Intelligent location of two simultaneously active acoustic emission sources: Part II

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***Abstract*— Part I describes an intelligent acoustic emission locator, while Part II discusses blind source separation, time delay estimation and location of two continuous acoustic emission sources.**

Acoustic emission (AE) analysis is used for characterization and location of developing defects in materials. 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 locate two independent simultaneously active acoustic emission sources on an aluminum band specimen. The method is promising for non-destructive testing of aircraft frame structures by acoustic emission analysis.

Introduction

A common goal of many non-destructive testing methods is to detect defects in materials. Acoustic emission analysis (AE) is a passive testing method used to locate and characterize defects which emit sound[10].

There are many ways to deduce the location of an AE source from electrical signals detected by a chain of sensors. 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. It should be pointed out that application of AE source characteristics, such as count, count rate, amplitude distribution, and conventional time delay measurement, becomes meaningless when dealing with continuous acoustic sources.

The basic information for AE source location consists of T-D between stress waves detected at different positions on a specimen. In the case of only one active AE source, T-D of continuous acoustic waves can be estimated using the cross-correlation function (CCF) of sensor signals described in Part I of this article[10], [7]. In the case of two (or more) simultaneously active AE sources, this method is not applicable, since analysis of the CCF leads only to the T-D of the most powerful AE signal. Detection of simultaneously active independent AE source signals therefore requires a more sophisticated approach.

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The purpose of our study was to find a suitable method for processing a mixture of two simultaneously active continuous AE signals to determine the T-D and, related to this, the coordinates of both AE sources. We found that the Blind Source Separation (BSS) method solves this problem satisfactorily. BSS is a general signal processing method involving the recovery of the contributions of different sources from a finite set of observations recorded by sensors, independent of the propagation medium and without any prior knowledge of the sources. BSS has already been successfully applied in medicine, telecommunications, image processing etc[8]. However, it is also a promising method for AE analysis of aircraft structures, because AE signals are often hidden in a mixture of signals from various sources. BSS could extract the specific signature of each AE source, which can further be used for location and characterization purposes, or to isolate AE sources from background noise. We conducted experiments with BSS on an aluminum beam on which two continuous AE sources were generated simultaneously by air flow.

Methods

In this section we explain two different methods for time delay estimation of AE sources. The first method is based on analysis of the CCF and is convenient for T-D estimation of one active continuous AE source as is described in Part I[10], [7], [12]. The CCF exhibits a peak when the delay parameter compensates the T-D between the sensor signals [10]. The T-D is thus determined by the position of the highest peak of the CCF. The second method is based on BSS algorithm and is convenient for T-D estimation of two (or more) simultaneously active continuous AE sources[9]. Location of two simultaneously active AE sources was performed by an intelligent locator based on a general regression neural network[5] as is described in Part I.

Multichannel Blind Source Separation has recently received increased attention due to the importance of its potential applications[3]. It occurs in many fields of engineering and applied sciences, including processing of signals from antenna array, speech and geophysical data processing, noise reduction, biological system analysis, etc. It consists of recovering signals emitted by unknown sources and mixed by an unknown medium (material where waves propagate), using only several observations of the mixtures. The only assumptions made are the linearity of the mixing system and the statistical independence of original signals.

BSS methods may be classified in several ways. One possible classification that can be made depends on whether the mixtures are instantaneous or convolutive [4]. Convolutive mixtures correspond to a mixing system with time dependent memory. They represent a more general case than instantaneous mixtures, and they have in particular acoustic applications. Recently, the principle of independent component analysis (ICA) was applied in BSS, and it was found to be a simple and powerful tool[6]. This study deals with the separation of two convolutively mixed independent continuous AE signals by ICA and the intelligent locator was used to locate two independent continuous AE sources based on T-D [5].

