A Sub-Space Method to Detect Multiple Wireless Microphone Signals in TV Band White Space

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***Abstract*—Hurdles still remain in the realization of dynamic spectrum access (DSA) systems due to the uncertainty associated with spectrum sensing at extremely low signal to noise ratio (SNR) conditions. One such challenge is to detect the presence of wireless microphones (WMs) in the TV band. In this paper, we propose a method for detecting the presence of multiple narrow-band analog frequency-modulated signals that are generated by WMs. In addition, the algorithm can determine the center frequencies of multiple signals. We use real WM signals experimentally captured under low SNR conditions to verify the detection performance of our algorithm.**

I. Introduction

In recent years, there has been significant research focus on TV band devices (TVBDs) that use dynamic spectrum access (DSA) technology. These devices are designed to operate unlicensed in unused radio spectrum when primary users are not operating. Because of the way that television stations are allocated spectrum in the United States, the TV bands have become the focus of FCC rule making [1] on TVBDs. TVBDs will operate in the same core TV Bands that licensed WMs operate in. Hence, future TVBDs are required to sense WM and TV signals under extremely low SNR conditions to avoid causing harmful interference to the licensed users.

WM signals are difficult to detect due to their unique characteristics and also due to the FCC's very demanding detection requirements. RF power output on WM transmitters ranges between 10 mW and 250 mW, though a common figure for professional systems is 50 mW. Professional WM systems operate in the high-band VHF and UHF TV bands. Within these bands, WM systems may operate on any unused frequency that is a multiple of 25 kHz. The vast majority of WM systems use analog wide-band frequency-modulation to improve reliability and audio quality. The maximum deviation from the carrier frequency is set to ± 75 kHz by the FCC. This means that the power output is spread over a relatively wide range when the microphone sees a large input signal, making detection more difficult. There are a few systems that use a digital link to prevent signal interception, but these systems represent a very small portion of the WMs in use today. The FCC specified in Docket 08-260 [1] that TVBDs must be able to detect a WM signal as weak as -114 dBm. In addition, since a WM signal may operate anywhere within a TV channel (or, in fact, on the border of two TV channels), the TVBD must be able to search over a relatively wide bandwidth for a WM signal that is narrow-band in comparison. Moreover, the received signal strength will likely vary as a strong function of time due to fading introduced by transmitter mobility, meaning that a signal may be detected at some times and not at others.

Since TVBDs will be integrated into consumer electronics, it is highly unlikely that they will have external antennas or tight RF front-ends. This increases the possibility that spurious signals will be received or generated by the RF front-end. The end result is that the receiver and detection algorithm is likely to see these spurious signals and potentially classify them incorrectly as WM signals. This is undesirable as it may lead the device to wrongly believe a free TV channel is occupied, thereby reducing the TVBD spectrum utilization.

Several spectrum sensing algorithms have been proposed in the literature. Energy detection is the simplest sensing algorithm to implement but the least reliable and requires knowledge of the noise power [2]. Matched filtering based sensing requires complete knowledge of the transmitted signal, which is impractical in most cases. More sophisticated methods such as cyclostationarity-based detection [3] and eigen value-based detection [4] do not require the knowledge of noise power and perform better than energy detection under low signal-to-noise ratio (SNR) conditions too. The co-variance sensing algorithm [5] performs signal detection based on the co-variance of the received signal. While this method is effective, sub-space methods have proven to be more robust particularly since they are able to separate the noise and signal sub-spaces under low SNR conditions too. Yet another class of methods use the method of maximum entropy. One such algorithm [6] assumes some knowledge of the signal characteristics and required the use of a match filter. In contrast, our proposed algorithm only requires knowledge about the noise characteristics.

This paper presents an algorithm that can detect multiple WM signals in a 6 MHz wide bandwidth in the spectrum. In particular, the algorithm computes the correlation matrix of received signal samples and singular-value decomposition (SVD) of the correlation matrix to determine the number of signals that are present. It then decomposes the space into the signal sub-space and noise sub-space. The autocorrelation of the signal is recovered from the signal sub-space and the center frequencies of the multiple WM signals are determined by Fourier analysis. We distinguish our work from previous work [4], [7] on sub-space methods in two ways. First, we extend previously proposed methods based on SVD to detect multiple signals with the help of multiple thresholds on the test statistics. We note that the multiple thresholds are typically

