Intelligent location of simultaneously active acoustic emission sources: Part I

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***Abstract*— The intelligent acoustic emission locator is described in Part I, while Part II discusses blind source separation, time delay estimation and location of two simultaneously active continuous acoustic emission sources.**

The location of acoustic emission on complicated aircraft frame structures is a difficult problem of non-destructive testing. This article describes an intelligent acoustic emission source locator. The intelligent locator comprises a sensor antenna and a general regression neural network, which solves the location problem based on learning from examples. Locator performance was tested on different test specimens. Tests have shown that the accuracy of location depends on sound velocity and attenuation in the specimen, the dimensions of the tested area, and the properties of stored data. The location accuracy achieved by the intelligent locator is comparable to that obtained by the conventional triangulation method, while the applicability of the intelligent locator is more general since analysis of sonic ray paths is avoided. This is a promising method for non-destructive testing of aircraft frame structures by the acoustic emission method.

INTRODUCTION

Acoustic emission (AE) concerns non-destructive testing methods and is used to locate and characterize developing cracks and defects in material. In non-destructive testing of aviation frame structures, acoustic emission is a well accepted method [8]. The location problem is usually solved by various triangulation techniques based on the analysis of ultrasonic ray trajectories [10], [1], [3]. Solving and programming the related equation is rather cumbersome and cannot be simply performed if the structure of the tested specimen is geometrically complicated. Acoustic emission testing of aircraft structures is a challenging and difficult problem. The structures involve bolts, fasteners and plates, all of which move relative to one another due to differential structural loading during flight. The complex geometry of the airframe results in multiple mode conversions of AE source signals, compounding the difficulty of relating the source event to the detected signal.

In order to avoid difficulties with equation solving and programming of the triangulation procedure, several empirical approaches based on learning from examples have already been proposed [5]. We developed an intelligent locator capable of learning from examples which we therefore called an intelligent locator. The purpose of developing the intelligent locator is to replace information obtained from the analysis of sonic ray trajectories by information obtained directly from simulated AE events on the specimen under test. In this way, the calibration procedure, which has to be performed anyway, could be generalized to the training of the intelligent locator.

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The development of such an intelligent locator has been described elsewhere [4]. In the locator developed a general regression neural network (GRNN) is employed [9], which acquires data about the detected AE signals and parameters of their sources during learning. The GRNN uses these data in testing when estimating the unknown source position from detected AE signals. For this purpose, associative GRNN operation is utilized. The basis of such operation is statistical estimation determined by the conditional average [6]. Consequently, the accuracy of the intelligent locator also depends on the learning procedure, and must be examined before testing.

This article describes the results obtained by testing the intelligent locator on experimental continuous AE sources. The purpose of this study was to test and examine the advantages of the intelligent locator compared to a conventional locator. as described in Part I. In Part II an experiment will be explained in which an intelligent locator was used to locate two simultaneously active continuous AE sources generated by leakage air flow. Location of more than one source at the same time on the test specimen is a new approach in acoustic emission testing, and is a very promising method for aircraft and airspace structural testing.

When preparing the experiments, we focused on locating evolving defects in stressed materials and constructions, and leakage of vessels. We therefore performed location experiments on four different specimens with three different AE sources. The specimens comprised bands, plates, rings, and vessels, while the AE sources were simulated by rupture of a pencil lead (pen test), material deformation during tensile test, and leakage air flow through a small hole in a sample. The positions of AE sources used in testing were well specified. Actual positions were compared with estimated ones, and the discrepancy was used to describe the inaccuracy of the locator. In this article, only the experiment with leakage air flow through a small hole in a sample is explained. In Part I, location of one continuous AE source is explained. This Part is intended for better understanding of Part II and comparison of results. In Part II, a new approach to the location of two simultaneously active continuous AE sources is explained.

Below, the article first explains the theoretical background for application of the conditional average to the location problem, then describes auxiliary AE signal processing, and finally demonstrates performance of the experimental intelligent locator.

THEORETICAL BACKGROUND

In this section we describe a non-parametric approach to empirical modeling of AE phenomena and solving the location problem. This modeling stems from a description of physical laws in terms of probability distributions. Since it has been explained in detail elsewhere, we present here just its basic concepts [6], [5].

