ACOUSTIC MICRO-SIGNATURES: NEW EXTRACTION CONCEPTS

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***Abstract* – The ability to extract weak signal components, or micro-signatures, from acoustic array data can be used to help classify targets with greater detail. In order to discover and evaluate micro-signatures in actual circular acoustic array data, a signal collection system and a new micro-signature extraction algorithm was developed. This micro-signature extraction algorithm replaces traditional time-frequency analysis techniques with a new high-resolution subspace-enhanced linear predictive extrapolation technique. This technique is used to extend the data within each analysis window in order to create a longer data sequence for conventional STFT time-frequency analysis. This paper presents this algorithm along with the results of applying it to actual acoustic array data.**

I. INTRODUCTION

Acoustic sensors have become the sensor of choice for Unattended Ground Sensor (UGS) applications such as ground vehicle detection and tracking. Signals collected from an acoustic array can be used to classify or identify a target vehicle and provide situational awareness within the sensor field. Acoustic sensors have many advantages due to their non-line-of-sight (NLOS) detection capability and the fact that they can be used to localize and identify targets at long ranges.

Vehicle type classification is a challenging signal processing task that requires target-specific components, or *signatures*, to be extracted from the acoustic data. These signatures are critical for accurate classification. Obviously, the more signatures available for a given vehicle target, the easier it can be to identify or classify that target with high accuracy.

Acoustic signals from vehicles often exhibit strong signatures that relate to mechanisms such as engine noise and track or tire noise. Weaker signal components are often not detected due to the limitations of traditional signal processing techniques. However, these weaker components, or *micro-signatures*, could be used to classify vehicle targets with greater detail.

A classical technique for identifying signatures in sampled nonstationary signals, such as acoustic array signals, has been the short-time Fourier transform (STFT). The STFT is a time-frequency analysis (TFA) technique that uses linear operations on sampled data. There also exist TFA techniques that use quadratic operations on sampled data, such as the Wigner-Ville function (WVF). These quadratic techniques are often able to achieve an improvement in time-frequency detail over that of the STFT, but this improvement is achieved by introducing significant cross-term artifacts that sacrifice considerable detectable dynamic range (DNR). The cross-terms, which are generated by multi-component signals (more than one signal present at an instant of time), additive noise, and analog-to-digital converter quantization effects, often obscure weaker signal components and make this technique impractical for weak signature extraction. Due to the practical limitations of the quadratic TFA techniques, an alternative signature extraction technique that achieves high time-frequency detail while preserving weak signal components is needed. Acoustic signals from moving vehicle targets are wide-band, multi-component, and non-stationary. In order to extract micro-signatures, it is necessary to use an algorithm that can provide good time-frequency detail without causing DNR degradation.

This paper will present the results of a new micro-signature extraction algorithm, applied to actual sampled data from a circular acoustic array that achieves the sharpness of a quadratic TFA, but without incurring the degradation caused by cross-term artifacts. Examples will be presented which show that improvements in signature extraction can be made over traditional methods.

II. COLLECTION SYSTEM & DATA

In order to evaluate micro-signatures in circular acoustic array data, a signal collection system was developed from commercially available hardware. Fig. 1 shows a photograph and block level diagram of the collection system, which was based around a National Instruments SCXI-1000 portable chassis with a SCXI-1531 multichannel pre-conditioning module and a SCXI-1600 DAQ module. The acoustic array was composed of seven piezo-ceramic microphones, each connected to a differential pre-amplifier. The amplifiers provided a gain of 32dB to boost the signal levels prior to entering the pre-conditioning module. The array was configured with seven microphones, six arranged on a 1.2 meter radius, and one in the center.

The microphones were also provided with 6-in. diameter windscreens to reduce wind noise. The array could be configured in a variety of ways, enabling us to explore other geometries.

The analog inputs from the microphone preamplifiers were filtered with an 8th order elliptic low-pass filter with a cutoff of 2.5 kHz. The analog signals from all channels were sampled simultaneously at 6 kHz and converted to digital sampled data with a 16-bit analog-to-digital converter. The data was then low pass filtered in software using a FIR filter with a cutoff of 670 Hz and the sample rate converted to 2000 Hz using decimation.