The mixing and filtering processes of unknown input signals $s_j(t)$ may have different mathematical or physical backgrounds, depending on specific applications. In this paper, we focus mainly on the simplest cases with n signals $x_i(t)$ linearly mixed in n unknown statistically independent, zero mean source signals $s_j(t)$. The composition is expressed in matrix notation as $\boldsymbol{x} = \boldsymbol{A} * \boldsymbol{s}$ [8], where '*' denotes a convolution, $\boldsymbol{x} = [x_1(t), \ldots, x_n(t)]^{\mathrm{T}}$ is the vector of sensor signals, $\boldsymbol{s} = [s_1(t), \ldots, s_n(t)]^{\mathrm{T}}$ is the vector of source signals and $\boldsymbol{A}$ is an unknown full rank $n \times n$ mixing matrix whose elements are finite inpulse response (FIR) filters. We assume that only vector $\boldsymbol{x}$ is available. The goal of ICA is to find a matrix $\boldsymbol{W}$, by which vector $\boldsymbol{x}$ can be transformed into source signals $\boldsymbol{u} = \boldsymbol{W} * \boldsymbol{x}$.

Matrix $\boldsymbol{W}$ is simply the inverse of $\boldsymbol{A}$. However, when noise corrupts the signals, matrix $\boldsymbol{W}$ must be found by an optimal statistical treatment of the inverse problem. The optimal matrix $\boldsymbol{W}$ can be estimated by a feed-forward neural network operating in the frequency domain. A learning algorithm with Amari's natural gradient can be written as[1]: $\tilde{\boldsymbol{u}} = \tilde{\boldsymbol{W}} \cdot \tilde{\boldsymbol{x}}$, $\tilde{\boldsymbol{W}}(\tau+1) = \tilde{\boldsymbol{W}}(\tau) + \alpha\, \Delta\tilde{\boldsymbol{W}}(\tau) + \eta\, \Delta\tilde{\boldsymbol{W}}(\tau-1)$, $\Delta\tilde{\boldsymbol{W}} = [\boldsymbol{I} - \tilde{\boldsymbol{y}} \cdot \tilde{\boldsymbol{u}}^{\mathrm{H}}]\, \tilde{\boldsymbol{W}}$, $\tilde{\boldsymbol{y}} = \tanh(\Re[\tilde{\boldsymbol{u}}]) + \imath \tanh(\Im[\tilde{\boldsymbol{u}}])$, where α is the learning rate, η is the constant of learning, $\boldsymbol{I}$ is the identity matrix and the tilde '~'represents a frequency domain.

The ICA algorithm runs off-line and proceeds as follows [11] (Fig. 1):

1) Pre-process the time-domain input signals, $\boldsymbol{x}(t)$: substract the mean from each signal.
2) Initialize the frequency domain unmixing filters, $\tilde{\boldsymbol{W}}$.
3) Take a block of input data and convert it into the frequency domain using the Fast Fourier Transform (FFT).
4) Filter the frequency domain input block, $\tilde{\boldsymbol{x}}$, through $\tilde{\boldsymbol{W}}$ to get the estimated source signals, $\tilde{\boldsymbol{u}}$.
5) Pass $\tilde{\boldsymbol{u}}$ through the frequency domain nonlinearity, $\tilde{\boldsymbol{y}}$.
6) Use $\tilde{\boldsymbol{W}}$, $\tilde{\boldsymbol{u}}$ and $\tilde{\boldsymbol{y}}$ along with the natural gradient extension [2] to compute the change in the unmixing filter, $\Delta\tilde{\boldsymbol{W}}$.
7) Take the next block of input data, covert it into the frequency domain, and proceed from step 4. Repeat this process until the unmixing filters have converged upon a solution, passing several times through the data.
8) Normalize $\tilde{\boldsymbol{W}}$ and convert it back into the time domain, using the Inverse Fast Fourier Transform (IFFT).
9) Convolve the time domain unmixing filters, $\boldsymbol{W}$, with $\boldsymbol{x}$ to get the estimated sources.

