



# **Reduction of In-Band Interferences' Effect Using Subspace Algorithms in Radio Channel Data**

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Accepted 3<sup>rd</sup> September 2016

*Abstract:* In-band interference increases the noise floor of delay profiles estimated from frequency modulated continuous wave (FMCW) sounder channel data and prevents weak multipath components from being detected. In this study two of the subspace methods named MUltiple SIgnal Classification (MUSIC) and EigenVector (EV) algorithm were used to reduce the effect of interference in delay profiles obtained from an FMCW channel data, and the results are compared with those from conventional FFT method. Results show that MUSIC and EV methods have similar results for time delay estimation, and perform better than the FFT method.

Keywords: In-band interference, RF interference, Music, EigenVector, frequency modulated continuous wave.

# 1. Introduction

Using the same band with desired signal, the interfering signals cannot be suppressed at the receiver, hence distorting the receiver output signal. The output of frequency modulated continuous wave (FMCW) channel sounder is sum of sinusoidal signals. But interference results in abrupt fluctuations in the detector output signal and raises the noise floor. The increase in the noise floor may prevent weak multipath components from being detected [1, 2].

In channel sounding, although the signal processing can be performed off-the-line, measurement campaigns are expensive and difficult to repeat. Since every channel data is valuable for a sound channel model, a technique that alleviates the effect of inband-interference in FMCW mobile radio channel data is desirable. Researchers have used various approaches to reduce the effect of in-band interference.

Previous attempts included clipping the level of interference to the level of desired signal or inserting zeros in place of interference corrupted data [3-5], or Prony modelling [6] of data or Minimum (MN) Norm estimate of the channel delay profiles [7].

Subspace methods have been successfully used in estimating frequency components of a signal. Subspace methods are based on Eigen-decomposition of the autocorrelation matrix into signal subspace and noise subspace. Among these methods are Pisarenko harmonic decomposition (PHD), multiple signal classification (MUSIC), Eigenvector (EV) and MN methods. In [8], a novel algorithm based on extended noise subspace MUSIC method was used for Direction Of Arrival (DOA) estimation under the strong interference conditions. In [9] MUSIC and EV are compared for single source; their performances in relation to errors in resolution were found to be similar, and both performed

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Note: This paper has been presented at the 3<sup>rd</sup> International Conference on Advanced Technology & Sciences (ICAT'16) held in Konya (Turkey), September 01-03, 2016. better than FFT and Pisarenko. For two sources, EV outperformed the other methods in relation to estimation of DOA. In this study MUSIC and EV algorithms are investigated for reducing the effect of interference in FMCW channel data, and the results are compared to those from FFT processing.

# 2. Subspace Methods for Frequency Estimation

Subspace methods are based on eigendecomposition of autocorrelation matrix into signal subspace and noise subspace, and are used for frequency estimation. These methods include PHD, MUSIC, EV MN methods. Pisarenko method uses only one eigenvector. With MUSIC and EV algorithms, the dimension of noise subspace is greater than one, and averaging over noise subspace can be used to improve the performance [10]. These methods are known as high resolution techniques that detect frequency components with a low signal to noise ratios (SNR) [11-12].

#### 2.1. MUSIC Method

We assume the received data, x(n) is a random process consisting of p complex exponentials in white noise with a variance of  $\sigma_w^2$ . Such a signal can be written as:

$$x(n) = \sum_{i=1}^{p} A_i e^{-jw_i n} + y(n)$$
(1)

where  $A_i$  is amplitude of the i-th complex exponentials and  $w_i$  is frequency of the i-th complex exponentials.

 $R_x$  is the MxM autocorrelation matrix of x(n) with M>p+1. If the eigenvalues of  $R_x$  are arranged in decreasing order ( $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_M$ ) and if  $v_1, v_2, \ldots, v_M$  are the corresponding eigenvectors, then these eigenvectors can be divided into two groups: the p signal eigenvectors corresponding to the p largest eigenvalues, and the M-p noise eigenvectors that, ideally, have eigenvalues equal to  $\sigma^2_w$ .  $\sigma^2_w$ . This decomposition can be given as follows:

$$R_x = \sum_{i=1}^M \lambda_i \nu_i \nu_i^H = \sum_{i=1}^p (\lambda_i^s + \sigma_w^2) \nu_i \nu_i^H + \sum_{i=p+1}^M \sigma_w^2 \nu_i \nu_i^H$$
(2)

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The white noise variance can be estimated by averaging the M-p smallest eigenvalues as follow:

$$\sigma_{\rm w}^2 = \frac{1}{M-p} \sum_{k=p+1}^{M} \lambda_k \tag{3}$$

The MUSIC method frequency estimation function is as follows [7]:

$$\hat{\mathbf{P}}_{\mathrm{MU}}(\mathbf{e}^{\mathrm{jw}}) = \frac{1}{\sum_{i=p+1}^{M} \left| \mathbf{e}^{\mathbf{H}} \mathbf{v}_{i} \right|^{2}}$$
(4)

where  $v_i$  are the noise eigenvectors and

$$e = \begin{bmatrix} 1 & e^{jw} & e^{j2w} & \dots & e^{j(M-1)w} \end{bmatrix}^T \text{ is an arbitrary vector.}$$

The locations of the p largest peaks of the estimation function give the frequency estimates for the p signal components.