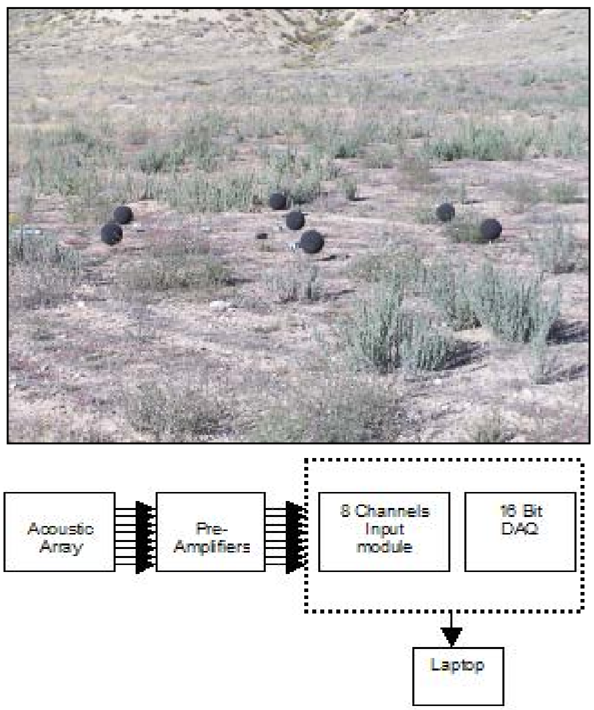

Figure 1: Picture of collection array (top). Block level diagram showing acoustic data collection system (bottom).

III. SUBSPACE DATA EXTRAPOLATION AND HIGH DEFINITION LINEAR TFA

The baseline linear TFA technique is the STFT. If $x(t)$ is the signal to be analyzed, define the short-time windowed signal

$$x_h(t,\tau) = x(\tau)h^*(\tau - t)\,, \qquad (1)$$

in which $h(\tau)$ is the analysis window with assumed center time $t = 0$, * denotes complex conjugation, and t represents the analysis time over $x(t)$. The Fourier transform of the short-time windowed signal is therefore

$$X_h(t, f) = \Im\{x_h(t,\tau)\} = \int_{-\infty}^{\infty} x_h(t,\tau)\exp(-j2\pi f\tau)d\tau \qquad (2)$$

which is the classical STFT. The localized STFT spectrum, or *spectrogram*, is simply the magnitude of the STFT

$$P_{STFT}(t, f) = \left|X_h(t, f)\right|^2 \qquad (3)$$

which is then plotted to form the 2-D TFA gram. The tradeoff in temporal resolution vs. frequency resolution is achieved by the selection of the analysis window shape and duration.

Rather than use the windowed data segment of Eq. (1), an alternative to enhance the frequency resolution capability of the STFT is to predictively extend the data within the window to increase the data interval by a factor of 2 to 4, and then substitute this extended data for the original data sequence (see Fig. 2). This has been shown to be feasible by Swinger and Walker [3].

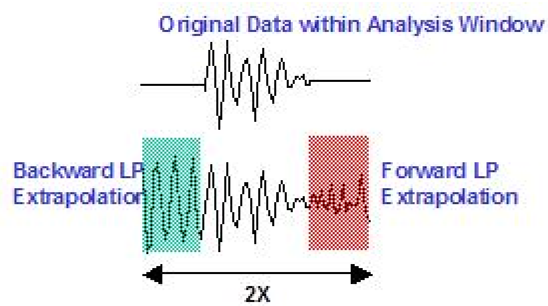

Figure 2: Data extrapolation concept.

Data Extrapolation with Covariance Method of Linear Prediction

The data extrapolation algorithm in this paper involves the use of the covariance method of linear prediction to estimate both the forward and backward linear prediction parameters based on the data within each analysis window. Once the parameters have been estimated, extrapolation by 2 in the forward time direction is obtained simply by forming

$$\hat{x}[n] = -\sum_{k=1}^{p} a_p^f[k]x[n-k] \qquad (4)$$

for $n = N+1$ to $n = N + N/2$ and extrapolation in the backward direction is obtained simply by forming

$$\hat{x}[n] = -\sum_{k=1}^{p} a_p^b[k]x[n+k] \qquad (5)$$

for $n = 0$ to $n = -N/2+1$. If the data is N samples in length, then we can form $N/2$ forward prediction data values and $N/2$ backward prediction data values, for a total of $2N$ data values that can be substituted for STFT TFR analysis.

