

HIGH-RESOLUTION ACOUSTIC DIRECTION-FINDING ALGORITHM TO DETECT AND TRACK GROUND VEHICLES

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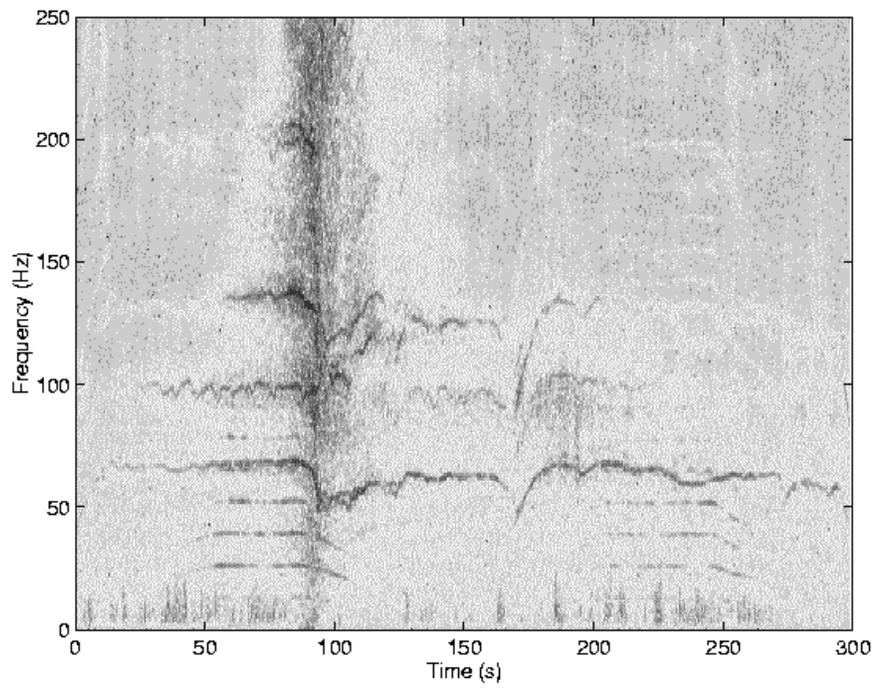
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Abstract

For our experiments, we use an incoherent wideband adaptive signal subspace algorithm for high-resolution aeroacoustic direction-finding. In this paper, we present experimental results for a circular array. In particular, the wideband incoherent MUSIC algorithm shows distinct improvements, as expected, over conventional beamforming in terms of accuracy and the ability to resolve multiple ground targets. Computational complexity is an issue, but can be reduced by using alternatives to full eigen-analysis for real-time implementation in the ARL sensor testbed.

1. Introduction

This paper describes work on array signal processing algorithms using small baseline acoustic arrays to passively detect, estimate direction of arrival (DOA), track, and classify moving targets for real-time implementation in the ARL sensor testbed [1]. Acoustic detection and tracking of ground vehicles in a battlefield environment is a challenging problem. Any dominant spectral lines in the acoustic signatures are nonstationary due to engine load and RPM changes during maneuvering. Terrain, atmospheric effects, and propagation characteristics that vary with time also produce significant signal variability. Figure 1 show the spectrogram of a maneuvering tracked vehicle during a test run conducted at Aberdeen Proving Ground (APG) in 1995. (Note the lack of energy beyond 150 Hz for this test run.) The usable frequency range for signal processing of ground vehicles is limited approximately to the range of 20 to 200 Hz for the detection range of interest (dominated below 20 Hz by wind noise, and dominated above 200 Hz by poor propagation characteristics). Sensor array baselines are physically constrained by system requirements and lack of spatial coherence to less than 10 ft. Because of the limited baseline and nonstationarities, conventional beamforming techniques provide poor spatial resolution, motivating the use of adaptive high-resolution DOA algorithms.



