Maximum Entropy Method High-Resolution Spectral Analysis Combined with Akaike Information Criteria as a Harmonic Line Analysis Pre-Processor

Dr. James E. Whitney, II
Assistant Professor
Department of Electrical and Computer Engineering
Morgan State University
whitney@eng.morgan.edu

Zelalem Tesfaye
Department of Electrical and Computer Engineering
Morgan State University
ztesfay@eng.morgan.edu

Theodore Ndje
Department of Electrical and Computer Engineering
Morgan State University
ndje@eng.morgan.edu

ABSTRACT

When performing the task of acoustic signal processing for vehicle identification and subsequent classification and tracking, it is necessary to obtain the fundamental frequency and related harmonic structure of the received acoustical signal. Currently, most processors utilize the Fast Fourier Transform (FFT) for this process. The use of a high-resolution spectral analysis method, such as the Maximum Entropy Method (MEM) may provide a quicker and more easily utilized spectrum with less spurious peaks in the spectral envelope.

INTRODUCTION

In battlefield situations, it is desirable to identify the location, number, and type of vehicles in the arena. Several methods are currently in use which have operating frequencies which range from several Hertz (acoustical) to wavelength-based methods, i.e., LIght Detection And Ranging (or, LIDAR). In this work, the emphasis is on extracting the maximum spectral information from the signal received on an acoustical array. This spectral information can then be further processed to aid in vehicle type classification [1].

The Fast Fourier Transform (FFT) is typically used to extract spectral information from the time series impinging on the sensor system. The FFT and second-order autocorrelation processing methods are dependent on information contained in the current data segment under observation, and are hampered by short data lengths. By using high-resolution spectral analysis methods, the data is modeled as the output of an n-th order model driven by a white noise sequence. Provided that the correct model is chosen, increased performance is obtained for shorter data lengths. The resolution of the resulting spectrum is not limited to equally spaced frequencies, thus allowing higher resolution searching for peaks at candidate frequencies.

Proc. IRIS Acoustic and Seismic Sensing, 1998, Vol. II

Maximum Entropy Method (MEM)Spectral Estimation

The maximum entropy method is a high-resolution modeling technique which attempts to mitigate the effects of finite length data. This characteristic is particularly useful when dealing with small data lengths. For a given data/autocorrelation length the MEM attempts the maximize the average information content, or entropy of the process [2,3,4]. This is attained by extrapolating the autocorrelation function to represent the most random time series, whose first 'M' autocorrelation values are those of the known data sequence. The MEM spectrum is given by Eq. 1

$$S_{MEM}(\omega) = \frac{1}{\sum_{k=-M}^{M} \Psi(k) e^{-j\omega k}} \qquad \textbf{(Eq. 1)}$$

where,

M – model order

$\psi(k)$ – correlation coefficient for prediction-error filter coefficients

The Levinson-Durbin recursion is used to find the prediction error filter coefficients. In this work, the spectrum is then normalized with respect to the frequency having the largest magnitude. The log of these normalized magnitudes is used for subsequent processing.

Akaike Information Criteria (AIC)

To a large extent, successful utilization of high-resolution methods such as the maximum entropy method, depends on correct estimation of model order. Under-estimation of the model order may result in not obtaining all the harmonics associated with the current segment of data. Over-estimation of the model order results in non-related spurious peaks. One method for performing model-order selection is the Akaike Information Criteria (AIC). The AIC represents a minimization of the Kullback-Leibler mean information. The AIC is given by [3,5]

$$AIC(k) = N \ln(\rho_k) + 2k \qquad \textbf{(Eq. 2)}$$

where,

k – model order

N – Number of data samples

and, ρ_k - estimate of the k-th order AR model white noise variance

In this implementation, the MEM algorithm calculates the value of the AIC at each iteration. Currently, no logic is utilized to automatically select the minimum model order. Several possibilities exist for automating this process, for example, tracking changes in slope or absolute slope of the AIC with time could be used to select a stopping point. Therefore, as currently implemented, the model is given some hypothetically large model order, M. By starting with a low-order model and incrementing up to M, a curve of model order versus AIC value is generated. The optimum model order is then selected as that value where the slope of this curve is close to zero, i.e., no further substantial reduction in the AIC. This value of model-order is then used to calculate the MEM spectrum.

