ABSTRACT
Receiver systems designed to simultaneously act on multiple wideband signals of interest must be able to differentiate between the different wideband signals of interest in the electromagnetic environment. Separation of interference sources from signals of interest relies on a system having either spatial or spectral diversity to detect and remove the interference sources. If interference sources are co-located in either frequency or space with the signal of interest classical techniques fail to resolve the signals of interest within the interference. This paper presents a new signal disambiguation algorithm with both spatial and spectral diversity that is able to act in a congested electromagnetic environment and distinguish between multiple signals of interest while rejecting noise co-located in frequency and/or space with the signals of interest.

Index Terms—Adaptive arrays, Adaptive algorithm, Detection algorithm.

1. INTRODUCTION
Beamforming applies complex filter weights to each channel of a multi channel receiver. Applying the filter weights and summing the output provides an estimate of the desired signal of interest (SOI) [1]. Modern receiver designs form multiple simultaneous beams by simultaneously applying multiple sets of filter weights to the array data to form estimates of multiple SOI. Defining filter weights for a beamformer requires knowledge of the direction of arrival (DOA) of the SOI and possibly knowledge of each interference source’s DOA. Classical statistical DOA estimation techniques can provide estimates of the DOA of all signals in a given electromagnetic environment. Furthermore, statistical detection techniques can detect the presence of signals at a given angle or in the environment as a whole. What is required for a modern receiver is a separation of the electromagnetic environment into SOI and interference signals with an associated DOA for each. There is currently no single statistical technique able to perform this task. This paper does not attempt to provide the signal and interference disambiguation using a single statistical process. Rather, this work creates an efficient manner for disambiguating signals and interference sources using recent developments from cognitive radio research.

Consider a SOI with known spectral content. If the interference signals and signals of interest have spectral separation, then filtering the receiver’s array data separates the SOI from the interference. Applying a DOA estimation algorithm to the filtered array data yields only the DOA associated with the SOI. When there is no spectral separation between the SOI and interference signals, however, DOA estimation algorithms return the DOA for both the SOI and the interference signals with no method of distinguishing between SOI and interference DOA.

This paper presents a new signal disambiguation algorithm that uses spatial and spectral sub-banding to detect and estimate the DOA for multiple SOI in an interference environment. The algorithm is able to distinguish between multiple SOI and interference signals co-located in the same spectral region as the SOI.

The paper is organized as follows. Section 2 presents the design of the signal disambiguation algorithm to include the spectral estimation and detection algorithms embedded in the larger algorithm. Section 3 applies the disambiguation algorithm to a simulated electromagnetic environment and presents the results showing how the signals are separated. Section 4 concludes the paper by presenting final thoughts on the disambiguation algorithms performance.

2. DISAMBIGUATION ALGORITHM
The signal disambiguation algorithm is an adaptive algorithm that acts directly on sampled receiver array data. A priori the algorithm knows only the type of SOI and the expected spectral location of the SOI. The disambiguation algorithm uses the spectrum of the SOI as a discriminator and rejects all signals not matching the correct spectral profile. Interference sources and SOI are identified by their direction of arrival information. The DOA information is integral to the algorithm’s operation and was the natural choice for signal identification. Figure 1 is a diagram of the disambiguation algorithm structure.
Fig. 1. Diagram of disambiguation algorithm showing the multi-taper method spectral estimation and proposed method for separating signals of interest from interference sources.

2.1. Spectral and Spatial Filtering

The first processing step is to spectrally filter the data from each receiver channel to eliminate all signals that do not match the SOI spectral profile. For narrowband signals this processing step may be enough to completely separate the SOI from interference, however, with wideband signals and interference sources it is possible that some of the spectral content from an interference source remains present in the filtered array data. Spatial processing removes any remaining interference signals from the data. Applying spatial processing requires first estimating the DOA of all signals in the filtered array data and applying spatial filters (beamformers) toward each detected SOI. Each set of spatially filtered data is then checked against the SOI spectrum discriminator a second time and all non-conforming signals are discarded as interference signals.