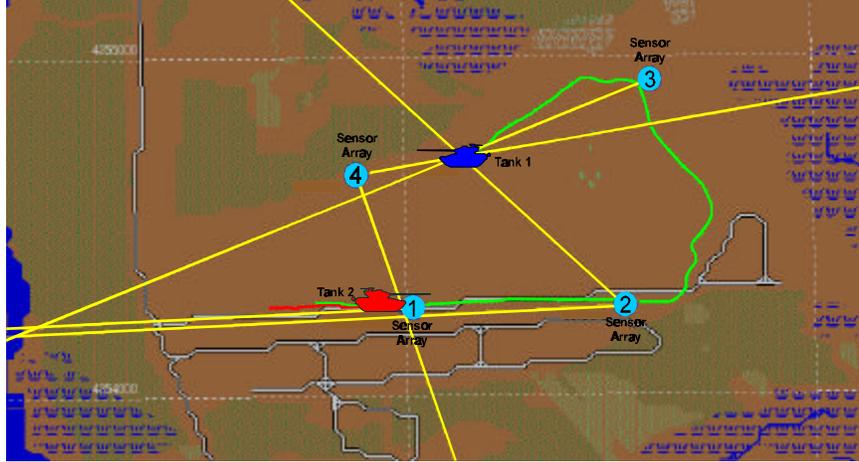


Figure 2. CIP display shows the sensor positions on a terrain map of the test area and the estimated DOA to the targets.

3. High-Resolution Direction-Finding Algorithm

3.1 Background

Conventional DS beamforming has been implemented in the acoustic testbed at the sensor-array level. The sensor array's PC collects acoustic data at a 2-kHz sampling rate from the microphones and estimates the DOA. The DOA estimates are updated and sent back to the gateway once a second for further processing. At the gateway, the DOA reports from multiple sensors are correlated to form a track for each vehicle. In addition, the gateway saves all DOA reports for post-test analysis. Vehicle tracks calculated by the gateway, along with DOA reports from the sensors, are transmitted back to the CIP for display and analysis by the system user (see figure 2). The DS beamformers perform well for a single-source environment; however, their ability to resolve closely spaced sources is limited by the small baselines of the arrays. Therefore, the resolution of the DS beamformer is greater than 5 degrees (based on the parameters used).

3.2. Implementation of MUSIC

Figure 3 shows the steps for implementing incoherent wideband MUSIC. To overcome the nonstationary nature of the acoustic source, the data is segmented before processing into fixed blocks, and stationarity is assumed over each data block. We have found that the assumption of signal stationarity is reasonable for intervals on the order of 1 second or less. Over each processing interval, it is assumed that a single frequency bin is occupied by only a single source. This takes advantage of the nonstationarity of the sources, and simplifies the MUSIC algorithm. Although a source may be masked in a particular processing interval, this effect is unlikely to continue because the sources are changing frequencies as a function of time. Preprocessing is required to adaptively select the operating frequencies (the \mathbf{w}_k). $y_i(n)$ denote the output of the i th sensor from an array of N sensors, and let $Y_i(\mathbf{w})$ denote $DFT\{y_i(n)\}$. The average sum of $|Y_i(\mathbf{w})|^2$ is then obtained to adaptively select frequency bins of interest. This can be performed in a variety of ways, from simple thresholding based on frequency bin signal-to-noise ratio (SNR), to more complex schemes, such as harmonic association.

After the \mathbf{w}_k 's have been selected, the next step is formation of the estimated spatial correlation matrix for each \mathbf{w}_k , over each data block, given by

$$\hat{R}_Y(\mathbf{w}_k) = \hat{Y}(\mathbf{w}_k)^H \hat{Y}(\mathbf{w}_k), \quad (1)$$

where $\hat{Y}(\mathbf{w}_k) = [Y_1(\mathbf{w}_k), Y_2(\mathbf{w}_k), \dots, Y_n(\mathbf{w}_k)]^T$ and H is the Hermitian operator (complex conjugate transpose). Once $\hat{R}_Y(\mathbf{w}_k)$ is formed for each \mathbf{w}_k , the narrowband MUSIC algorithm is applied repeatedly [3]. The first step is eigenanalysis of $\hat{R}_Y(\mathbf{w}_k)$ to obtain the noise subspace. Taking $\hat{R}_Y(\mathbf{w}_k)$ to be $N \times N$ then, by the assumption that only one source can occupy a frequency bin over a processing interval, the noise subspace consists of the $N-1$ eigenvectors

