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MULTI-CHANNEL SIGNAL DETECTION USING TIME-VARING ESTIMATION TECHNIQUES

Kofi Ghartey, Douglas Cochran and Antonia Papandreou-Suppappola

Telecommunications Research Center, Department of Electrical Engineering
Arizona State University, Tempe, AZ 85287–7206
E-mail: ghartey@asu.edu, cochran@asu.edu, papandreou@asu.edu

ABSTRACT

We propose to improve the performance of a generalized coherence (GC) detector using noise-suppressed estimates obtained from time varying (TV) techniques. In source detection and localization, the presence of a common but unknown signal must be detected using data from several noisy channels. If one of the channel outputs has a sufficiently high SNR, then it could be pre-processed to improve detector performance. This work uses the matching pursuit decomposition (MPD), and instantaneous frequency (IF) estimation to form an estimate of the highest SNR channel output. The signal estimate is then processed by a GC detector or a generalized likelihood ratio test (GLRT) detector to detect the presence of the signal on the remaining, noisier channels. Detector performance is shown to be significantly improved via simulations.

1. INTRODUCTION

Multi-channel signal detection is widely used for source detection and localization, for example in biomedical diagnosis and machine monitoring. Often, a common but unknown signal is to be detected and its source located using noisy data collected from two or more spatially distributed sensors [1]. The GC, which extends the two-channel magnitude squared coherence (MSC) detector, has been successfully used as a detection statistic for any M channels [1–3]. However, the performance of a GC detector decreases when used for low SNR data. This decrease may be counteracted by the addition of extra channels to the GC detector system [1]. Improvement, however, requires the SNR of every newly added channel to be at least 6 dB greater than the lowest SNR channel in the system [1].

The addition of an extra channel may be improbable or simply too costly in some applications. Hence, if one could obtain a relatively high SNR on one of the existing channels, then this channel output could be pre-processed to improve the performance of the ensuing detector [4]. In a two channel detector, for example, we will show in this paper that we can obtain an estimate of the signal from the high SNR channel, and then use it in a GLRT [5] on the second, lower SNR, channel. As expected, the performance will depend on the quality of the signal estimate.

This work examines the use of TV signal processing techniques, namely the matching pursuit decomposition (MPD) algorithms and TF instantaneous frequency (IF) estimators as pre-processing tools to provide signal estimates as inputs to GC detectors or GLRT detectors. We will demonstrate that such pre-processing steps yield improvement gains over a regular GC detector, as well as extra signal information.

2. GC MULTI-CHANNEL DETECTION

The GC has been established as a statistic for measuring the similarity between two or more data sequences [2, 3], and therefore lends itself well to the detection of a common but unknown signal on several spatially distributed sensors. For any M data sequences, $x_i(n), i = 1, ..., M$, each of length N, the GC statistic, $\lambda^2_{M,N}$, is defined from [2, 3] as

$$\lambda^2_{M,N}(x_1, ..., x_M) = 1 - \frac{g(x_1, ..., x_M)}{||x_1||^2 ... ||x_M||^2} \qquad (1)$$

where $g(x_1, ..., x_M)$ is the determinant of the Gram matrix

$$\mathbf{G}(x_1, ..., x_M) = \begin{bmatrix} \langle x_1, x_1 \rangle & \dots & \langle x_1, x_M \rangle \\ \vdots & \ddots & \vdots \\ \langle x_M, x_1 \rangle & \dots & \langle x_M, x_M \rangle \end{bmatrix}.$$

Here, $\langle x, y \rangle = \sum_{n=0}^{N-1} x[n] y^*[n]$ and $||x||^2 = \langle x, x \rangle$. For $M = 2$ channels, the GC in Equation (1) simplifies to the magnitude squared coherence (MSC) estimate that is given by

$$\lambda^2_{2,N}(x_1, x_2) = \frac{|\langle x_1, x_2 \rangle|^2}{||x_1||^2 ||x_2||^2} = \lambda^2. \qquad (2)$$

The GC detector follows Figure 1.

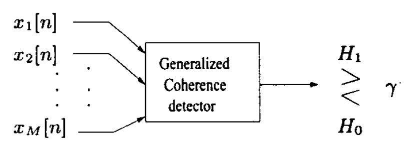

Figure 1: Multiple channel GC detector.