Because the signals of interest, and possibly the interference signals, are wideband classical DOA estimation techniques such as MUSIC and ESPRIT are not applicable. DOA estimation requires more computationally complex methods when the signals are wideband. Most such methods use subbanding to estimate all signals in the electromagnetic environment. For accuracy such methods need to use coherent techniques; one such algorithm is the focusing method of Kaveh [2].

Kaveh frequency sub-bands the measured array data. He then formulates a narrowband covariance matrix \( \mathbf{R}(f) \) from each sub-band. Each narrowband covariance matrix is then focused to a center frequency such that all signals appear to have the center frequency as

\[
\mathbf{R}_f(f_c) = \mathbf{T}(f_i) \mathbf{R}(f_i) \mathbf{T}^H(f_i),
\]

where the computation is performed over a discrete set of frequencies \( f_i \) based upon the number of FFT points used to sub-band the data; \( (\cdot)^H \) is the Hermitian operator. Each \( \mathbf{T}(f_i) \) is found using the singular value decomposition of \( \mathbf{R}(f_i) \) as [3]:

\[
\mathbf{T}_{f_i} = \mathbf{U}(f_i) \mathbf{V}^H(f_i).
\]

Direction of arrival estimation is exacted by applying the multiple signal classification (MUSIC) algorithm to the average of all \( J \) focused sub-matrices where \( J \) is the number of frequency divisions used to sub-band the array data. The averaged, focused, covariance matrix is found as:

\[
\mathbf{R}_{foc} = \sum_{i=1}^{J} \mathbf{T}(f_i) \mathbf{R}_f \mathbf{T}^H(f_i).
\]

After the DOA estimation is complete, a spatial filter bank is formed placing a frequency invariant spatial beam toward each estimated DOA. At this point the electromagnetic environment has been parsed into spatial beams each pointing toward a signal with spectral content co-located with the known SOI spectral content.

2.2. Three-of-Three Detection

The three-of-three detection algorithm operates on the premise that only SOI will have spectral content across the entire a priori known SOI spectral range. A spectral estimate of each spatial sub-band is formed and a generalized likelihood ratio test (GLRT) is applied to each third of the spectral estimate. If a SOI is present the GLRT for each sub-band returns hypothesis \( H_1 \) i.e., that a signal is present. If less than three sub-bands return \( H_1 \) then the signal in that spatial sub-band does not have the desired spectral content and is not an SOI.

The signal detection method of applying a GLRT to a spectral estimate is taken from the cognitive radio literature. In cognitive radio spectral estimates are used to detect spectral holes by applying a GLRT [4]. The current problem is the opposite, to find filled spectral regions but the methodology is the same.

Signal detection requires an unbiased low covariance spectral estimate. Cognitive radio uses the multi-taper method (MTM) spectral estimate of Thomson [5]. Thomson et al. developed the MTM estimator based on the work of Slepian with discrete prolate spheroidal sequences (DPSS) [5, 6].

Thomson applied discrete prolate spheroidal sequences (DPSS) to multi taper spectral estimates. Thomson’s multi taper spectral estimate is formed from the averaging of a number of direct spectral estimates as:

\[
\hat{S}^{(mt)}(f) \triangleq \frac{1}{K} \sum_{k=0}^{K-1} \hat{S}_k^{(mt)}(f),
\]

where

\[
\hat{S}_k^{(mt)}(f) \triangleq \Delta t \left| \sum_{t=1}^{N} h_{t,k} X_t e^{-i2\pi ft\Delta t} \right|^2,
\]
$h_{t,k}$ is the data taper (DPSS) for the $k^{th}$ direct spectral estimator $\hat{S}^{(mt)}_{k}(\cdot)$ and $X_t$ are realizations of a stationary process of which a spectral estimate is desired. The MTM spectral estimators used in practice are regularized versions of the standard MTM estimate provided in (4). The regularized MTM estimates are defined as [7]:

$$\bar{S}^{(mt)}(f) \triangleq \frac{\sum_{k=0}^{K-1} \lambda_k \hat{S}^{(mt)}_{k}(f)}{\sum_{k=0}^{K-1} \lambda_k},$$

where $\lambda_k$ is the eigenvalue associated with the $k^{th}$ DPSS.