corresponding to the $N-1$ smallest eigenvalues of $\hat{R}_Y(\mathbf{w}_k)$, and these form $\hat{U}_n(\mathbf{w}_k)$. The MUSIC beampattern is then computed. For each look angle \mathbf{q} , the beampattern is given by

$$\hat{P}_{MUSIC}(\mathbf{q}) = \left[E(\mathbf{w}_k, \mathbf{q})^H \hat{U}_n(\mathbf{w}_k) \hat{U}_n(\mathbf{w}_k)^H E(\mathbf{w}_k, \mathbf{q}) \right]^{-1}. \quad (2)$$

The array manifold or steering vector, $E(\mathbf{w}_k, \mathbf{q})$, is defined as

$$E(\mathbf{w}_k, \mathbf{q}) = \left[e^{2pf_k \Delta t_1}, e^{2pf_k \Delta t_2}, \dots, e^{2pf_k \Delta t_N} \right]^T, \quad (3)$$

where $\Delta t_i = \frac{d}{c} \sin \mathbf{f}_i$, $\mathbf{f}_i = \mathbf{q} - \mathbf{a}_i$, where \mathbf{a}_i is the relative angle to the normal for sensor $i = 1, 2, \dots, N$, d is the radius of the circular array, and c the speed of sound in air.

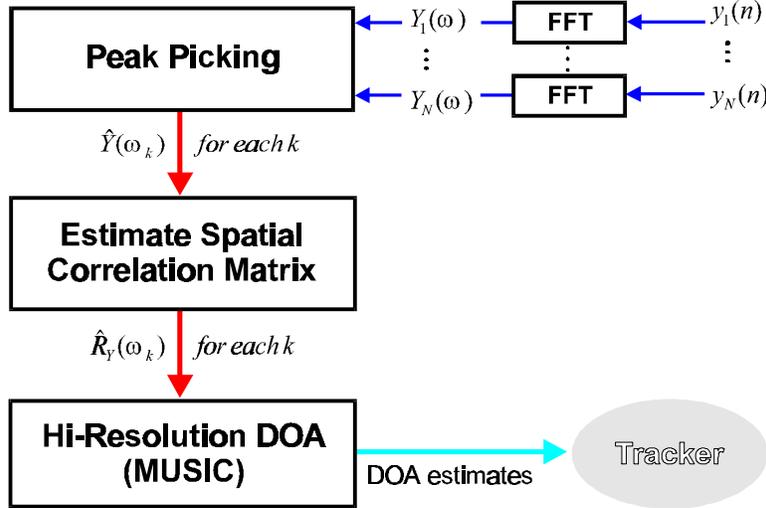


Figure 3. Implementation of the MUSIC algorithm.

After the beampatterns are calculated for all \mathbf{w}_k 's, they are incoherently averaged together to form a resulting MUSIC beampattern [2, 3]. Finally, the source DOA's are estimated by selecting the angles corresponding to the peaks in the resulting averaged beampattern. For each update, the raw DOA estimates from the sensor arrays are transmitted to the gateway for tracking. The tracker correlates the DOA estimates from the sensor arrays, and maintains a tracking history for each acoustic source. Currently, the testbed uses an alpha-beta tracker [1], which is robust with respect to missing or outlying DOA estimates.

3.3. Computational Issues

The computational complexity of MUSIC is governed mainly by the eigen-analysis calculation, which is $O(N^3)$. However, this can be reduced by applying methods that calculate the signal subspace only, as opposed to the full eigen-analysis, because in our implementation the signal subspace is assumed to consist of one component only. By further assuming that only one source occupies a frequency bin, the algorithmic complexity and the estimation of the number of sources are simplified. The complexity can be reduced even further by precomputing $E(\mathbf{w}_k, \mathbf{q})$ for all the frequency bins in the range of interest at an additional memory cost. An alternative method is to use a coarse beamformer (e.g., DS) during preprocessing to reduce the number of look angles. Therefore, $\hat{P}_{MUSIC}(\mathbf{q})$ is computed for fewer values of \mathbf{q} . In addition, a simple and computationally efficient form of $E(\mathbf{w}_k, \mathbf{q})$ has been implemented. Other more complex forms of $E(\mathbf{w}_k, \mathbf{q})$ can be used to incorporate the sensitivity and gain calibration of the sensors. However, the response of the sensors can change over time due to changes in the atmosphere, requiring the sensors to be recalibrated, and the parameters used in $E(\mathbf{w}_k, \mathbf{q})$ to be updated and stored periodically (which is generally not feasible for low-cost unattended systems).

