A method for Acoustic emission source location and structural damage warning

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Abstract: Locating structural damage is important aspect of structural damage diagnosis. To address the present situation that the acoustic emission (AE) location method has a high requirement for signal fidelity and no warning signal, a miniature measuring device based on acoustic emission (AE) is combined with electroencephalogram (EEG) technology in this work. Firstly, a miniaturised measuring device and a four-node distributed measuring network are constructed. In addition endpoint detection based on wavelet transform and a hardware synchronisation mechanism are used to reduce the traditional requirements of signal fidelity. An EEG experiment was finally used to verify the effects of warning light with different frequencies on the human brain.

1. Introduction
Acoustic emission (AE) is a type of transient elastic wave produced in a material surface or local area that has undergone plastic deformation, crack formation or expansion under the influence of an external or internal force or temperature[1, 2].

At present, most of the structural damage location methods based on AE use the different arrival time method. However there are some unfavourable factors, including reflection, refraction of the AE signal, and waveform transformation occurring at the material interface and the interface between the coupling agent and the sensor [3]. This means that the AE sensor cannot receive the obvious AE signal or might even receive the wrong signal. Therefore, the maximum correlation peak will be weakened or the wrong peak can be easily selected [4].In addition, structural damage localisation methods currently mainly focus on the design of the positioning device and the algorithm, seldom focusing on the construction of the alerting mechanism after localisation.

In view of the above research status, in this work, a miniaturised AE measuring device with a field-programmable gate array (FPGA) as the core and a distributed measuring network with four nodes were designed and constructed. Based on the hardware device, structural damage is located, and visual warning function is completed base on EEG.

2. Device platform
A distributed measuring network with four nodes is designed which have preeminent time synchronisation to ensure precise location of the AE source. In addition, according to the results of the EEG experiment, three kinds of lights with different frequencies are selected as visual warning signals.

The function block diagram of the sensor node is shown in figure 1 (a). The sensor node is shown in figure 1 (b). The measuring network consists of four sensor nodes, which are referred to as nodes A,
B, C and D, as shown in figure 1 (c). The main node A is used to calibrate the time of the remaining sensor nodes in the measuring network. Each sensor node is interconnected through three communication lines called AE_Done, Rst and T_Cb. Time synchronisation between nodes is completed with AE_Done and T_Cb signals. The above technical measures ensure effective time synchronisation between the nodes of the distributed measuring network and the starting time for data collected by each node in the measuring network is consistent.

3. Method

3.1 Endpoint Detection

The AE signals are prone to morphological changes and mode transformation during transmission so the acoustic waves arriving at the AE sensors may be different forms of wave, such as longitudinal, transverse, surface or plate waves[5, 6]. Wavelet multi-scale characteristics are used to decompose the signal then a single modal signal is selected to execute the endpoint detection, which can effectively reduce the requirements of traditional time-delay estimation methods for signal fidelity. There are many literatures about the decomposition and reconstruction of wavelet and will not be repeated here.

The signals were decomposed and reconfigured using a wavelet function, which was collected by the AE sensor nodes. They can be expressed respectively as:

\[ L_1(t) = n_1(t) \]
\[ L_2(t) = \beta x_1(t) + n_1(t) \]

Where \( n_1(t) \) is the random noise of the system; \( x_1(t) \) is the effective AE signal and \( \beta \) is the attenuation factor of the signal. \( L_1(t) \) is defined as the noise segment and \( L_2(t) \) is defined as the signal segment. First, the threshold of the sensor node is set. Once the signal value reaches the threshold, the AE event is considered to have been captured by the sensor node, which can be expressed by the following equation:

\[ h(x) = \frac{1}{2} f[L_2(t)] = \frac{1}{2} P(s) \]

where \( P(s) \) is the positive peak of the signal when the acquisition device is in the captured state.

The peaks of the signal are defined as the amplitude mutation points and the peak sequence is obtained. It can be expressed as:
\[ g_t(s) = f_{\text{peak}} \{ L_2(t) \} \]

where \( g_t(s) \geq \frac{1}{3} P(s) \). The endpoint time, \( t \), can be obtained by the time series corresponding to the wave peak sequence:

\[ t = F \{ f [g_t(s)]_{\text{min}} \} \]

where \( t \) is the minimum of the time series.