EXPERIMENTAL RESULTS

In this section, the combined MEM/AIC algorithm is applied to data obtained from Army Research Laboratory in Adelphi, Maryland. The particular data set is RUN19, collected at Aberdeen Proving Ground H-Field. The vehicle is a tracked vehicle traveling at a constant velocity of 20 miles-per-hour. The data was sampled at 1000 Hz. The data was gathered from an eight-foot diameter, 7-element circular array. Each array element was a low-cost microphone covered by a wind sock. Six of the elements were equally spaced around the circumference of the array. The array element denoted as 'element 4' was located in the center of the array.

Figure 1 illustrates the spectrum of the data obtained using a standard 1024-point Fast Fourier Transform (FFT). The spectrum was calculated from the first 1024 points, or 1.024 seconds, of data in the file. A Hamming window was applied to the data. In the next two figures, Figures 2 and 3, the same 1024 data points are used to calculate the MEM spectrum. Figure 2 illustrates the AIC value versus model order. These AIC values were calculated by running the model sequentially starting with a first order model to a model using 100 parameters. The noise variance is obtained as part of the error in the forward-backward parameters when calculating the MEM spectrum. This noise variance is then used in Eq. 2 to calculate the AIC. It can be seen that the AIC is minimized for model orders greater than 30. Figure 3 shows the MEM spectrum obtained utilizing 35 parameters. Figure 4 illustrates a 4096-point FFT data obtained using the first 4.096 seconds of data. Figures 5 and 6 illustrate the resulting AIC curve and MEM plot.

The last two plots, Figures 7 and 8, illustrate the case where the model order was increased 43 percent, to 50 parameters, for the 1024 point case and 15 percent, to 40 parameters, for the 4096 data point case.

DISCUSSION

For the case where 1024 points of data are used, the FFT obtained dominant spectral peaks at 5.8, 9.8, 11.7, 20.5, 38, 54, 68, 73, 100, 114, 131, 178, 200, 238, 268, 301, 470, and 497 Hz. The threshold for defining dominant spectral peaks was arbitrarily set to $|X(f)|$ greater than 20000. The MEM spectrum was calculated using 35 model parameters. In this case, spectral peaks were denoted as those peaks which deviated from the average surrounding spectrum magnitude. It can be seen that the spectrum is initially shelved from 3.7 Hz to 12.6 Hz and 29 Hz to 40 Hz. The first discernable peak is at 68 Hz. This initial peak is followed by peaks at 71, 100, 111, 138, 177, 206, 241, 273, 304, 431, 471, and 500 Hz. In this case, most of the spectral components for frequencies of 68 Hz and greater showed good correlation between the two methods. For this model order the MEM was not able to obtain a reasonable fundamental frequency. However, the spectrum of the remaining frequency components are more easily discernable using the MEM spectrum.

In the case using 4096 points of data, the FFT obtained dominant spectral peaks at 5, 13, 17, 20, 67, 72, 99, 133, 201, 240, 270, 298, 431, and 472 Hz. In this case, spectral peaks were denoted qualitatively as 'frequency components which varied substantially from the surrounding spectrum'. The MEM spectrum was generated using 4096 data values and 35 model parameters. The resulting MEM spectrum indicated spectral peaks at frequencies of 16.8, 68.3, 74, 99, 112, 138, 176, 204, 240, 273, 304, 434, and 470 Hz. There is a shelved section of the spectrum from approximately 35-41 Hz. In this case the MEM obtained its lowest frequency at 16.8 Hz, which

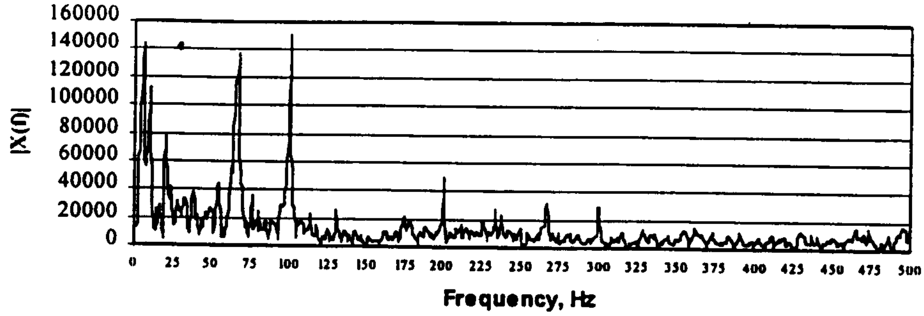

Figure 1 1024-Point Hamming-windowed FFT.