The object of empirical modeling is the relationship between variables which are simultaneously measured by a set of sensors. In our example the variables are source coordinates and AE signal characteristics. Let them be represented by a vector of M components: $\boldsymbol{x} = (\xi_1, \ldots, \xi_M)$. In the empirical description of an AE phenomenon we repeat the observation N times to create a database of prototype vectors $\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$. Instead of formulating a relation between the components of $\boldsymbol{x}$ we instead treat this vector as a random variable and express the joint probability density function f by the estimator

$$f(\boldsymbol{x}) = \frac{1}{N} \sum_{n=1}^{N} \delta(\boldsymbol{x} - \boldsymbol{x}_n) \,. \tag{1}$$

Here δ denotes Dirac's delta function. For the purposes of modelling, we must also estimate the probability density in the space between the prototype points. This is achieved by expressing the singular delta function in Eqs. 1 by a smooth function, such as for example the Gaussian

$$w_n(\boldsymbol{x} - \boldsymbol{x}_n, \sigma) = \exp\left[\frac{-\|\boldsymbol{x} - \boldsymbol{x}_n\|^2}{2\,\sigma^2}\right], \qquad n = 1, \ldots, N \,. \tag{2}$$

in which σ denotes the smoothing parameter.

The data vectors determine an empirical model of the probability density function. Their acquisition corresponds to the learning phase of the empirical modeling. Let us further assume that observation of AE phenomenon provides only partial information that is *given* by a truncated vector

$$\boldsymbol{g} = (\xi_1, \ldots, \xi_S; \emptyset) \,, \tag{3}$$

in which $\emptyset$ denotes missing components. The problem is to estimate the complementary vector of missing or *hidden* components:

$$\boldsymbol{h} = (\emptyset; \xi_{S+1}, \ldots, \xi_M); \tag{4}$$

such that the complete data vector is determined by concatenation

$$\boldsymbol{x} = \boldsymbol{g} \oplus \boldsymbol{h} = (\xi_1, \ldots, \xi_S, \xi_{S+1}, \ldots, \xi_M) \,. \tag{5}$$

A statistically optimal solution to this problem is determined by the conditional average estimator, which is expressed by a superposition of terms [6]

$$\hat{\boldsymbol{h}} = \sum_{n=1}^{N} B_n(\boldsymbol{g})\, \boldsymbol{h}_n, \quad \text{where} \tag{6}$$

$$B_n(\boldsymbol{g}) = \frac{w(\boldsymbol{g} - \boldsymbol{g}_n, \sigma)}{\sum_{k=1}^{N} w(\boldsymbol{g} - \boldsymbol{g}_k, \sigma)} \,. \tag{7}$$

The basis functions $B_n(\boldsymbol{g})$ represent a measure of similarity between the truncated vector $\boldsymbol{g}$ given by a particular observation and truncated vectors from the database $\boldsymbol{g}_n$. The higher the value of $B_n(g)$ the higher the contribution of $\boldsymbol{h}_n$ to the sum 7 estimating $\hat{\boldsymbol{h}}$. Hence, estimation of the hidden vector $\hat{\boldsymbol{h}}$ resembles associative recall, which is characteristic of intelligence. The conditional average represents a general non-parametric regression [6].

During the learning phase of operation an intelligent locator of AE sources accepts AE signals and source coordinates and stores prototype data vectors, while during application it accepts only AE signals and estimates the corresponding source position. Each of these phases can be performed in a separate unit which can be interpreted as a layer of a sensory-neural network.

In order to ensure acceptable properties of the locator, the smoothing parameter σ must be properly chosen[2]. The purpose of δ function smoothing is to estimate the probability density function between the prototype data points. A unique method for optimal specification of the smoothing parameter is as yet unknown. In this case, it is numerically simpler to specify σ by the half distance to the closest neighbor point:

$$\sigma_n = 0.5 \min_i \|\boldsymbol{g}_i - \boldsymbol{g}_n\| \,, \qquad \text{for all } i \neq n \,. \tag{8}$$

Signal pre-processing

The intelligent locator comprised a sensor antenna, signal pre-processing unit and source locating unit, as shown in Fig. 1. The first unit calculates the time delay Δt from AE signals $y_1(t)$ and $y_2(t)$, while the second unit estimates the source position $\hat{z}$ from the time delay Δt. AE signals $y_1(t)$ and $y_2(t)$ are detected by sensors and filtered using a Butterworth bandpass filter. Without the bandpass filter, time delays cannot be easily mapped to source positions on the sample band, and therefore the applicability of this method depends on the proper choice of bandpass filter function $H(f)$. We found on dispersive specimens that information in the continuous AE signal about source position is located in a narrow frequency band. A wave packet with approximately constant wave velocity along the specimen must be extracted by this filter. The filter function $H(f)$ is determined during training procedure of the locator.