Assume the N-point data sequence $x[1],\dots,x[N]$ is to be used to estimate the pth-order AR parameters. The forward linear prediction error is

$$e_p^f[n] = x[n] - \hat{x}^f[n] = x[n] + \sum_{k=1}^{p} a_p^f[k]x[n-k]\,. \qquad (6)$$

The forward linear prediction error may be defined over the range from $n=1$ to $n=N+p$, if one assumes that the data prior to the first sample and after the last sample are zero. The $N+p$ forward linear prediction error terms represented by Eq. (6) may be summarized, using matrix notation, as

$$\begin{pmatrix} e_p^f[1] \\ \vdots \\ e_p^f[p+1] \\ \vdots \\ e_p^f[N-p] \\ \vdots \\ e_p^f[N] \\ \vdots \\ e_p^f[N+p] \end{pmatrix} = \underbrace{\begin{pmatrix} x[1] & \cdots & 0 \\ \vdots & \ddots & \vdots \\ x[p+1] & & x[1] \\ \vdots & \ddots & \vdots \\ x[N-p] & & x[p+1] \\ \vdots & \ddots & \vdots \\ x[N] & & x[N-p] \\ \vdots & \ddots & \vdots \\ 0 & \cdots & x[N] \end{pmatrix}}_{\mathbf{X_p}} \begin{pmatrix} 1 \\ a_p^f[1] \\ \vdots \\ a_p^f[p] \end{pmatrix} \qquad (7)$$

in which $\mathbf{X}_\mathrm{p}$ is an $(N+p)\times(p+1)$ rectangular Toeplitz data matrix. For the covariance case we define the forward linear prediction error terms over the range $n=p+1$ to $n=N-p$. Then, the $N-p$ forward linear prediction error terms may be represented in matrix-vector notation as

$$\begin{pmatrix} e_p^f[p+1] \\ \vdots \\ e_p^f[N-p] \\ \vdots \\ e_p^f[N] \end{pmatrix} = \underbrace{\begin{pmatrix} x[p+1] & \cdots & x[1] \\ \vdots & \ddots & \vdots \\ x[n-p] & \cdots & x[p+1] \\ \vdots & \ddots & \vdots \\ x[N] & \cdots & x[N-p] \end{pmatrix}}_{\mathbf{X_p}} \begin{pmatrix} 1 \\ a_p^f[1] \\ \vdots \\ a_p^f[p] \end{pmatrix} \qquad (8)$$

in which $\mathbf{X}_\mathrm{p}$ is now a $(N-p)\times(p+1)$ rectangular Toeplitz data matrix.

The forward linear prediction squared error magnitude to be minimized is simply

$$\rho_p^f = \sum_{n=p+1}^{N} \left| e_p^f[n] \right|^2\,. \qquad (9)$$

The normal equations that minimize the squared error at order p can be shown [2] to have the matrix form

$$\mathbf{X}_p^H \mathbf{X}_p \begin{pmatrix} 1 \\ a_p^f \end{pmatrix} = \begin{pmatrix} \rho_p^f \\ 0_p \end{pmatrix}. \qquad (10)$$

Similar expressions can be developed for the backward linear prediction case [2].

Data Extrapolation with Signal Subspace Enhancement

The application of signal subspace techniques via the singular value decomposition (SVD) can improve the estimates of the forward and backward linear prediction parameters. The data matrix, $\mathbf{X}_\mathrm{p}$, in Eq. (8) has the following singular value decomposition

$$\mathbf{X}_p = \sum_{n=1}^{p} \sigma_n^f \mathbf{u}_n^f (\mathbf{v}_n^f)^H\,. \qquad (11)$$

in which the σ_n^f terms are positive singular values, and the $\mathbf{u}_n$ and $\mathbf{v}_n$ terms are the eigenvectors of the data matrix. If a signal consists of m signals in additive noise, then the m eigenvectors associated with the m largest singular values primarily span the m signal components. The $p-m$ eigenvectors of the remaining smaller singular values primarily span the noise components. Assuming the singular values have been ordered by decreasing value, e.g., $\sigma_1^f > \sigma_2^f > \cdots > \sigma_{p1}^f$, then a reduced rank approximation of the data matrix may be formed by truncating the SVD relationship of Eq. (11) to the m principal singular values (the so-called signal subspace)

$$\hat{\mathbf{X}}_p = \sum_{n=1}^{m} \sigma_n^f \mathbf{u}_n^f (\mathbf{v}_n^f)^H\,. \qquad (12)$$

This will reduce the noise contribution to the data matrix, effectively enhancing the SNR. The reduced rank data matrix of Eq. (12) is then used in lieu of the full data matrix in Eq. (10) to produce the reduced rank linear prediction parameter solution.

IV. APPLICATION TO ACTUAL ACOUSTIC ARRAY DATA

The high-resolution time-frequency analysis method presented in this paper can be used for micro-signature extraction from acoustic array data to reveal more detail. To illustrate the benefits of the new approach, consider the various TFA's shown in Figures 3 through 6. These TFA's demonstrate the application of both the STFT TFA technique and the new subspace data extrapolation TFA technique to actual sampled acoustic array data.