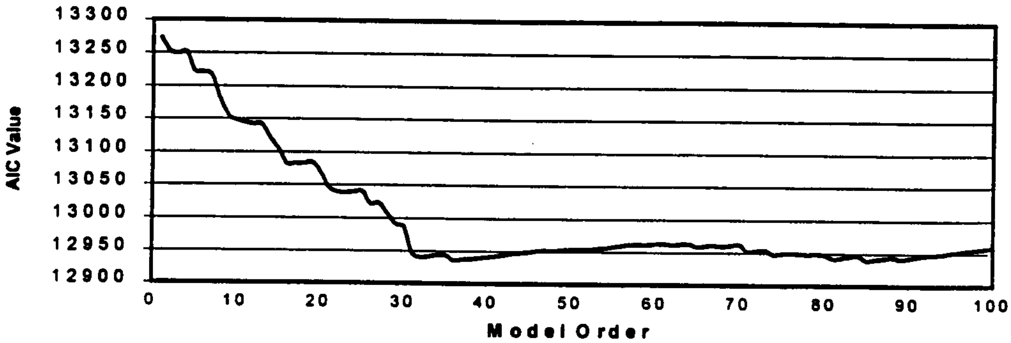

Figure 2 AIC for 1024 data samples.

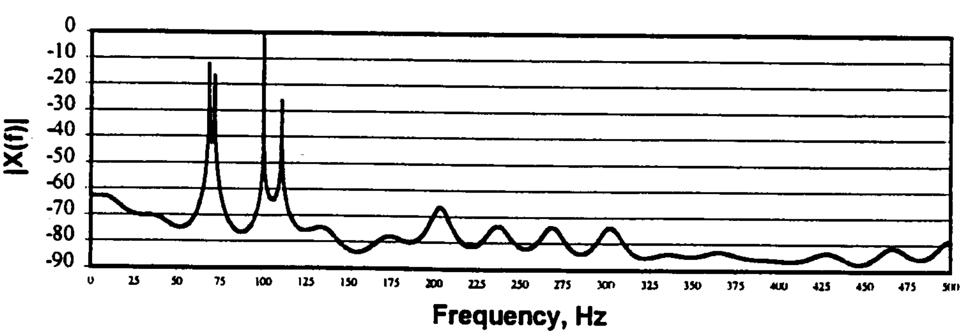

Figure 3 MEM spectrum, 1024 data samples, 35 model coefficients.

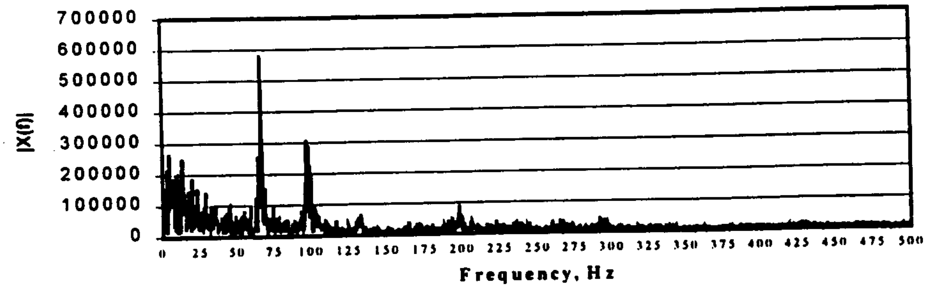

Figure 4 4096-point Hamming-windowed FFT.

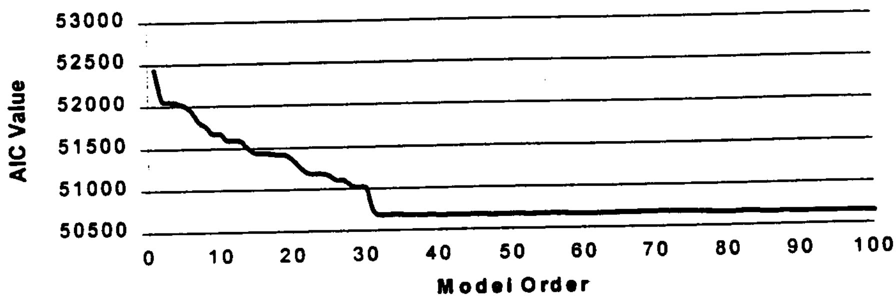

Figure 5 AIC for 4096 data samples.