An invaluable property of the GC in detector design [1, 2] is that its statistical properties are well understood for the H_0 hypothesis. The probability of false alarm, P_{FA}, can therefore be calculated from the H_0 hypothesis, and its corresponding probability of detection, P_D, can be obtained via Monte Carlo simulations. Derivations in [1] show the P_{FA} of an MSC detector ($M = 2$) as $P_{FA} = (1-\gamma)^{N-1}$, where γ is the detection threshold and N is the number of signal samples. For a three channel detector,

$$P_{\text{FA}} = (1-\gamma)^{N-1} + (N-1)(N-2)(1-\gamma)^{N-1} \log (1-\gamma) + (N-1)^2[(1-\gamma)^{N-2} - (1-\gamma)^{N-1}].$$

3. ESTIMATION IN MULTI-CHANNEL DETECTION

A signal in time generally possesses no spectral information and most of its temporal information may be lost as it is decomposed into its frequency components via the Fourier transform [6]. Thus, time-varying signals require analysis in the joint time-frequency (TF) plane for complete characterization including the temporal localization of spectral peaks. We propose the use of TF techniques, namely the matching pursuit decomposition (MPD) iterative algorithm and IF estimation techniques to obtain a noise-suppressed estimate of the highest SNR channel output in a multi-channel detector. This estimate can then be used for better detection of the common signal on the other, lower SNR, channels as will be shown in Section 4.

3.1. Modified MPD algorithm

Signal decomposition over a dictionary of functions that are well localized both in time and frequency is widely encountered in signal processing and harmonic analysis [7]. Such functions are called TF atoms [7,8]. A dictionary can be formed from a basic Gaussian atom that has been TF shifted and scaled to cover the region of the TF plane of interest [7].

While a dictionary of Gaussians may be suitable for any signal, it is computationally expensive and slow as it takes longer to converge. It was shown in [8] that if we know a priori the structure of the signal to be decomposed, then the dictionary atoms can be formed to adapt closely to the signal. To decompose a linear FM (LFM) chirp, for example, would require a dictionary consisting of a basic Gaussian chirp that has been TF shifted over the TF plane and undergone a transformation that causes a constant shift of its IF [8]. For an LFM such a transformation would correspond to a shift on its FM chirp rate of the received signal. The received signal can then be expanded as [4, 7, 8]

$$x(t) = \sum_{n=-\infty}^{\infty} a_n h(t-\tau_n) e^{j2\pi v_n t} e^{j2\pi \frac{\beta_n}{2} t^2},$$

where $h(t) = e^{-j2\pi t^2}$ is the FM chirp, (τ_n, v_n) are the TF shifts at the nth iteration of the MPD, β_n is the change in FM rate, and a_n is a weighting coefficient corresponding to the correlation between the nth dictionary atom and the LFM.

For any signal in noise with a high SNR, signal components will be more localized than noise terms in the TF plane. Hence, during decomposition, signal terms will be extracted first [7, 8]. The matching pursuit uses this property to extract signal terms from noisy signals until some iteration, when nearly all signal atoms have been extracted or when the residual signal energy approximately equals the energy of the noise [7]. Note that MPD detection with Gaussian atoms has been studied in [7].

3.1.1. MPD in GC detection

In many multi-channel signal processing applications, one of the channels will have a relatively high SNR than all others in the system. Our multi-channel detection method proposes to extract the common signal from the highest SNR channel using the modified MPD algorithm. The extracted signal, say $x_1[n]$, will then be used to detect the presence of the signal from the remaining low SNR channels, as depicted in Figure 2.

This method has been extensively studied in [4]. In a two-channel system, potentially optimal detector performance can be obtained with the GLRT, instead of an MSC, and we discuss this in the next section.

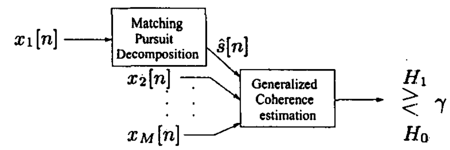

Figure 2: Block diagram of the GC detector that utilizes the MPD algorithm. Here, $x_1[n]$ is assumed to be the output of the highest SNR channel, and $\hat{s}[n]$ is the MPD estimate.