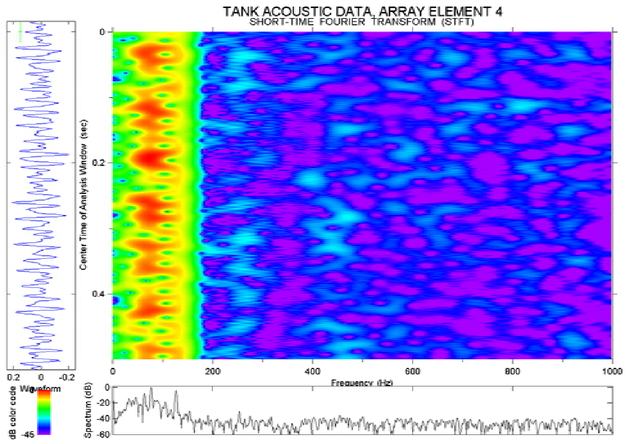

Figure 3: STFT TFA computed using Tank acoustic data.

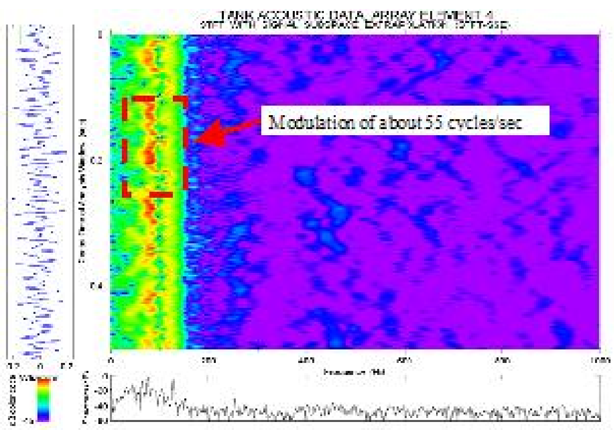

Figure 4: New subspace data extrapolation TFA computed with same tank data.

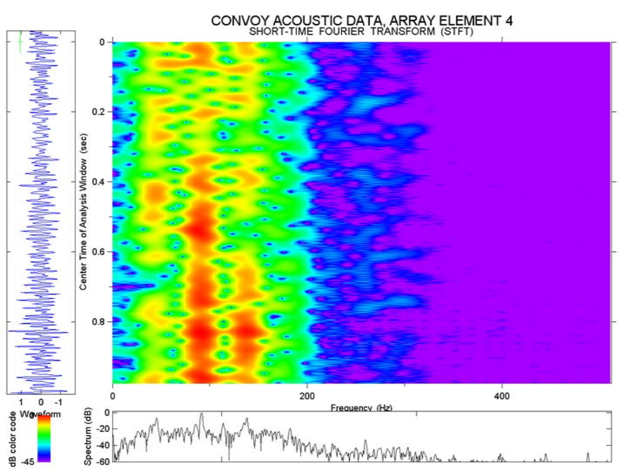

Figure 5: STFT TFA computed using Convoy acoustic data.

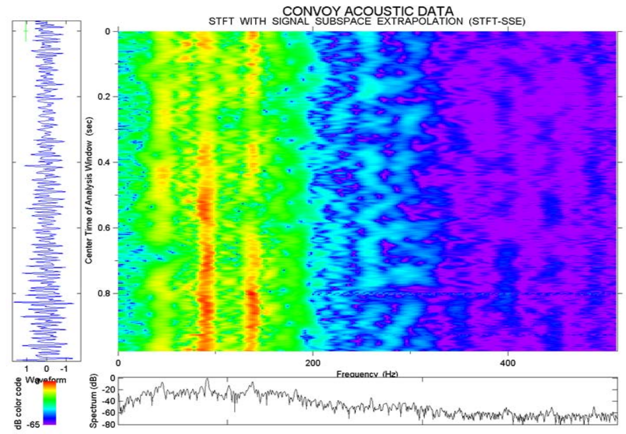

Figure 6: STFT New subspace data extrapolation TFA computed with same convoy data.

For example, the STFT TFA in Fig. 3 is not able to resolve multiple nonstationary signal components from actual sampled data collected of a M60 tank. However, the new subspace technique does resolve two dominant signal components at about 68Hz and 108Hz. In addition to resolving these components it reveals a time-frequency modulation on the 68Hz component of about 55Hz that was completely obscured in the STFT TFA. Similar improvements in resolvable detail are shown in Fig. 5 and Fig. 6, using actual sampled data collected of a two vehicle convoy. In Fig. 6, three main signal components are resolved with additional nonstationary detail. Additional research into the sources of these newly resolved signal components may lead to target-specific signatures that can be used to increase the accuracy of classification algorithms. Future collections and processing will focus on exploring this further.

ACKNOWLEDGMENT

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