Other methods (e.g., harmonic line association (HLA)) can be used to limit the number of operating frequencies. The HLA algorithm detects the frequency bins that are above a set SNR threshold level. The bins are then sorted and combined into harmonic groups. Each harmonic group contains frequency bins that are harmonically related to a fundamental frequency of an engine rate. The HLA will declare a harmonic group valid (i.e., a source is detected) if there are at least m ($m = 2, 3, 4$ or 5) components in that group; otherwise, there is no source detected. The use of HLA in this way, however, requires that the acoustic sources belong to a group of known sources [1].

4. Data Analysis and Experimental Results

The raw DOA results for DS and wideband MUSIC algorithms are presented for ground vehicles traveling around a 2-km² area of open grass field. For each test run, one of the vehicles was equipped with a GPS sensor to provide accurate positioning ground truth. For comparison purposes, both algorithms are performed over $\mathbf{q} \in [0, 360]$ degrees in 1-degree increments. The mean squared error (*MSE*) and the mean absolute error (*MAE*) for each test run are computed with the outliers removed [2]. Figure 4 shows raw DOA results for a 250-second 1-target test run. Note that the number of erroneous estimates is much less for MUSIC, which will improve detection and tracking of multiple sources. In general, over a number of test runs conducted during this field test at APG, $MSE \approx 20$ and $MAE \approx 3.5$ for DS, while $MSE \approx 3.5$ and $MAE \approx 1.5$ for MUSIC.

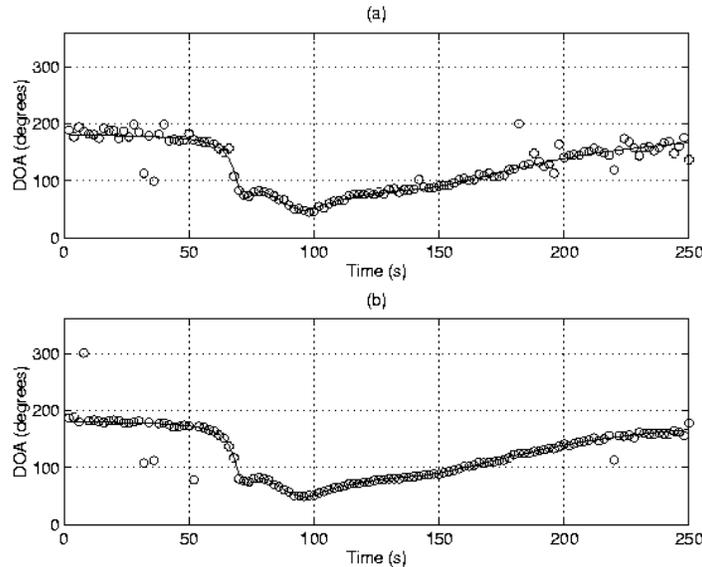


Figure 4. Raw DOA estimates versus GPS ground truth for (a) DS and (b) MUSIC beamformers.

Figure 5 shows the beampatterns of one processing interval (1 second) for DS and MUSIC for a 2-target test run. The sources are located at $\mathbf{q} = 50$ and $\mathbf{q} = 180$, respectively. Individual beampatterns were calculated for a set of 10 frequency bins, with the highest SNR and the resulting 10 beampatterns averaged together [2]. Note the sharpness of the peaks in the MUSIC beampattern in comparison to the DS beampattern, demonstrating the high resolution of the wideband MUSIC method for this problem. If the sources are closely located, the DS beamformer will not be able to detect and separate them.