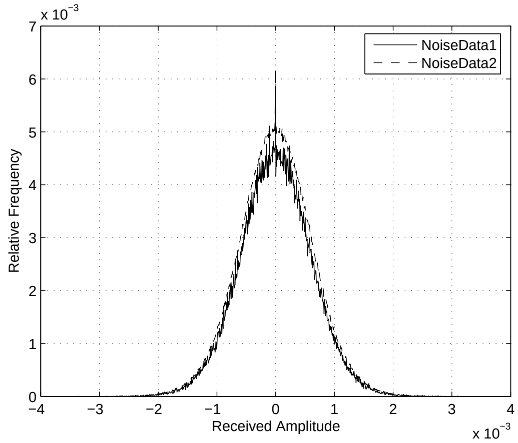

Fig. 1. Histogram of background noise computed from measurement data.

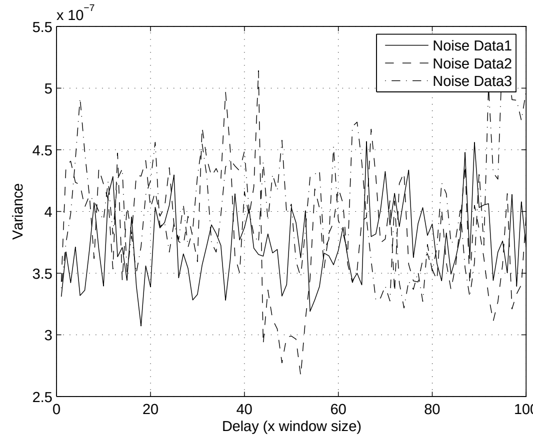

Fig. 2. Variance of background noise at different time instances.

required when the noise is colored. Second, we use real captured signals to verify the detection performance of the algorithm. Third, we aimed at reducing the complexity of existing methods for multi-antenna systems [5] by employing a simple antenna selection scheme as against the more complex approach of coherently combining the signals from the two antennas. While simulation studies on the performance evaluation of sub-space methods under various SNR conditions have been presented in the literature, this paper provides an empirical verification of the proposed algorithm to assess its real-world performance. The experimental data on spectrum occupancy that has been used for the algorithm verification is representative of harsh channel conditions with received power ranging between -100 to -105 dBm.

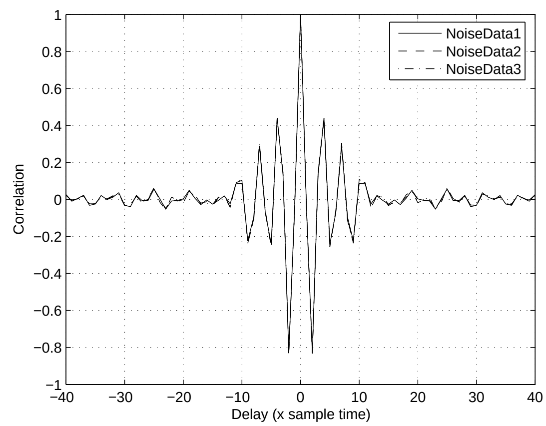

Fig. 3. Autocorrelation of band-limited background noise samples.

II. Measurement Campaign and Noise Characterization

For the purpose of noise characterization and algorithm performance evaluation, different data sets were generated containing unmodulated WM signals, modulated WM signals, and background noise respectively. The modulated and unmodulated signal sets had a WM carrier at 8 MHz, and were sampled at 33 MHz. The signal was bandpass-filtered to simulate a 6 MHz television channel. The received power level in these data sets was specified as being between -100 dBm and -105 dBm.

The various statistical properties of the background noise are examined next. The histogram of the noise samples, shown in Figure 1, appears to be a truncated Gaussian, although we did not formally test the histogram for Gaussianity. With the assumption that the noise is Gaussian, we can simplify the complexity of the algorithm significantly. The histogram is also observed to follow similar trends in different noise data sets ($NoiseData < 1:2 >$).

Figure 2 shows the variance of background noise computed over different time instances from three different noise data sets ($NoiseData < 1:3 >$). The plot indicates that the noise variance does not vary significantly as a function of time. A similar observation was made with the noise mean.

Figures 3 and 4 show the autocorrelation and power spectral density (PSD) of the noise samples. The PSD clearly shows that the noise was band-pass filtered prior to sampling. The autocorrelation plot reflects this as well, showing correlation up to approximately 15 samples. In addition, the noise correlation properties do not vary significantly across the noise data sets.