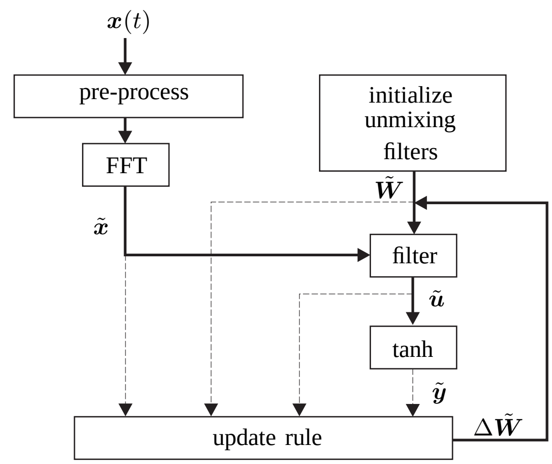


Fig. 1. Block diagram of ICA algorithm

Experiments

We performed experiments with two independent continuous AE sources on an aluminum band of dimensions $4000 \times 40 \times 5\,\mathrm{mm}^3$. Reflections at the end of the band were reduced by wrapping the ends in putty. The testing area was on the longitudinal axis in the middle of the band, where 23 holes of diameter 2 mm and mutual separation 100 mm were prepared as shown in Fig. 2.

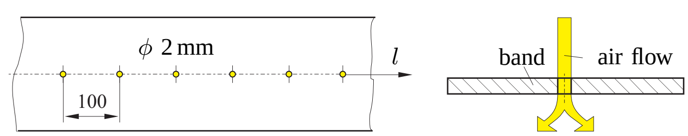


Fig. 2. AE generation by air flowing through the hole

Two AE sensors were mounted 100 mm away from the terminal holes, that is 2.4 m from each other. The origin of the coordinate system was in the middle of the band and the testing area extended from -1.1 m to $+1.1$ m. AE signals were excited by two independent air jets flowing through the holes. The source position was arbitrarily selected at $+100$ mm and $+800$ mm. Air jets were formed by two nozzles of diameter 1 mm using pressure 7 bar. The experimental setup consisted of the test specimen (aluminum band), two AE sensors (pinducers), two AE sources (air jets), two amplifiers, a digital oscilloscope (A/D converter) and a computer (BSS module, locator, plotter) as shown in Fig. 3. Three experiments were performed : (1) T-D estimation using a CCF of two AE signals that were not simultaneously active; (2) T-D estimation using a CCF of two AE signals which were simultaneously active and (3) T-D estimation of AE signals using ICA. Location of sources, based on T-D, by the intelligent locator was performed in all three cases.

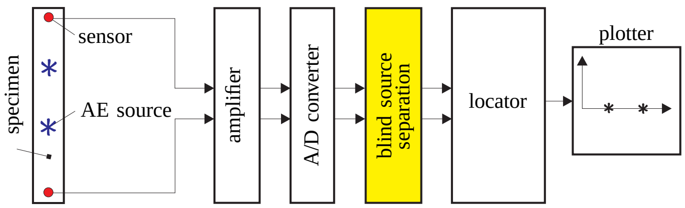
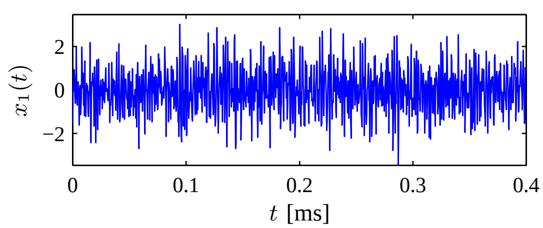
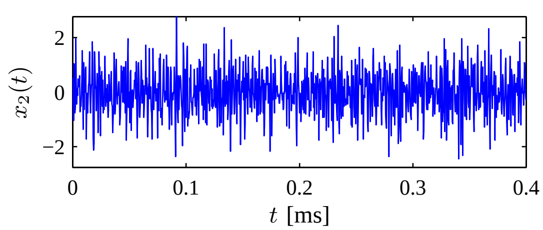


Fig. 3. Experimental set-up

In the first experiment only one air jet was activated for a particular measurement. In the second experiment both air jets were activated. Sensor signals were linear convolutive mixtures of two independent continuous AE sources as shown in Fig. 4. The auto-correlation R_{11}, R_{22} and cross-correlation functions R_{12}, R_{21} were calculated from sensor signals. Only one T-D of two signals can be estimated from the highest peak in both CCF, regardless of the number of independent AE sources on the test specimen as shown in Fig. 5. This means that a CCF can not be used for automatic T-D estimation of multiple AE signals on the test specimen. The CCF exhibits various peaks which belong to various independent AE sources, but it is ussually impossible to relate these peaks to corresponding coordinates of AE sources.



