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Intelligent location of two simultaneously active acoustic emission sources

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Abstract

Acoustic emission (AE) analysis is used for characterization and location of developing defects in materials. The location of AE on complicated aircraft frame structures is a difficult problem of non-destructive testing. This article describes an intelligent AE source locator which comprises a sensor antenna and a general regression neural network, which solves the location problem based on learning from examples. 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. AE sources often generate a mixture of various statistically independent signals. A difficult problem of AE analysis is separation and characterization of signal components when the signals from various sources and the mode of mixing are unknown. Recently, blind source separation (BSS) by independent component analysis (ICA) has been used to solve these problems. The purpose of this paper is to demonstrate the applicability of ICA to separate and locate two independent simultaneously active AE sources on an aluminum band specimen. The method is promising for non-destructive testing of aircraft frame structures by acoustic emission analysis.

Keywords: Defects; Non-destructive testing; Acoustic emission; Source location; Blind source separation

1. Introduction

Acoustic emission (AE) concerns non-destructive testing methods and is used to locate and characterize developing cracks and defects in material. The corresponding problems may be classified by the type of acoustic source mechanism as the location of a continuous emission source, such as that generated by a leak, or as the location of discrete emission, such as an AE burst caused by a growing crack. This paper describes a method for processing continuous AE signals to determine the time delay (T-D) between signals and thus to provide information for location of AE sources.

In non-destructive testing of aviation frame structures, acoustic emission is a well accepted method [18]. The location problem is usually solved by various triangulation techniques based on the analysis of ultrasonic ray trajectories [4,7,20]. Locator based on this method is called conventional locator. 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 [10]. We developed a locator capable of learning from examples which we therefore called an intelligent locator. The purpose of developing the intelligent

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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.

The development of such an intelligent locator has been described elsewhere [9]. In the locator developed a general regression neural network (GRNN) is employed [19], 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 [11]. 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 Sections 2 and 3. In Section 4 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 by using blind source separation. This is the improvement of the intelligent locator. 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 pressure vessels. We therefore performed location experiments on four different specimens with three different AE sources. The specimens comprised bands, plates, rings, and pressure vessels, while the AE sources were simulated by rupture of a pencil lead (pen test), material deformation during tensile test, and leakage air ow 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, because this is the most interesting one and represents a contribution to AE research field. This test with leakage air flow is divided into two separate experiments – experiment 1 and experiment 2. In Section 2, location of one continuous AE source is explained. This Section is intended for better understanding of Section 3 and comparison of results. In Section 3, a new approach to the location of two simultaneously active continuous AE sources by using blind source separation is explained. In both sections we are using the intelligent locator for source location, while in Section 2 a cross-correlation function (CCF) is used for source evaluation, and in Section 3 a blind source separation method is used for source evaluation.

2. Location of one active source using intelligent locator

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

2.1. Theoretical background of intelligent locator

In this section we describe a non-parametric approach to empirical modelling of AE phenomena and solving the location problem. This modelling 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 [10,11].

The object of empirical modelling 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 (time delays), which are obtained from sensory signals $\boldsymbol{y}(t)$. Let them be represented by a vector of M components: $\boldsymbol{x} = (\xi_1, \dots, \xi_M)$. In the empirical description of an AE phenomenon we repeat the observation N times to create a database of prototype vectors $\{\boldsymbol{x}_1, \dots, \boldsymbol{x}_N\}$. 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 Eq. (1) by a smooth function, such as for example the Gaussian

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

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 modelling. Let us further assume that observation of AE phenomenon provides only partial information that is *given* by a truncated vector

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

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

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