Figures 5 and 6 show the autocorrelation and PSD of the data samples containing a modulated WM signal. As expected, the autocorrelation differs significantly from Figure 3 in that the correlation with signal present extends out far past 15 samples. It is this property that allows us to use a correlation-based technique to determine whether a WM signal is present in a given data set or not. The autocorrelation of the data samples containing a silent WM signal resembles that in Figure 5, with the exception that the correlation is lesser.

Based on the analysis presented in this section, we observe that the noise is stationary with a near-Gaussian distribution, but it is not white. Rather, the noise is band-limited (colored) due to filtering and sampling in the receiver.

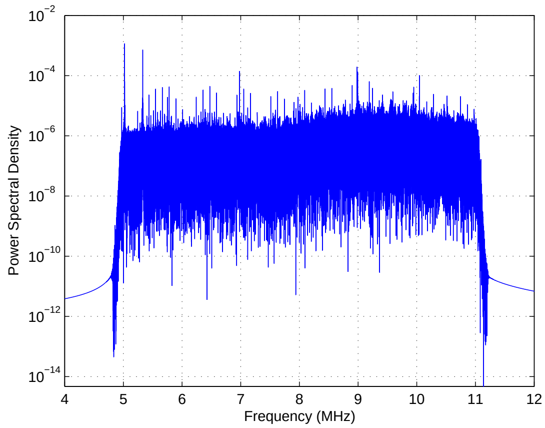

Fig. 4. PSD of band-limited background noise.

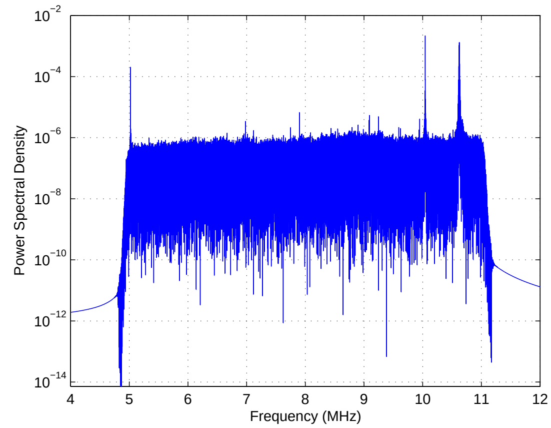

Fig. 6. PSD of modulated WM signal with colored noise.

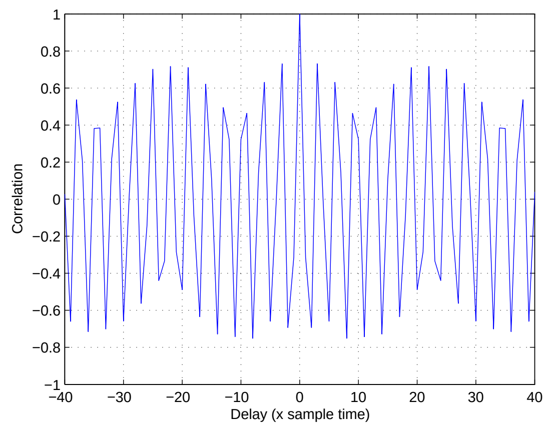

Fig. 5. Autocorrelation of loud (modulated) WM signal with colored noise.

III. SVD Based WM Sensing Algorithm

The working of our proposed algorithm can be classified into two main phases, viz., training phase and detection phase. Main steps involved in these two phases are as follows:

Training Phase:

1) Characterize the noise by using the training data sets ($NoiseData$) having no wireless microphone signal.
2) Compute the average noise correlation matrix from all the training data sets.
3) Subtract this average noise correlation matrix from the correlation matrix of each $NoiseData$ to get the *whitened noise correlation matrices*.
4) Determine the thresholds of the test statistics from the singular values of the whitened noise correlation matrices.

Detection Phase:

1) Compute the correlation matrix of the received signal.
2) Whiten the noise by subtracting its correlation matrix from the received signal correlation matrix.
3) Find the SVD of the resulting correlation matrix and determine the number of signals present by comparing the test statistics with the thresholds.
4) If the signals are present, decompose the space into signal sub-space and noise sub-space.
5) Recover the autocorrelation of the signal from the signal correlation matrix (signal sub-space).
6) Find the center frequencies by the Fourier analysis of the signal autocorrelation.

