming ANN training on each specific structure. Disadvantage of particularly trained ANN algorithm is in its non-transferability to any other object. A new ANN-based AE source location approach is proposed in this paper to overcome such limitation. The method replaces standard arrival time differences at the ANN inputs by so called signal arrival time profiles, independent on material and scale changes. The ANN training can be also performed theoretically on geometrical models (i.e. without any experimental errors) and learned ANN is then applied on real structures of different dimensions and materials. Such approach enables considerable extension of ANN application possibilities. The use of new AE source location method is illustrated on experimental data obtained during aircraft structure part testing.

Keywords: AE source location, artificial neural networks, arrival time profiles.

Introduction

Acoustic emission (AE) method is widely applied in non-destructive testing of various technical structures. After the signal detection, accurate location of AE source is the primary goal of the defect analysis and the basic requirement for further damage mechanism characterization. AE source coordinates are mostly determined by common triangulation algorithm based on arrival time differences of AE signals recorded by several transducers [1]. The algorithm computes the polar coordinates \((r, \alpha)\) of AE sources using analytical formulas. Time differences \(\Delta t\) of AE signal arrival times to different transducers along with elastic wave velocity are necessary input data for triangulation source location algorithm (see Fig. 1).

Analytical formulas are known for isotropic plates. However, there are many practical situations, in which the triangulation algorithm fails, especially if the more complex structure is tested. Procedures based on ANN are used in such cases as an alternative approach to triangulation algorithm. Contrary to the classical methods, the ANN-based location procedures have two important advantages: they are suitable for AE source location in highly anisotropic media, and elastic wave velocity is not necessary input parameter of the algorithms [1 - 3].

The basic ANN-based algorithm uses time differences as input parameters similarly to common triangulation algorithm. However, the correct arrival time (signal onset) determination is the crucial factor for the algorithms using time differences and, therefore, the methods can give erroneous results, especially in cases of high noise background level. To solve the problem, certain modification of ANN-based method for AE source location was proposed [4]. The method uses common AE signal parameters, such as RMS, rise time, maximum signal amplitude, etc, which represent redundant input data set for ANN location algorithm. The algorithm is flexible, because it enables selection of the optimal parameters set in each specific situation. Nevertheless,
the sensitivity analysis of trained neural networks has extracted RMS parameter as the most significant signal feature suitable for AE source location, which corresponds with the basic features of dispersive elastic-wave propagation. The information about the source location, which is hidden in energy parameters, can be better extracted when we use certain modifications of RMS signal parameter, as it was shown and successfully tested in [4].

Contrary to the computational power of ANN's, their application possibility is strongly restricted due to several reasons. The first problem is collecting sufficiently extensive training and testing data sets, which may be excessively time-consuming, expensive or even impossible in many practical cases. The next important reason is the non-portability of particular trained network to any other situation. ANN should be learned and applied in exactly the same task only, i.e. the similar computation in the same input-output parameter space is required. Hence, the above-mentioned method using RMS signal parameter for AE source localization need not represent suitable solution.

To solve both above problems of ANN-based AE source localization, a new approach was proposed. This innovative localization method uses new way of signal arrival time parameterization (called signal arrival time profiles), independent on the material and scale changes. Under some non-restrictive conditions, such approach employs the ANN training on numerical model data (i.e., without experimental errors) and allows the application of learned ANN on real structures with diverse scales and materials.

Fig. 1. Demonstration scheme of AE signal measurement (2D model).