### 2.2. EV Method

The exponential frequencies are estimated in EV algorithm as follows:

$$\hat{\mathbf{P}}_{\text{EV}}(\mathbf{e}^{jw}) = \frac{1}{\sum_{i=p+1}^{M} \frac{1}{\lambda_i} \left| \mathbf{e}^{\mathbf{H}} \mathbf{v}_i \right|^2}$$
(5)

The only difference between MUSIC and EV method is the use of inverse eigenvalues. EV method was found to produce fewer spurious peaks [12].

# 3. FMCW Channel Data

FMCW systems are used in radar applications and radio channel propagation measurements [13]. Radio channel propagation data used in the current study was collected in Manchester city center using an FMCW sounder. The center frequency of the transmitter was 1945 MHz with 60 MHz bandwidth. This bandwidth was swept linearly over sweep duration. We used data intervals corresponding to approximately 5 MHz RF bandwidth for comparing performances of different frequency estimation techniques..

The APDP of the channel data can provide information on the time delay and amplitude of the multipath components. With the FMCW sounding, the detector output is in the form of the sum of sinusoids of different frequencies. Frequencies of these sinusoids correspond to time delays of the multipath components and the amplitudes correspond to the amplitudes of the multipath components. Presence of in-band interference (RF interference) causes abrupt fluctuations in the detector output signal, and increases noise floor which can easily be observed in delay profile estimates of the channel.

Channel data for one whole sweep (i.e. corresponding to 60 MHz RF band) with interference is shown in Fig. 1.a, interference free section of the sweep in Fig. 1.b, and interference corrupted section of the sweep (both corresponding to 5 MHz RF band) in Fig. 1.c. As it can be seen in Fig.1.c. that the interference caused abrupt fluctuation, and distorted the sum of sinusoidal form. Note that number of samples per sweep depends on the sampling frequency and sweep repetition rate. For this example, sweep repetition rate was 100 Hz, and detector output was sampled at 1 MHz, hence giving 10000 samples per sweep.



Figure 1. The FMCW receiver output in the time domain

Corresponding average multipath delay profiles for the data given in Fig 1.b and c are illustrated in Fig.2. These profiles were obtained using FFT method where data from each sweep were Fourier transformed, then magnitude averaged over time (i.e. across sweeps). As it can be seen in Fig.2, in-band interference has increased the noise floor (red) by about 15dB. This increase in the noise floor obscured weak multipath components with time delays between  $13 - 20 \mu s$ . For the interference-free section (illustrated in black in Figure 2), a few very weak multipath components were detected; one below -15 dB at about 14 us time delay and a few below -20 dB with various time delays between 17 us and 20 us. These weak multipath components were not identified from the interference-corrupted data (illustrated in red in Fig 2). There are two possible reasons for this: i) these components may be even weaker due to slight difference in propagation mechanisms in the RF band corresponding to this data interval, or ii) the increase in the noise floor obscured the weak multipath components with time delays between 14 - 20 us.



Figure 2. Average PDP estimates for 5MHz sections with and without interference

# 4. Results

We chose two propagation channel data with in-band interference, and applied FFT method and the two subspace methods (MUSIC and EV) to the data.

## 4.1. Channel 1 data

The detector output data in the time domain and delay profile estimates for this channel data are presented in Fig. 1 and Fig. 2, respectively. Fig. 3 presents the average DP for channel 1 data for FFT (red), MUSIC (black) and EV (blue) methods. As it can be seen, the MUSIC and EV methods considerably reduced the noise floor as compared to the FFT method,, the EV method performing slightly better than the MUSIC. However, MUSIC and EV failed to detect the very weak multipath components with times delays of 14 us to 20 us (see results in black in Fig. 2). Looking the at noise floor levels from the MUSIC and EV methods, one would not expect to detect the multipath components below -20dB, and it is possible that the component with -17 dB relative power and 14 us time delay may be even weaker for this interference-corrupted section [3].



Figure 3. Average DP estimates from the interference corrupted data given in Fig. 1.c: using FFT (red), MUSIC (black) and EV (blue) methods

#### 4.2. Channel 2 data

Fig. 4 presents the average DPs for an interference-corrupted section of channel 2 data using the three frequency estimation methods. Multipath components for channel 2 were denser than those for Channel 1, and interference level was not as severe as that of the channel 1. The FFT method (red) resulted in a noise floor level around -20 dB. The peaks around 6 us and 7.5 us indicates presence of multipath components. However these components are only 3-4dB above the noise floor, and would remain under a noise threshold which is usually identified to be at least 5dB above the noise floor, and therefore they would not be considered as detected.

On the other hand, the MUSIC and EV methods reduced the noise floor down to a level around -40dB, and detected the weak multipath components around 6 us and 7.5 us time delays.



Figure 4. Average DP estimates for channel 2 data using FFT (red), MUSIC (black) and EV (blue) methods

#### 5. Conclusion

The results show that the two subspace methods, MUSIC and EV methods, perform better than FFT method with interferencecorrupted data. The two subspace methods enabled detection of weak multipath components which could not be detected by the FFT method.

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