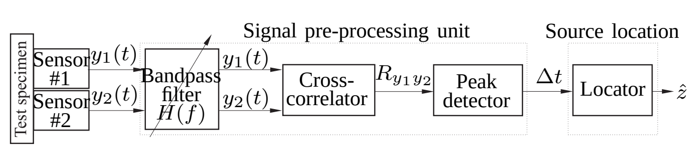

Fig. 1. AE signal processing by the intelligent locator

Two conventional methods for time delay estimation between two signals are known: threshold function and cross-correlation function. Estimation of time delay by the threshold function is simple, but only applicable in the case of discrete AE. More general, but also more demanding, is time delay estimation from the cross-correlation function of AE signals [11]. The cross-correlation function:

$$R_{y_1 y_2}(\tau) = \sum_{t=1}^{T} y_1(t)\, y_2(t+\tau)\,, \tag{9}$$

generally exhibits a peak when parameter τ corresponds to the time delay Δt between signals $y_1(t)$ and $y_2(t)$. The time delay is thus determined from the position of the peak of the cross-correlation function. One advantage of the application of the cross-correlation function is that it does not depend on the discrete or continuous character of AE signals. This method for time delay estimation is only applicable when one AE source is active at the time of detection. In the event of two or more simultaneously active continuous AE sources, a different approach should be used which will be discussed in the Part II.

A filter function is calculated during calibration of the intelligent locator as follows. During calibration, a set of prototype sources is generated on the test specimen by a pen test at a prepared coordinate net[8]. This net in most cases has linear sections, where the prototype sources are positioned on a straight line. In this case, we know that time delays between signals are also linearly dependent. If we have a test specimen with a complicated geometrical structure, then a pre-calibration process has to be performed in which we have to choose a geometrically simple part of the specimen and carry out a pre-calibration procedure on this part such that time delays between signals are linearly dependent.

For calibration we used AE signals generated by a pen test. We obtained 12 pairs of AE signals from two sensors concatenated with known coordinates of sources. The positions of simulated sources were uniformly distributed along a straight line on a specimen. In such cases, time delay Δt is linearly related to source position z. This is of advantage for optimal determination of bandpass filter because the reference is a straight line. Calculation of time delays on the same set of prototype AE signals was repeated 70 times. The bandpass filter of $\Delta f = 10$ kHz was shifted by 1 kHz at each repetition from 5 to 75 kHz. Time delays were calculated at each repetition and the distribution obtained was compared with a straight line, as shown in Fig. 2. The frequency bandwidth was considered optimal when the root mean square error (RMSE) was minimal, as shown in Fig. 3(a). The optimal frequency band for this specimen was 35-45 kHz and the velocity of elastic waves was $1.7\,\mathrm{km\,s^{-1}}$. The filter was further used for pre-processing samples of prototype as well as test sources. As shown in Fig. 3(b), the pairs $(z, \Delta t)$, estimated from filtered signals, fit a straight line, except one outlier, which results from experimental error.

Experiment

The intelligent AE source locator is shown schematically in Fig. 4. It includes an automatic data-acquisition system controlled by computer and a network of AE sensors.

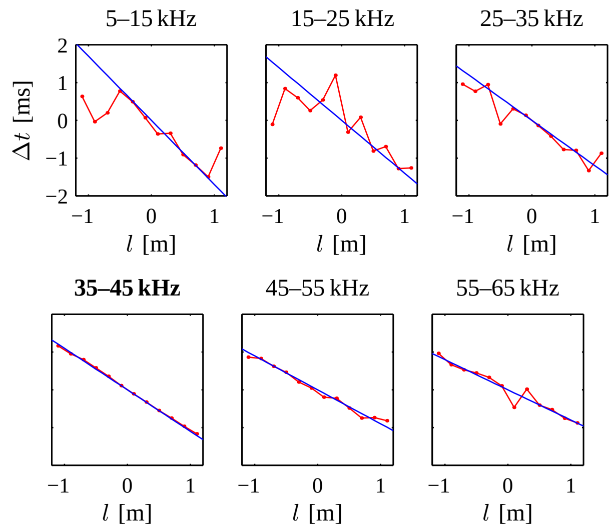

Fig. 2. Distribution of time delays and their linear approximation along the band specimen. By this procedure an optimal bandpass filter can be determined.