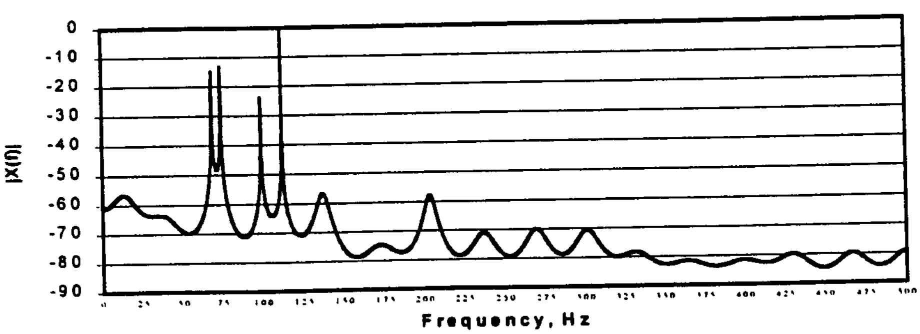

Figure 6 MEM spectrum, 4096 data samples, 35 coefficients.

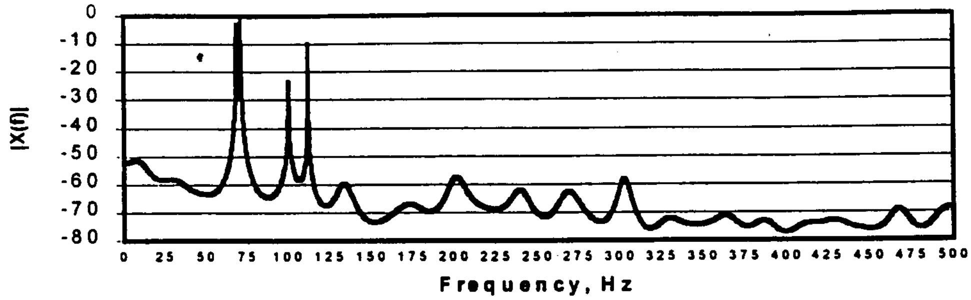

Figure 7 MEM spectrum, 1024 data samples, 50 coefficients.

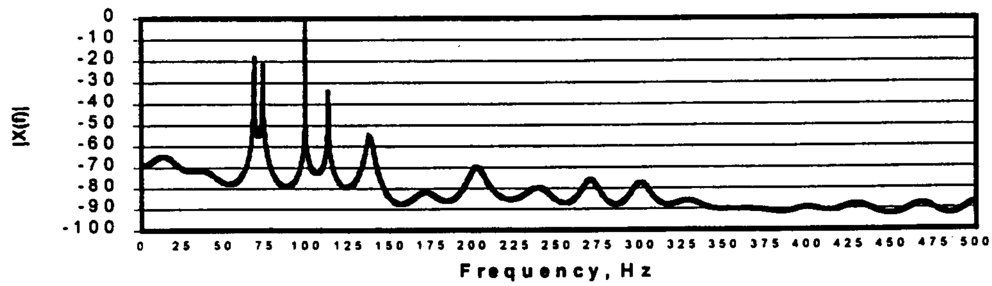

Figure 8 MEM spectrum, 4096 data samples, 40 coefficients.

is in a typical range for fundamental frequencies [1]. However, as the FFT obtained frequencies below 16.8 Hz, this may not be the true fundamental.

In the case where the model order was increased 43 percent, to 50 parameters, for the 1024 point case he low frequency peak is located at 7.3 Hz. For the 4096 data point case, where the model order was increased 15 percent, to 40 parameters, the low-frequency peak is located at 13.16 Hz. In both cases, the ability to model the lower frequency peaks has been enhanced without the addition of spurious peaks.

CONCLUSION

A harmonic line analysis pre-processing method has been proposed, which combines the high-resolution MEM spectral analysis technique with the Akaike Information Criteria. The experimental results show that the spectrum undergoes smoothing of non-dominant frequencies which may make determination of harmonic components and harmonic line analysis easier.
It should be noted that this technique is primarily viable for vehicles with strong line spectra, such as reciprocating-engine powered vehicles. In some cases, the processor could be used to obtain the spectrum of broadband, or turbine powered tracked vehicles. In this case the processor could obtain spectral information about track slap frequency and mechanical harmonics, but the fundamental frequency and harmonics associated with the propulsion unit would most likely be unattainable.

BIBLIOGRAPHY

1) " Fifth Annual Battlefield Acoustics Symposium ", September 23-25, 1997, Fort Meade Maryland, Army Research Laboratory.

2) Press, Fannery, Teukolsky, Vettering "Numerical Recipes (FORTRAN): The Art of Scientific Computing", Cambridge University Press, 1990.

3) Kay, S. "Modern Spectral Estimation: Theory and Applications", Prentice-Hall Signal Processing Series, 1988.

4) Haykin, S. "Adaptive Filter Theory, 2nd Edition", Prentice Hall Information and System Sciences Series, Thomas Kailath, editor, 1991.

5) Marple, S. L., "Digital Spectral Analysis with Applications", Prentice-Hall, 1987.