Feasibility of Using Imperfect Microphone Arrays in Noise Source Location

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Abstract: A microphone array is used for the purpose of noise source location using the unwrapped phase method. Optimization techniques and neural network methods were used to locate a noise source with a matched microphone array and an array containing faulty microphones. Comparison of the data from the microphone arrays is shown. It is demonstrated that a microphone with a significant signal to noise ratio or a faulty microphone can be pinpointed within the microphone array using neural networks.

INTRODUCTION

Large arrays of inexpensive microphones have found applications in areas such as acoustic holography, noise source location, and sound intensity measurement. One of the problems associated with large arrays is the presence of faulty microphones, how to detect and locate them. This paper addresses the use of the Unwrapped Phase Technique (UPT), coupled with optimization and neural networks, as a diagnostic tool on a large microphone array used for noise source location. The UPT is presented in the first section together with the least square fit method adopted to automate distance evaluations. In the second section, experimental results show how a faulty microphone can be located within the array using neural networks applied to various combinations of microphones.

UNWRAPPED PHASE TECHNIQUE

The UPT has been used for noise source location. The technique is based on the cross-spectral density between a reference signal, measured at the source, and the signal picked by a microphone located at a certain distance from the source. Bendat and Piersol (1) have shown that the distance from the source to the microphone can be determined from the phase of the cross-spectral density as:

\[ d = \frac{c \cdot \theta_{xy}(f)}{2 \pi f} \]

where \( d \) is the distance between the source and the microphone, \( c \) is the speed of sound, \( \theta_{xy}(f) \) is the cross-spectral phase, and \( f \) is the frequency. The measurement is simplified when the phase is unwrapped by adding \( 2\pi \) every time it reaches \( +180^\circ \). Owens (2) applied this theory to locate a rattling bolt on a vibrating plate. In Ref. (3), it was demonstrated how neural network could be applied to improve the accuracy of the source location technique.

The unwrapped phase gives a smooth straight line if a microphone is placed directly above the source and there are no reflecting surfaces, i.e., if the microphone picks up only one signal coming directly from the source. Unfortunately, the phase slope changes in the presence of reflectors or multiple sources. An improved phase plot is obtained by eliminating the points where the coherence between source and microphone signals falls below 0.9. This plot shows scattered packets of data. A least square fit is performed on the packets of data that satisfy two rules defined quantitatively by the user: each packet of data should contain a minimum number of points and these points should be close to each other. The slopes obtained from the least square fit are then used to evaluate the source/microphone distances. Each phase plot may yield several distances, therefore, two approaches are used to further process the data: optimization and artificial neural networks (ANN).

The optimization is performed with a simplex algorithm to guess the correct source coordinates from the various distances obtained from the phase plot. A two-layered recurrent ANN is simulated in MATLAB® with a hyperbolic tangent sigmoid and a linear transfer function for first and second layers, respectively. The ANN is trained using Jordan Elman's algorithm (4) with the simulated data for the actual distance, as well as distance data masked by noise of 41.5 dB (119 rms) SNR.
EXPERIMENTAL RESULTS AND ANALYSIS

Four microphones were placed at a height of 44.7” above a small speaker that served as a source. A wide-band random noise of 0-5000 Hz was broadcast by the speaker and measured by the array. Three tests were performed for different speaker positions. The UPT was applied to the signals from each microphone with the signal sent to the speaker as the reference. The calculations were made using a 3 Hz resolution and 127 averages. The experimental data, Figure 1, shows that the slopes that yield the correct source distance tend to be the ones that have the largest number of points, the least deviation from the mean slope (error) or both. Figure 2 shows the phase plot from a bad microphone, 49.8” from the source (13 dB SNR) which yields a distance of 61.4” (50.8” for a good microphone).

![Figure 1. Phase from a good Microphone 4](image1)

![Figure 2. Phase from a bad Microphone 4 (13 dB SNR)](image2)

Table 1 summarizes the optimization and ANN data from the faulty array. It shows that the faulty microphone is easily detected by applying the ANN to various combinations of microphones. Optimization and ANN yield large yet similar errors, except in the absence of microphone 4, which shows that microphone 4 is faulty. Note that ANN(i,j,k,l) represents the combination of microphones used when estimating the distances.

<table>
<thead>
<tr>
<th></th>
<th>X</th>
<th>Y</th>
<th>Z</th>
<th>RMS Error</th>
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</thead>
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<tr>
<td>True Location</td>
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<td>19.8”</td>
<td>4.0”</td>
<td>0</td>
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<td>12.2”</td>
<td>1.6”</td>
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<td>7.12”</td>
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<td>14.0”</td>
<td>0.2”</td>
<td>7.75”</td>
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</tbody>
</table>

CONCLUSION

The unwrapped phase technique, coupled with artificial neural networks, provides an effective tool for locating faulty microphones within a large array. Training of the ANN, however, can be quite time consuming, depending on the size of the array. It was also shown that optimization can verify the presence of a faulty microphone, but cannot locate it.

REFERENCES