The AE sensors are piezoelectric transducers (pinducers). The diameter of the transducer active area is 1.3 mm, And so it can be considered a point-like sensor. The signals from sensors are fed to a digital oscilloscope where they are digitized and transferred to a PC. Operation of the intelligent locator is determined by software in the PC that controls data acquisition and estimates the position of unknown AE sources.

The locator operates in two different modes:

1) In learning or calibration mode, a set of N pen tests is performed in which complete information about the AE phenomenon is acquired. The operator must prepare an orientation net the shape of which depends on the shape of the test specimen. The recommended shape is an equidistant net, since such position of prototype sources yield a minimum error of the locator. ¿From source coordinates and time delays between pre-processed AE signals, the prototype vectors are created and stored in the memory of the neural network as a data base.
2) In application mode, only time delays between AE signals are provided. There are then associated in the neural network with the estimated source coordinates.

In the case of discrete AE, the time delay can visually be estimated from a marked jump in the burst of the AE signal, or can be instrumentally determined using a threshold function. Hence, in the case of continuous AE, time delays cannot be simply estimated, although a cross-correlation function has already been used for this purpose. In our approach, we therefore applied a cross-correlation function. The purpose of this experiment was to determine the accuracy of location of continuous AE sources on a one-dimensional specimen.

Two experiments on aluminum band specimen are explained in this article. We tested the locator on an aluminum band specimen of dimensions $4000 \times 40 \times 5\,\mathrm{mm}^3$. Reflection of AE signals at the ends of the band specimen was reduced by sharpening the ends. For testing we selected a test area

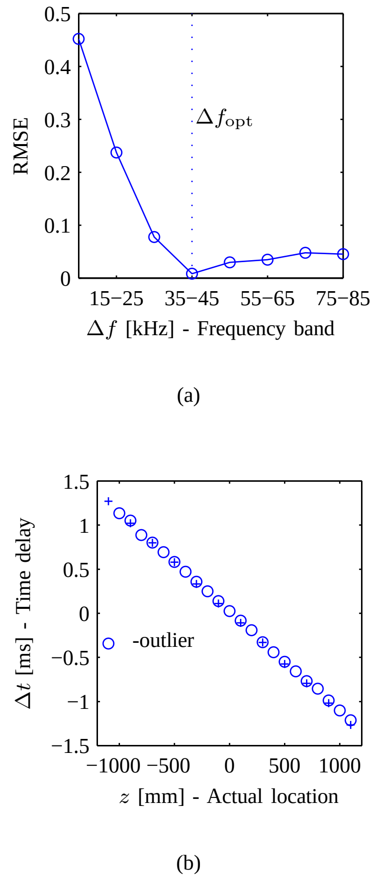

Fig. 3. Time delays for prototype and test sources by using the bandpass filter of frequency 35-45 kHz. **a)** Deviation of prototype source position from a straight line for different filter frequency bandwidth. **b)** Time delays of prototype and test sources; Legend: + prototype source, ○ test source

in the middle of the band specimen where 23 holes were prepared. The distance between holes was 100 mm and the diameter of holes was 2 mm. Two AE sensors were mounted 100 mm away from the terminal holes. For the purpose of locator training, we generated 12 prototype sources separated by 200 mm, while all 23 holes were applied for locator testing. In this experiment, we calibrate the locator by pen test and examine it by continuous AE generated by air flow. The air flow was produced by expansion of compressed air through nozzle of 1 mm diameter. The nozzle was mounted 1 mm above the band specimen surface.

Two experiments were performed. In the first experiment, only one continuous AE source was active on the band specimen, while in the second experiment two continuous AE sources were active simultaneously on the band specimen. Successive simultaneous location of two sources is explained in Part II.