A GLRT is chosen over other detection techniques because it satisfies the Neyman-Pearson criteria of maximizing probability of detection for a given probability of false alarm while utilizing the available data. A standard likelihood ratio test, that also satisfies Neyman-Pearson criteria is not applicable because the test statistics for the environment estimation algorithm are formed from estimated data, and so the exact probability density functions of the data samples are not known.

The form of the GRLT used for signal detection is given as

$$T_{LRT}(\bar{S}^{(mt)}(f)) = (K - 1) \cdot \sum_{k=0}^{N-1} \ln \left[ \bar{S}^{(mt)}(f_k) \right] \frac{\mathcal{H}_1}{\mathcal{H}_0} \xi''$$

with $T_{LRT}$ as the test statistic and $\xi''$ as the threshold value for spectrum sensing.

After the three-of-three detect algorithm is applied to each spatial-sub-band the results are collated and a listing of the number of SOI with a corresponding DOA estimate for each SOI provided.

3. DISAMBIGUATION ALGORITHM PERFORMANCE TEST

Verifying the disambiguation algorithm performance is done through application of the algorithm to a simulated set of array data. The array is a 64 element uniform linear array with half wavelength element spacing for a maximum design frequency of 750 MHz. The array output is sampled at 1.5 Gsamp/sec. The electromagnetic environment consists of three signals. One signal is the SOI incident at broadside, Table 1 provides the signal parameters for the three signals in the environment.

<table>
<thead>
<tr>
<th>Signal</th>
<th>Bandwidth</th>
<th>$f_c$</th>
<th>DOA</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOI</td>
<td>300 MHz</td>
<td>400 MHz</td>
<td>0°</td>
</tr>
<tr>
<td>Int 1</td>
<td>200 MHz</td>
<td>300 MHz</td>
<td>−45°</td>
</tr>
<tr>
<td>Int 2</td>
<td>200 MHz</td>
<td>600 MHz</td>
<td>30°</td>
</tr>
</tbody>
</table>

Figure 2 provides a spectral estimate of the spectrum for the electromagnetic environment. The there is no noticeable separation of signals in the estimate and so the interference sources cannot be differentiated form the SOI using frequency filtering.

Fig. 2. MTM Spectral Estimate of the Interference Environment

The MUSIC spectrum of the electromagnetic environment after a third order Butterworth filter with cutoff frequencies at 300 MHz and 600 MHz is plotted in Figure 3. There are three signals present in the filters data at the angles of $0^\circ$, $−45^\circ$, and $30^\circ$ demonstrating that spectral content from all three signals is present in the filtered data.

Fig. 3. MUSIC Spectrum For Filtered Environment Data

The data is then spatially filtered into three spatial sub-bands. The MTM spectral estimate of the $−45^\circ$, $0^\circ$, and $30^\circ$ spatial sub-bands are plotted in Figure 4, Figure 5, and Figure 6 respectively. The three subdivisions of the spectrum for the three-of-three detection algorithm are plotted as dashed lines in each plot. In Figure 5, representing the SOI, spectral content is present in all three sub-bands and the GLRT returns a one for all sub-bands indicating that a SOI is present. For Figure 4 and Figure 6, however, spectral content is only present in one of the three spectral bands and the GLRT only returns a one for one sub-band indicating that neither of the spatial sub-bands contains a SOI.
Correlating the data from all three sub-band shows that the output from the disambiguation algorithm is able to locate the correct SOI incident from broadside even though the interference sources were partially specially co-located with the SOI.

4. CONCLUSIONS

Modern passive receivers attempting to locate and estimate multiple SOI in an electromagnetic environment have to detect and locate all SOI embedded in directional interference signals. If the interference signals are spectrally co-located with the SOI separation cannot be achieved through simple filtering operations.

This paper demonstrated a signal disambiguation algorithm that operates in congested interference environments and is able to distinguish SOI from interference sources and provide estimates of DOA for all SOI in the environment. This algorithm is capable of distinguishing between SOI and interference sources when there is a large degree of spectral overlap between the SOI and the interference sources.

5. REFERENCES