3.1.2. MPD in GLRT detection

A GLRT detector pertains to the detection problem where a deterministic signal with unknown parameters is to be detected in additive white Gaussian noise [5]. The MPD will be used to obtain a reasonably good estimate of the transmitted signal from the high SNR channel permitting the use of a GLRT. The MPD decomposed signal estimate has a low mean squared error (MSE) [4]. Thus, the resulting detector (though not optimal) is expected to be close to the optimal MF detector performance depending on the MPD success. A GLRT detector that uses the MPD algorithm is shown in Figure 3 with two channels. The GLRT detection statistic for the output of a noisy channel is derived in [5] as

$$T(x) = \sum_{n=0}^{N-1} x[n]\hat{s}^*[n] - \frac{1}{2}\sum_{n=0}^{N-1} |\hat{s}[n]|^2. \tag{3}$$

The detection threshold for a fixed probability of false alarm P_{FA} is $\gamma = \sqrt{\sigma^2 \mathcal{E}_{\hat{s}}/N} \cdot Q^{-1}(P_{FA})$ [5]. Here, $\mathcal{E}_{\hat{s}}$ is the energy of the signal estimate, and $Q^{-1}(\cdot)$ is the inverse Q-function.

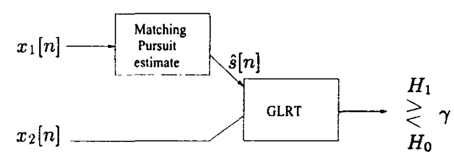

Figure 3: Block diagram of the GLRT detector using two channels that utilizes the MPD estimate, $\hat{s}[n]$.

The MPD has high memory usage and is computationally expensive. As a result, despite the huge performance gains provided by the GLRT-MPD and MSC-MPD (two channels), one has to consider the trade-off between high performance and cost. Another TF technique capable of generating a noise-suppressed equivalent of the high SNR channel, but with lower computational and memory requirements than the MPD, is the use of TF instantaneous frequency estimation techniques.

3.2. TF IF estimation

The IF depicts the time varying spectral peaks of a non-stationary mono-component signal [9]. Mono-component signals have only a single or narrow range of frequencies for any time instant [9]. However, methods have been developed to estimate the IF of multi-component signals [10]. For simplicity, we limit this section of our study only to mono-component signals.

The IF of any signal follows the highly localized regions of its TF distribution, and a mapping of this region yields the IF estimate [11]. Every TF representation is best suited for some signal structure and the ideal choice of TF distribution for IF estimation is the one that produces the best TF resolution for the signal under consideration. For this work, we consider LFM chirps whose Wigner distribution (WD) provides good localization of chirps in the TF plane. For a signal $y(t)$, the WD is defined as [6], $W_y(t,f) = \sum_{n=-\infty}^{\infty} y(t+nT)y^*(t-nT)e^{-j4\pi fnT}$. The IF estimate, $\hat{f}_i(t)$ follows as, $\hat{f}_i(t) = \arg\{\max_f [W_y(t,f)]\}$.

3.2.1. *TF IF estimation in GC and GLRT detection*

Any complex signal, $s(t)$, with constant amplitude, A and IF, $f_i(t)$, can be expressed as $s(t) = Ae^{j2\pi\int f_i(t)dt}$ [9]. If one could obtain very good estimates of the signal's amplitude and IF, then a noise-suppressed estimate of the signal can be reconstructed from these estimates as $\hat{s}(t) = \hat{A}\,e^{j2\pi\int \hat{f}_i(t)dt}$. This section proposes to use this signal estimate, instead of the MPD estimate, to reduce the computational cost and still yield improved detector performance. Note that we follow the method of [11]. However, we only use the WD as it is ideal for LFMs. The IF based signal estimate depends on the estimates $\hat{A}$ and $\hat{f}_i(t)$. Hence, any bias in the IF estimates will have a significant effect on the detector performance.