Signals were processed as shown in Fig. 1. The first step in processing was calculation of cross-correlation function of AE signals. The corresponding signal was sent through a bandpass Butterworth filter of bandpass from 35 to 45 kHz. Determination of this filter is explained earlier in this article.

Results

The results of locator testing are shown in Fig. 5(a). The absolute location error for each test source is shown in Fig. 5(b). Location error in the experiment ranges from 1.3 mm to 60 mm with average value $\varepsilon_a = 20$ mm (ignoring the outlier). If we describe the error with respect to the distance between sensors (2.4 m), the relative value is less than 1%. Increasing the number of prototype sources can reduce the error. Despite the complexity of continuous AE signals, the location problem was solved satisfactorily with respect to The accuracy required in non-destructive testing. Results also show that a standard calibration procedure with discrete AE signals generated by pen test can be used for locator training.

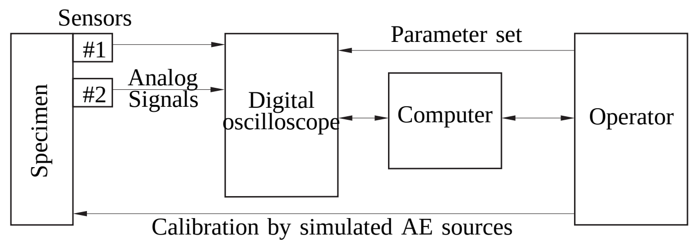

Fig. 4. Experimental setup of intelligent locator

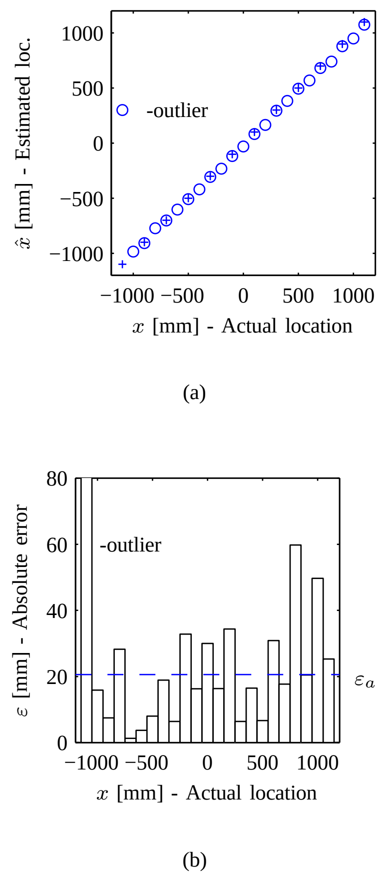

Fig. 5. Result of continuous AE source location on the band. **a)** Estimated versus actual location of test sources; Legend: + prototype source, ○ test source. **b)** Absolute location error; ε_a - average error.

Discussion and Conclusion

Estimation of source coordinates by the conditional average is subject to systematic error caused by smoothing of the delta function [5]. This error can be reduced by increasing the number of prototype sources. Since it is not always possible to increase the number of prototype sources due to the complexity of experiments, a compromise must be found by trial and error.

Experimental error is acceptable, so we decided to make additional tests, as will be discussed in Part II.

This study shows that a conventional AE locator operating on the triangulation method can be successfully replaced by an intelligent locator that learns from examples. The results show that the intelligent locator can locate sources with acceptable accuracy in cases of: (1) discrete AE on band and plate, (2) continuous AE on band, (3) discrete AE on plate with hole (ring), (4) discrete AE generated by specimen rupture during the tensile test, and (5) discrete AE on pressure vessel. Is has been also shown that the locator can perform zonal locating[7].

Comparing mean errors of all experiments and the distances between prototype sources, we find that the average error is always less than 30% of the distance between prototype sources, while the maximal error is always less than 50% of the distance between prototype sources. The accuracy of the locator can be controlled by the number of prototype sources excited during training. The experimental error of the locator is a consequence of wave dispersion on a specimen that operates as a waveguide, reflections from boundaries, and attenuation. We found for dispersive waves that an optimal wave packet must be found which has approximately constant velocity along the test specimen. Estimation of time delay between AE signals by the cross-correlation function is only applicable for one active AE source. If there are several simultaneously active AE sources, then blind source separation should be used, as will be shown in Part II.

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