The received signal samples can be modeled as $x(n) = s(n) + \eta(n)$. The correlation matrix of the received samples can be represented as $\mathbf{R}_x = \mathbf{R}_s + \mathbf{R}_\eta$, where $\mathbf{R}_x = E\left\{x(n)\, x^H(n)\right\}$ is the correlation matrix of the received samples, $\mathbf{R}_s = E\left\{s(n)\, s^H(n)\right\}$ is the correlation matrix of the transmitted signal samples, and $\mathbf{R}_\eta = E\left\{\eta(n)\, \eta^H(n)\right\}$ is the correlation matrix of the noise samples. Note that, s^H denotes the conjugate transpose of vector s and this notation is applied for other matrices and vectors in this paper. In the case when the noise is white and for a smoothing factor L [4], $\mathbf{R}_\eta = \sigma_\eta^2\, \mathbf{I}_L$, where $\mathbf{I}_L$ is an identity matrix of order L. $\mathbf{R}_x$ is computed from the data set containing WM signal. $\mathbf{R}_x$ is an $L \times L$ matrix, where we have used L=500 for our implementation. The value of L was empirically determined as a trade-off between complexity and performance.

A. Noise Whitening

Since the noise is correlated, the noise has to be whitened by removing the correlation components in the noise. By doing so, we confer with the theory of the SVD based spectrum sensing algorithm [7] which assumes that the noise is white. From the noise data sets ($NoiseData < 1 : 3 >$), we can compute an estimate of noise correlation matrix $\widehat{\mathbf{R}_\eta}$ by taking the average of the correlation matrices of the three data sets. The noise correlation matrix can then be used to cancel off the noise correlation component in the received signal correlation matrix, as given by

$$\widehat{\mathbf{R}_s} = \mathbf{R}_x - \widehat{\mathbf{R}_\eta} = \mathbf{R}_s + \mathbf{R}_\mu, \tag{1}$$

where $\mathbf{R}_\mu$ is the correlation matrix of the residual noise. $\widehat{\mathbf{R}_s}$ is the estimate of the correlation matrix of the WM signal assuming that the correlation matrix $\mathbf{R}_\mu$ of the residual noise is negligible compared to $\mathbf{R}_s$.

B. SVD and Test Statistic Threshold

The SVD method can be applied to the cleaned correlation matrix of received signal $\widehat{\mathbf{R}_s}$ to obtain

$$\widehat{\mathbf{R}_s} = \mathbf{U}\ \mathbf{S}\ \mathbf{V}^H = [\mathbf{U}_s \mathbf{U}_\mu] \begin{bmatrix} \mathbf{S}_s & 0 \\ 0 & \mathbf{S}_\mu \end{bmatrix} [\mathbf{V}_s \mathbf{V}_\mu]^H, \qquad (2)$$

where $\mathbf{S}_s$ and $\mathbf{S}_\mu$ are diagonal matrices whose values correspond to the singular values in the signal subspace and noise subspace, respectively. The proposed algorithm uses the ratio of the alternate singular values as the test statistic to determine the number of WM signals present. It is straightforward to show that each WM signal produces two non-zero singular values during SVD of the received signal correlation matrix. Thus, for N_s WM signals, $diag(\mathbf{S}_s)$ will be $[\lambda_1, \lambda_2, \ldots \lambda_{2N_s}]$ and $diag(\mathbf{S}_\mu)$ will be $[\lambda_{2N_s+1}, \lambda_{2N_s+2}, \ldots \lambda_L]$, where $\lambda_1 > \lambda_2 > \ldots \lambda_L$. If there is only one WM signal present, $diag(\mathbf{S}_s) = [\lambda_1, \lambda_2]$ and $diag(\mathbf{S}_u) = [\lambda_3, \lambda_4 \ldots \lambda_L]$.

If only white noise were present, $\lambda_{2x-1}/\lambda_{2x+1} \cong 1$, where x is an integer from 1 to $(L-2)/2$. If N_s number of signals were present, $\lambda_1/\lambda_3 >> 1 \ldots \lambda_{2N_s-1}/\lambda_{2N_s+1} >> 1$ and $\lambda_{2N_s+1}/\lambda_{2N_s+3} \cong 1 \ldots \lambda_{L-3}/\lambda_{L-1} \cong 1$.