4. SIMULATIONS AND PERFORMANCE COMPARISON

We demonstrate the improved performance of our proposed methods by simulating a two-channel detection problem with complex chirp sequences of length $N = 300$ and for varying SNRs. We first consider an MSC detector that uses the channel 1 decomposed signal from (a) the MPD algorithm (MSC-MPD), and (b) the IF estimation technique (MSC-IF). We repeat (a) and (b) using a GLRT, instead of the MSC, to form the GLRT-MPD, and GLRT-IF detectors. All methods are simulated using 1000 Monte Carlo simulations, and the results are demonstrated using receiver operating characteristic (ROC) curves in Figures 4 – 8.

4.1. MSC with different signal estimates

4.1.1. *MPD with MSC approach*

Figure 4 shows the performance of the MSC-MPD (dash-dotted) compared to the MSC (solid lines) for a fixed -19 dB SNR on channel 2, while the channel 1 SNR decreases from 10 dB to -10 dB. This ascertains that the MSC performs well for high channel 1 SNRs, but its performance retrogresses as channel 1 becomes noisier. Our proposed pre-processing method retains high performance even for low channel 1 SNRs (as seen by the closeness of the MSC-MPD ROC curves in Figure 4). As no pre-processing was performed on channel 2, any increase or decrease in channel 2 SNR will have similar performance gains or losses (respectively) in both MSC and MSC-MPD detectors. However, for a very low SNR on channel 2, the common signal will be overwhelmed by noise such that no amount of pre-processing on the output of channel 1 will yield any performance gain as shown in Figure 5.

An ideal MPD is terminated after all signal terms have been extracted or when noise terms become the most localized terms in the TF representation of the residual signal [7, 8]. Thus, if the MPD is terminated long before this critical point (i.e. under-decomposed), then some dominant terms in the transmitted signal will be lost and hence a larger MSE for the noise-suppressed estimate and consequently poorer performance gain will be obtained. Similarly, if the MPD is continued even after this critical point (i.e. over-decomposed), noise terms will be included in the

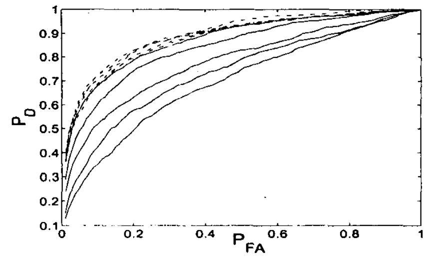

Figure 4: ROC curves showing the stable performance of the MSC-MPD (cluster of dash-dotted lines) to the diminishing performance of the MSC as channel 1 SNR decreases from 10 dB in increments of 5dB, with a fixed channel 2 SNR = -19 dB.

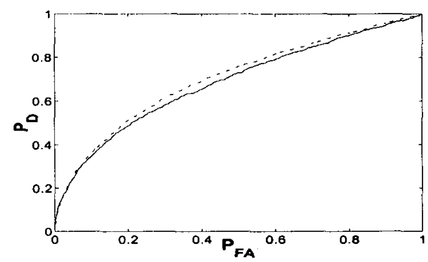

Figure 5: ROC curves for MSC (solid line) and MSC-MPD detector performances for 0 dB SNR on channel 1 and -25 dB on channel 2.

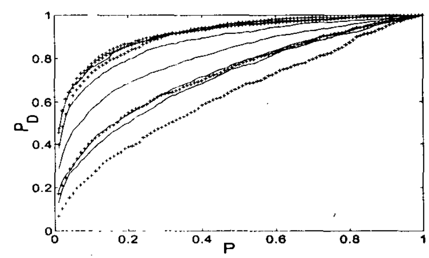

Figure 6: ROC curves comparing the MSC (solid lines) to the MSC-IF as the SNR of channel 1 decreases from 10 dB, 5 dB, 0 dB, -5 dB, and -10 dB respectively. Channel 2 SNR is -19 dB.

noise-suppressed estimate. The performance comparison of the two methods is further studied in [4].