(a) Sensory signal #1



(b) Sensory signal #2

Fig. 4. Mixtures of two independent continuous AE sources aquired by two sensors

In the third experiment the ICA algorithm was used to solve this problem satisfactorily. The ICA algorithm results in demixing FIR filters which extract the independent source signals from sensory signals. By inverting the demixing filters $\boldsymbol{W}$ we obtain mixing filters $\boldsymbol{A}$. In the case of two independent

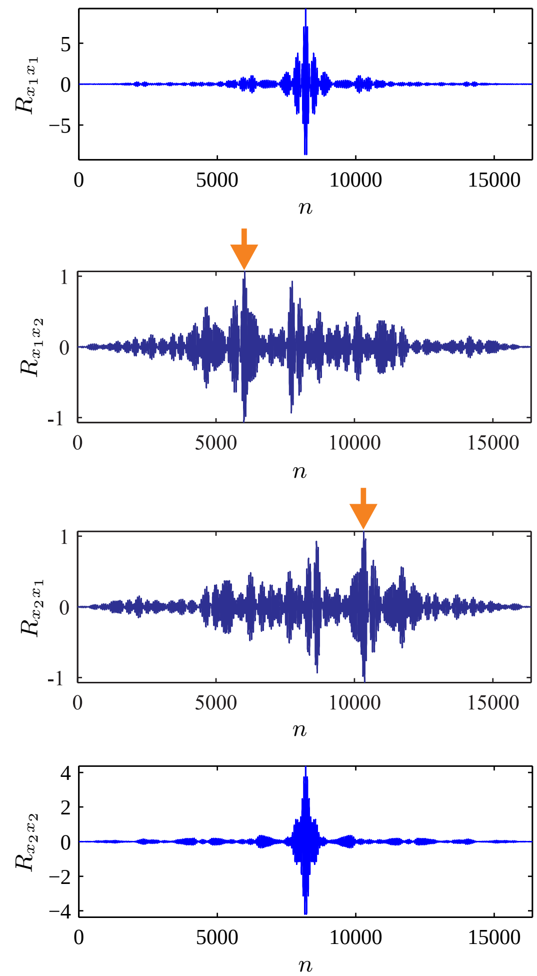


Fig. 5. Auto- and cross-correlation functions of sensory signals; down-arrow marks the highest peak

AE sources and two sensors, the components of $\boldsymbol{A}$ are four FIR mixing filters, as shown in Fig. 6. There are two direct a_{11}, a_{22} and two cross mixing filters a_{12}, a_{21}. The first index of the filter represents the number of the sensor, while the second index represents the number of the source. The position of the highest peak of the cross FIR filters determines the T-D between two signals from two sensors. If we substract the coordinate of the highest peak of a direct mixing FIR filter a_{11} from the coordinate of the highest peak of cross filter a_{21} we obtain the T-D of first independent AE source, since each of the highest peaks in the FIR filters belongs to different independent AE signals.

Results

The results of T-D estimation of two continuous independent AE sources are shown in Fig. 7. Three experiments were done. In the first experiment, the T-D was estimated by a CCF of two AE sources which were not active simultaneously as marked by '○'. Locations of these two sources estimated by the intelligent locator were +181 mm and +784 mm. The second experiment was performed with both AE sources active simultaneously. T-D were also estimated by a CCF. The highest peak