As is the case in all the detection algorithms, we need thresholds to make a decision about the presence of the WM signals. The threshold values are determined by applying the SVD to the whitened noise correlation matrices and finding the ratios of the singular values, as given by:

$$\lambda_1/\lambda_3 = \lambda_{\tau_1}, \qquad (3)$$

$$\lambda_3/\lambda_5 = \lambda_{\tau_2}, \qquad (4)$$

$$\ldots$$

$$\lambda_9/\lambda_{11} = \lambda_{\tau_5}. \qquad (5)$$

In the practical setup, we apply the above technique over various noise realizations and try to find the distributions of the singular value ratios. However, due to the limitations in the amount of training data, we can not get the exact distributions and set our thresholds to the maximum values of the ratios found over all noise realizations ($NoiseData$). For the algorithm implementation, it is assumed that there are no more than five WM signals in the measurement data set, and therefore there are five test statistics and five thresholds. The decision to restrict the detection to five signals has been made by empirically observing the performance of the algorithm after setting it to detect larger number of signals. However, the maximum number of WM signals detectable is an easily adjustable variable.

C. Center Frequencies of WM Signals

After identifying the number of WM signals present, the locations of the WM signals are determined by finding the corresponding number of highest peaks from the PSD of the cleaned data. The PSD can be found by taking the FFT of the first row of the correlation matrix $\mathbf{R}_s$, which can be reconstructed from the SVD decomposition shown in equation 2, as given by

$$\mathbf{R}_s = \mathbf{U}_s\ \mathbf{S}_s\ \mathbf{V}_s^H. \qquad (6)$$

Since the correlation matrix $\mathbf{R}_s$ is reconstructed only from the signal subspace, the resulting PSD obtained from $\mathbf{R}_s$ is much cleaner than that obtained from correlation matrix $\mathbf{R}_x$ or even $\widehat{\mathbf{R}_s}$. This makes determining the location of the WM signals much easier and more robust. Note that, if there are data from multiple receiver antennas, the results are chosen from the antenna whose received signal samples infer the highest number of signals.

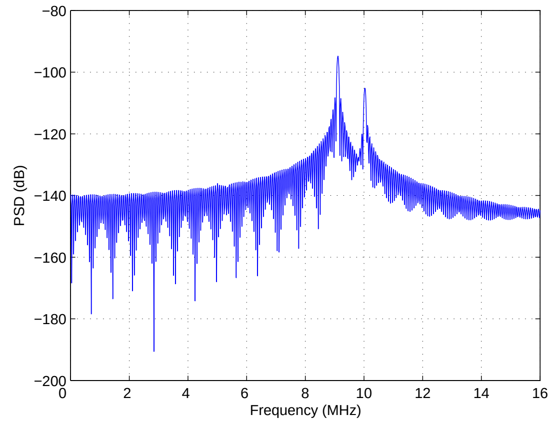

Fig. 7. PSDs obtained from the cleaned-up autocorrelation function $\mathbf{R}_s$.

IV. Empirical Results

The proposed algorithm has been verified and tested on real over-the-air data. The empirical thresholds that were used for our detection are as follows: $\lambda_{\tau_1} = 1.8741, \lambda_{\tau_2} = 1.4505, \lambda_{\tau_3} = 1.5743, \lambda_{\tau_4} = 1.4806$ and $\lambda_{\tau_5} = 1.3152$. Figure 7 shows the PSD obtained from the cleaned-up autocorrelation function $\mathbf{R}_s$ for a data set containing WM signal.

The results have shown that multiple signals can be detected. Independently of the proposed algorithm, the measurement data was also analyzed by visual inspection. In visual inspection, some of the data sets revealed that there are more (nearly twice) number of signals than the ones detected by the proposed algorithm. One possibility is that there could be intermodulation products present in the received signal that share the same subspace as the WM signals itself, in which case the SVD algorithm may not observe any singular values corresponding to the intermodulation products. Hence, the intermodulation products cannot be distinguished from the WM signals in the signal subspace of the SVD.

V. Conclusion and Future Direction

Detecting WM signals in poor SNR conditions using test equipment is a difficult task. Doing the same task with a consumer-grade receiver over a wide band will prove to be even more challenging. This paper has shown how the use of correlation matrices and SVD can detect the presence of extremely weak WM signals and determine what frequencies they operate on.

The current version of the proposed algorithm faces one drawback. It is not capable of examining each signal individually to determine whether it exhibits the characteristics of a frequency-modulated analog audio signal. The next step in this process is to incorporate this information into the algorithm, as well as the capability to calculate potential IM3 products and compare the results to the detected signals to reduce the possibility of false positives (especially over multiple TV channels). More measurement campaigns have to be conducted under different wireless environments in order to obtain more statistically accurate calculations of the test statistic thresholds. One other important research direction would be to evaluate the complexity and performance of the proposed algorithm on software radio platforms including small form factor handsets. We also intend to perform more detailed analysis of the proposed algorithm in order to determine the complexity - performance tradeoffs.

Acknowledgment

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