Definition of Arrival Time Profile (ATP)

The new way of signal arrival time treatment is inspired by the preliminary expert analysis of AE source location. The whole monitored structure is separated into several zones according to signal first arrival to each sensor (see Fig. 2). In this way, the AE source can be roughly localized using the information which sensor is the nearest one. To describe the signal detection chronology more precisely, so-called arrival time profiles are proposed.
Let's suppose hypothetical configuration of several AE sensors $S_1, \ldots, S_N$ placed on planar material (in a case of four sensors see Fig. 1), detecting elastic waves emitted by AE sources in various locations. Signal propagation time from the source to sensor $i$ is denoted $T_i$ (arrival time period). Then, the arrival time profile (ATP) is a vector of numbers $p_i$ defined as follows:

$$p_i = \frac{NT_i - \sum_{j=1}^{N} T_j}{\sum_{k=1}^{N} \left| T_k - \frac{1}{N} \sum_{j=1}^{N} T_j \right|}$$

(1)

No AE analyzer measures that arrival time periods $T_i$ before the precise AE source location is performed. Only the AE signal arrival times $t_i$ are available. Nevertheless, if we assume $t_s$ as the time of AE source initiation, it is easy to revise the original formula, while $T_i = t_i - t_s$:

$$p_i = \frac{N(t_i - t_s) - \sum_{j=1}^{N} (t_j - t_s)}{\sum_{k=1}^{N} \left| t_k - t_s - \frac{1}{N} \sum_{j=1}^{N} (t_j - t_s) \right|} = \frac{Nt_i - \sum_{j=1}^{N} t_j}{\sum_{k=1}^{N} \left| t_k - \frac{1}{N} \sum_{j=1}^{N} t_j \right|}$$

(2)

Fig. 3. Arrival time information processing
Computation of arrival time profiles is similar to general data standardization. In a first step, the mean value of arrival times is subtracted from each $t_i$. Such data is then normalized by the mean of its absolute values. Figure 3 illustrates described arrival time information processing.

**Independence of ATP on Wave Velocity and Scale Changes**

Let us denote $d_i$ the distance between AE source and sensor $i$, and $v$ the elastic wave velocity. By substitution of relation $T_i = d_i/v$ to (1) we obtain:

$$p_i = \frac{N}{\sum_{k=1}^{N} \left( \frac{d_k}{v} - \frac{1}{N} \sum_{j=1}^{N} d_j \right)} = \frac{N d_i - \sum_{j=1}^{N} d_j}{\sum_{k=1}^{N} \left( \frac{d_k}{v} - \frac{1}{N} \sum_{j=1}^{N} d_j \right)}$$

Arrival time profiles can be also calculated using the distances $d_i$, which enables the learning of neural networks with numerically computed data from the distances measured on proportional model of considered structure (i.e. without experimental errors) and, afterwards, testing by processed real arrival times. The elastic wave velocity is cancelled out in eq. 3, so the arrival time profiles are independent on elastic wave velocity. Analogical cancellation of any common multiple of distances $d_i$ proves the independence to structure scale changes.

**Theoretical Aspects**

The potentialities of newly proposed parameterization using arrival time profiles were at first examined numerically. Theoretical case of 2D plate of any isotropic material and scale was taken into account. Due to the complex topology of ATP parametric space, it was necessary to find sensor configurations warranting numerical stability of the method. Possible division by small numbers in eq. 3 may generate rapidly changing data that neural network cannot learn. Typically, this occurs in regions where the distances of AE sources to all considered sensors are similar.

Fig. 4. Numerical testing of sensor configurations.
Three different configurations of four sensors (black dots) are shown in Fig. 4. To compute the training data, the rectangular domain from 5 to 150 and from 5 to 60 units of the scale was taken into account for x- and y-coordinates, respectively. Equidistantly spaced points having 2.5 units of the scale between each other cover the whole area. For all such virtual AE sources, the distances to considered sensors were computed and, consequently, eq. 3 was applied. Before neural network learning, data standardization is realized. The two-hidden-layer back-propagation networks (see Fig. 5) were trained to estimate the original coordinates of AE source using corresponding arrival time profile. Finally, all training points (their arrival time profiles) were projected by neural network onto the original area (see crosslets in Fig. 4).