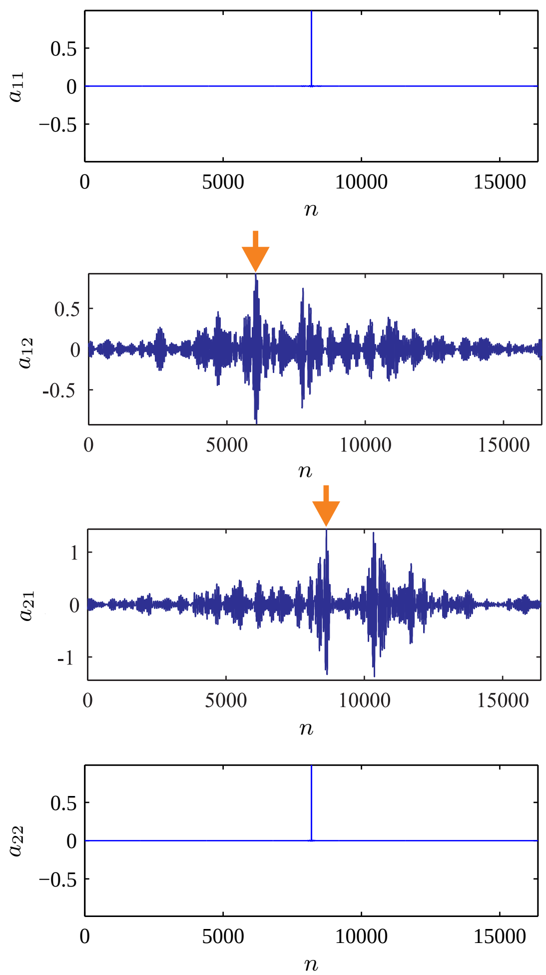


Fig. 6. Mixing filters obtained by ICA of sensory signals; down-arrow marks the highest peak

position corresponds to the source location marked by '– –' and was +784 mm. The third experiment was performed using ICA for T-D estimation and location by intelligent locator. The result is marked by '□'. Estimated positions of this two sources were +179 mm and +784 mm respectively. If we compare the coordinates of both independent AE sources estimated by the first experiment and by the third experiment, we find a good correspondence. If we compare estimated AE source coordinates with actual coordinates, which were +100 mm and +800 mm respectively, we observe a slight disagreement due to experimental error. Experimental error is about 3% regarding the distance between sensors. Absolute error in this case is 79 mm and 16 mm respectively. The results also depend on the number and distribution of prototype sources marked by '•', which are essential for operation of the intelligent locator. If the number of prototype sources is increased, location error is reduced. In our case the prototype sources were distributed along the beam from -1.1 m to $+1.1$ m separated by 0.1 m, so that systematic error of the locator was set to several procents.

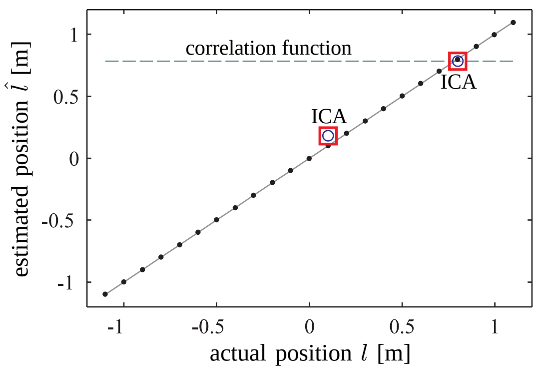


Fig. 7. Results of location of two continuous independent AE sources. Symbols: '□' – AE sources obtained by ICA; '○' – estimated AE sources obtained by cross-correlation function in two steps, when just one of two AE sources was active at time of measurement; '– –' – estimated AE sources obtained by cross-correlation function when two AE sources were active simultaneously; '●' – prototype AE sources required for location using intelligent locator; '–' – distribution of actual sources.

Discussion and Conclusion

CCF is applicable to T-D estimation only in the case of one active AE source. The goal of our research is to develop a new method to estimate T-D between AE signals in the case of multiple simultaneously active continuous AE sources. We have shown that, for this purpose, ICA is an applicable option. ICA finds a linear coordinate system (the unmixing filters) such that the resulting signals are statistically independent. This is an advantage of ICA over CCF. It represents a new approach to processing of AE data and further expands the applicability of AE analysis in the field of non-destructive testing. In machines or in an industrial environment, multiple sources are usually active Simultaneously, often representing environmental disturbances. The corresponding complex signals are not directly applicable to characterization of particular sources. However, separation of contributions by ICA analysis in fact represents a kind of filtering, increasing the applicability of filtered signals to characterization of sources in complex environments. Future research will be focused on location of multiple AE sources on two-dimensional and three-dimensional specimens.

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