4.1.2. *IF with MSC approach*

The IF estimation technique was shown to be a viable alternative for the MPD algorithm but yielded favorable MSEs only for a limited range of SNRs. This is attributed to the trade-off between performance and computational cost for signal estimates. Figure 6 compares the performance of the MSC-IF to the MSC over the range of channel 1 SNRs considered for the MSC-MPD. The MSC-IF out-performs the MSC for high channel 1 SNRs, but is more susceptible to noise than the MSC-MPD. The favorable region of operation for the MSC-IF is between -5 dB and 5 dB, compared to the -12 dB and 10 dB of the MSC-MPD. However, within this favorable region, the MSC-IF performs equally well as the MSC-MPD.

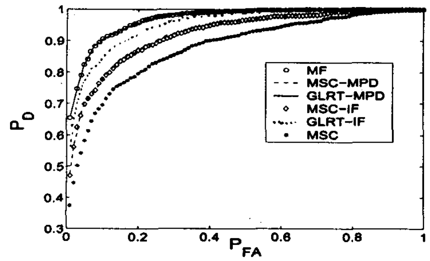

Figure 7: ROC curves for, 5 dB SNR on channel 1 and -19 dB SNR on channel 2.

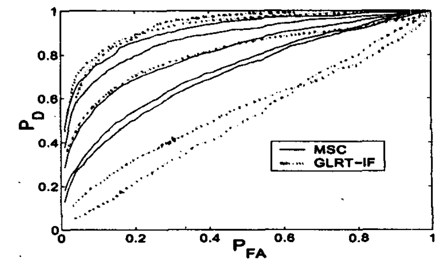

Figure 8: ROC curves comparing the MSC (solid lines) to the GLRT-IF (dots) as the SNR of channel 1 changes from 10 dB, 5 dB, 0 dB, -5 dB, and -10 dB, respectively.

4.2. GLRT with different signal estimates

4.2.1. MPD with GLRT approach

In the two-channel GLRT detector, we observe improved detector performances over the MSC-MPD. As the noise-suppressed estimate obtained from the high SNR channel has a very small magnitude squared error (MSE), the resulting performance of the GLRT-MPD is comparable to that of an optimal matched filter (MF), where the signal is completely known. Figure 7 shows the performance of a GLRT-MPD (solid line) to be approximately the same as an optimal MF (circles) as they overlap each other. This simulation used 5 dB SNR on channel 1 and -19 dB SNR on channel 2. While negligible performance gains are obtained with the MSC-MPD for such high channel 1 SNRs (see Figure 4), we observe significant gains with the GLRT-MPD.

Except for the increase in gain, the performance pattern of the GLRT-MPD follows that of the MSC-MPD. Note that with the optimal or near optimal performance, the GLRT-MPD also permits reasonable detection even at lower channel 2 SNRs, when all the above mentioned methods succumb to the poorer detector performance associated with lower SNRs.

4.2.2. IF with GLRT approach

Figure 8 summarizes the performance of the GLRT-IF over the range of channel 1 SNRs considered for the preceding methods. The GLRT-IF though, outperforms the MSC (solid lines) for high SNRs, has the narrowest range of channel 1 SNRs (0 dB – 5 dB) for improved performance gain. The magnitude of the performance gain for the GLRT-IF, even within its favorable region of operation, is the least among all the proposed methods. This is because the GLRT requires a low MSE signal estimate, compared to the high signal MSE obtained via IF estimation.

For operation within a favorable region, common to all proposed methods (see Figure 7), the tremendous improvement in detector performance (even at much lower channel 1 SNRs) of the GLRT-MPD makes it very suitable for two-channel detection in high noise applications when compared to the MSC-MPD. However, the MSC-IF or GLRT-IF can be used instead of the MSC-MPD or GLRT-MPD when computational power and memory are limited. From Figure 7, for a relatively high SNR on channel 1, the IF approach will be chosen over the MPD for a trade-off between cost and performance.

5. CONCLUSION

In [4], we showed that the performance of the MSC could be improved with the MPD. Here, we successfully used the GLRT with MPD to obtain near optimal detector performances. For applications with a limited computational budget, we have successfully demonstrated that IF estimation techniques (instead of MPD) could be used, together with a GC or GLRT to improve the performance of a multi-channel MSC detector. An aspect of this study that needs further attention is its extension to multi-component and multi-type signals. We also assumed a known highest SNR channel. If this assumption does not hold, then methods will have to be developed to identify this high SNR channel.

6. REFERENCES

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