![Fig. 5. Localization ANN scheme.](image)

Many theoretical experiments proved that for ATP defined by eq. 1, it is needed to configure sensors and select the training data so as to avoid learning with signal source locations having nearly the same distances to all sensors. The problem is well illustrated by the configuration 3 in Fig. 4. Nevertheless, it can be solved by another definition of ATP, where the mean of absolute values of centered arrival times in denominator is substituted by normalization period $T$ representing the time interval, which AE signal needs to propagate between two appropriately selected points. However, compared to original definition, such method demands additional measurement of normalization period on real structure, which can be a source of additional experimental errors.

Regarding the comparison of the new ATP-based algorithm with the ANN approach exploiting the time differences, both methods give similar results in accordance with the network learning speed, input sensitivity and final mean-square error (MSE) of network outputs. Possible little variances of outputs are caused rather by different versions of trained networks, than by arrival time parameterization method. However, the parametric space of time profiles provides many advantages. Beyond the mentioned portability to another scale and material, it is more robust with regard to input errors. Due to the subtraction of arrival time mean value, the error of particular signal edge determination is consequently spread out to all inputs.

It is well known that 2-D location of AE sources by triangulation algorithm using three transducers is ambiguous [5]. In Fig. 6 the two triangle configurations (rectangular and equiangular) of transducers are drawn. Areas of ambiguity are marked out for both configurations. Any AE source in dark grey area has the same time-differences corresponding to source in light grey area and vice versa. The problem is usually solved by exploitation of four transducers, while two different triplets of transducers are used in triangulation algorithm. However, theoretically it is still
not a correct solution, because the area of ambiguity is only reduced to insular points. Nevertheless, the probability of such AE source location is close to zero in the real world.

Fig. 6. Ambiguity of 2-D AE source location using 3 AE transducers.

Now, if we take into account the theoretical ambiguity "behind the three sensors" in Fig. 6, it is possible to interpret the erroneous accumulation of crosslets in analogous problematic areas in Fig. 4. As in the case of time differences, if one arrival time profile corresponds to different AE source locations, neural network cannot interpret such relation, since it is possible only for functional dependencies. However, the problem can be solved using more dimensional time profiles, i.e., by additional suitably placed sensors. The higher errors in some subsets of training area (e.g. near the sensors) are caused by closeness of points in time profiles parametric space.

**Practical Results**

To demonstrate the new AE source location method in practice, an experiment on a small aircraft part has been performed. The task was to localize AE sources on a steering actuator bracket (SAB), which is a part of the aircraft nose landing gear. AE signals were monitored and recorded by DAKEL XEDO AE system. For signal onset assessment, an "expert edge detection" algorithm of the elastic wave arrival was applied [6]. Although the method is relatively precise, its accuracy is much lower than the approximation error of neural network, especially for longer distances from AE source to sensor. Therefore, the two training areas of ANN were considered (left and right part of critical zone of SAB) instead of the “global” one.

The scheme in Fig. 7 shows the configuration of four transducers in case of the left training zone. The learning points were selected to equidistantly cover the zone among the sensors $S_2$, $S_3$, $S_4$ and $S_5$. To compute the arrival time profiles, eq. 3 was applied using the distances evaluated by the algorithm finding the shortest ways in raster (digital) picture of the structure. The length of the real elastic wave path through the material is approximated by the shortest polygonal line, while the connecting line segments between the nodes must come through the pixels representing the body. The third dimension of the structure could be neglected because of the small thickness of SAB.

Similarly to numerical testing of the method, neural network with two hidden layers having 39 and 17 neurons was trained by virtual AE sources corresponding to points equidistantly spaced 5 pixels between each other (see Fig. 7), covering the whole training area. Distances of
all such virtual AE sources to four sensors considered were computed, and eq. 3 was applied. During the learning process, weights and biases of the network were iteratively adjusted by fast resilient back-propagation training algorithm and generalization-improving regularization to achieve sufficiently low MSE (less than 0.001). For illustration of approximation error, all training points were projected by neural network back onto the SAB (see Fig. 8).