In this work, the hardware synchronisation mechanism is established to determine the different arrival times of the AE signal at the different sensor nodes. The process is relatively independent, which will greatly reduce the delay estimation error caused by the hardware difference and the distortion of the signal in the transmission process. The sensor nodes in the network undergo strict time synchronisation calibration and the endpoint detection by each sensor node is based on the node’s own background noise. Thus, it simplifies the algorithm and reduces the strict requirement for signal fidelity of traditional time-delay estimation methods.

3.2 Plane Positioning method

The sensor network layout of four nodes is shown in figure 2 (a).

![Sensor network layout](image)

The following equations can be established:

\[ (x - x_i)^2 + (y - y_i)^2 = R_i^2 = t_{xi}^2 v^2 \]

where \((x, y)\) are the coordinates of the AE source; \((x_i, y_i)\) are the coordinates of the AE source sensors; \(R_i\) is the distance between the AE source and the AE source sensor; and \(t_{xi}\) is the transmission time \((i = 1, \ldots, 4)\). The coordinates of the AE source can be obtained by solving the equation (6).

3.3 Visual Warning with Different Frequencies Based on EEG

At present, the research on structural damage localisation based on AE often neglects to establish a suitable warning mechanism for the positioning result. In this work, combining the positioning result with EEG technology, a visual warning mechanism for the positioning result is constructed. Brain waves are a biological electrical signal. Different thinking and emotional states can produce different brainwaves[7]. In this work, the beta wave (13-30Hz) energy is selected as the basis for damage assessment. The higher the beta wave energy value, the more serious the damage.

The four sensors are classified into three damage levels: High, medium and low. High is defined as the first-level damage corresponding to the sensor node that is closest to the sound source. Low is defined as third-level damage corresponding to the sensor node with the farthest distance from the sound source. Medium is defined as second-level damage corresponding to the remaining two sensor nodes.
4. Experiment

4.1 Plane Positioning

The distributed measuring network is composed of four sensor nodes. A pencil lead with a diameter of 0.5 mm, a hardness of HB and an extension of 3 mm was used in the experiment. AE signals were generated on a 500 × 500 × 2 mm steel plate and broken off the pencil lead at an angle of 30° on its surface. The experimental setup are illustrated in Figure 2 (b).

Experiments were carried out in triplicate on the five points. The results of the positioning experiment show that the maximum uniaxial error is 6.2% and the minimum uniaxial error is 1.97%, verifying the feasibility and accuracy of the method in this work. The maximum uniaxial error is 12.8% and the minimum error is 7.55% based on the cross-correlation time-delay estimation method. Comparing the average error of the two methods, as shown in figure 3, it can be seen that the proposed endpoint detection method based on the wavelet transform has higher accuracy compared to the traditional cross-correlation time-delay estimation method.

![Figure 3](image-url)

**Figure 3** (a) Average error in the X (b) and Y axes.

4.2 Visual Warning Based on EEG

The effects of different frequency on brainwave energy were determined in the experiment. Four volunteers were used in the experiment and all of them had normal vision without colour blindness. Figure 4 (a) shows the mean beta wave energy for the four volunteers under five kinds of red light with different flashing frequencies of 2, 5, 10, 15 and 20 Hz. Figure 4 (b) shows the total average beta wave energy collected by the four volunteers in Figure 4 (a).

![Figure 4](image-url)

**Figure 4(a)** Average beta wave energy under five kinds of red light with frequencies of 2, 5, 10, 15 and 20 Hz. (b) Total average beta wave energy collected from the four volunteers corresponding to (a).

Although different frequencies of light have different stimulating effects on different individuals owing to individual differences, it is clear that, the effects of 15 Hz and 2 Hz red light on human brain beta waves differ greatly. The 15 Hz red light has a strong stimulating effect while stimulation by 2 Hz red light is weak.

According to the experimental results, 15 Hz red light, 2 Hz red light and constant green light as the high, medium and low warning lights, respectively, corresponding to the different damage levels.
5. Conclusion
In this work, a miniaturised acquisition device for AE signals is developed and a measuring network is constructed to realise the combination of location structural damage and issuing a visual warning. Using endpoint detection based on wavelet transform and a hardware synchronisation mechanism, the requirements of traditional time-delay estimation methods for signal fidelity are reduced. EEG experiments verified that different colours and frequencies of lights had different effects on the beta wave energy in the human brain. Thus, it is helpful to the on-site staff if flashing frequency of the alarm lights are differentiated according to the damage levels.

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