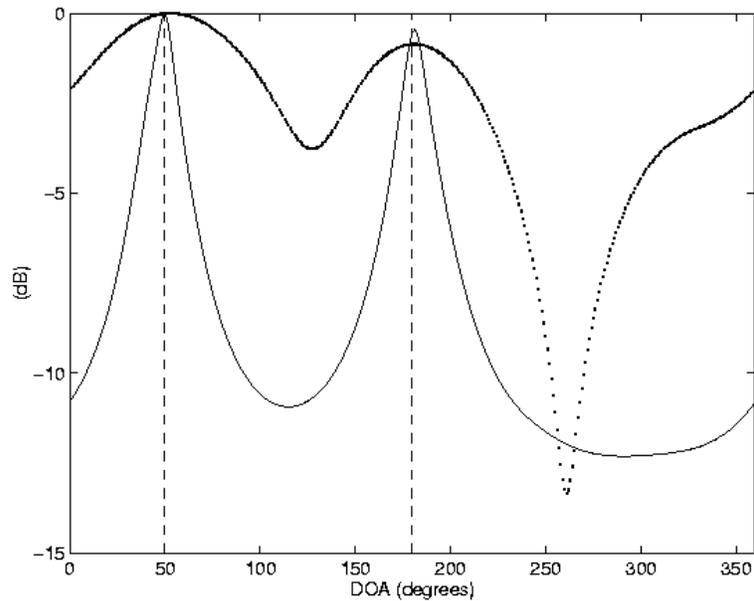


Figure 5. Beam patterns for two sources located at $q = 50$ and $q = 180$ for DS (dotted) and MUSIC.

Conclusions

Experimental results and analyses for both DS and MUSIC algorithms were presented. The acoustic sources are, generally, characterized as a sum of narrowband frequency components. Given adequate SNR, incoherent wideband MUSIC performed very well; produced more accurate DOA estimates; and yielded sharper distinct peaks in the beam pattern, in comparison to DS. The disadvantage of implementing MUSIC is the higher computational cost. The computational complexity is governed by the eigen-analysis calculation, which is $O(N^3)$. Alternative methods were discussed to speed up the MUSIC algorithm for real-time implementation. Other computationally efficient signal subspace algorithms have been investigated prior to MUSIC (e.g., ESPRIT algorithm) [5]. However, ESPRIT generally requires twice the number of sensors as MUSIC, and places restrictions on array geometries. Current work includes high-resolution coherent wideband array processing to achieve higher processing gain during time intervals of low SNR [2, 4, 6]. Future work of interest includes reducing computation by exploiting the radial symmetry of a circular array [7], and effects of calibration and sensor placement errors [8].

References

- [1] Adelphi, MD (May 1995).
- [2] T. Pham and B. Sadler, 'Adaptive wideband aeroacoustic array processing,' *8th IEEE Statistic Signal and Array Processing Workshop (SSAP96)*, Corfu, Greece (24-26 June 1996).
- [3] M. Wax, T. Shan, and T. Kailath, 'Spatio-temporal spectral analysis by eigenstructure methods,' *IEEE Trans. ASSAP*, Vol. 32, pp. 817-827, August 1994.
- [4] T. Pham and B. Sadler, 'Aeroacoustic wideband array processing for detection and tracking of ground vehicles,' *130th Meeting of the Acoustical Society of America*, St. Louis, MO (27 November - 1 December 1995).
- [5] T. Pham and B. Sadler, 'Acoustic tracking of ground vehicles using ESPRIT,' *SPIE Proceedings, Automatic Object Recognition V*, Vol. 2485, pp. 268-274, Orlando, FL (19-21 April 1995).
- [6] H. Wang and M. Kaveh, 'Coherent signal-subspace processing for the detection and estimation of angles of arrival of multiple wideband sources,' *IEEE Trans. ASSP*, Vol. 33, pp. 823-831 (August 1985).
- [7] M. Doron, E. Doron, and H. Weiss, 'Coherent wide-band processing for arbitrary array geometry,' *IEEE Trans. SP*, Vol. 41, No. 1, pp. 414-417 (January 1993).
- [8] A. Swindlehurst and T. Kailath, 'A performance based analysis of subspace-based methods in the presence of model errors, part 1: the MUSIC algorithm,' *IEEE Trans. SP* Vol. 40, No. 7, pp. 1758-1774 (July 1992).