Fig. 7. Configuration of AE sensors and training points for ANN.

Fig. 8. ANN projection of training points.
Trained neural networks were finally tested with real experimental data. Three sets of 25 AE signals recorded during pencil-lead break (PLB) tests were obtained. The original locations of PLB tests correspond to cross points of the dashed lines in Fig. 9. The arrival times of each group of 25 signals were determined by expert edge detection algorithm and eq. 2 was used to compute the arrival time profiles as ANN inputs. The outputs of the network were coordinates of estimated PLB test locations illustrated as crosslets in Fig. 9.

![Fig. 9. ANN PLB tests localization results.](image)

While analyzing the localization results, the inaccuracies of experimental measurement must be considered. These are mostly caused by the signal onset determination errors. Due to dispersion and reflections, the shape of signal envelope undergoes substantial changes with distance between the source and sensor. Hence, it is possible to expect higher signal edge detection error due to signal dissimilarity for sources near single sensor and simultaneously far from other transducers. Such situation is evident in PLB test location #3 (see Fig. 9), where the localization error is worse than in wider structure areas. For location #3, the PLB tests were done not too close to sensors. Next undesirable effect is that the centers of crosslet groups are not placed at original PLB test locations. This can be interpreted by different magnitude of the signal edge detection error in each of four channels, which can result in the shift of arrival time profiles. However, the results for locations #1 and #2 can be rated as very good, since the error is comparable with the aperture of sensors (9 mm) and better results are not expected. We can say that the majority of location errors is caused by experimental measurement inaccuracies, not by the low arrival time profile robustness, or neural network approximation variance.

After testing of complex methodology for AE sources with known localization, let us introduce the results measured during the laboratory fatigue tests of SAB. The bracket was loaded under stress cycles (R = 0, frequency 1 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.
detected AE signals were stored, and after certain loading periods, the detailed AE source location analysis was performed so as to detect crack initiation. Most AE events arose around the mounting holes of the bracket. Figure 10 shows the typical localization results of sources in the left part of SAB. Most of the AE sources originated from the clearly visible damages on the interior surface of the hole caused by the friction with mounting shank (shown in insert of Fig. 10).

Fig. 10. Results of real AE source localization. Insert shows damages inside the hole, producing most of AE.

Conclusions

A new approach to the AE source location is introduced in this paper. Described algorithm is based on neural networks exploiting newly defined signal arrival time profiles (ATP) as inputs. This innovative way of AE signal arrival time relativism facilitates considerable extension of ANN applications in practice. Processing of the real experimental data measured on a small aircraft part confirmed advantages of such approach. Main aspects of the method can be summarized as follow:

• The new method is inspired by the preliminary expert analysis of AE source location exploiting the signal detection chronology. To utilize such information more precisely, so-called arrival time profiles are introduced.

• Arrival time profiles enable numerical generation of sufficient ANN training data sets with optimal precision and no measurement errors. Afterwards, trained networks can be successfully tested on data coming from real experiment.

• Arrival time profiles are independent on elastic wave velocity and structure scale changes. Hence, the trained neural networks are applicable to all proportionally identical structures of any isotropic material.
• Theoretical experiments showed that it is needed to configure sensors and select the training data so as to avoid learning with signal source locations having nearly the same distances to all sensors.
• The time profiles parametric space is featured by robustness regarding the input errors. The subtraction of arrival time mean distributes one particular signal edge determination error to all inputs, which reduces the global input error.
• The new AE source location approach based on neural network with arrival time profiles was demonstrated by experiments on a small aircraft part of complicated shape.
• Resulting real localization error is influenced mostly by experimental measurement inaccuracies, i.e. it is not caused by neural network approximation variance.
• It has been proved that the arrival time profiles enable portability, robustness and easy applicability of ANN-based algorithm for AE source location.

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