Velocity Measurement for Passive Bistatic Radars using FM-radio Broadcast Signal as an Illuminating Signal

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ABSTRACT
This paper deals with the velocity estimation of a moving target by using bistatic radar.The illuminating signal used is an FM-Radio Broadcast signal. The main problems associated with bistatic radars are the noise and DPI (Direct Path interference). The estimation is achieved by reducing noise and direct path interference using adaptive filtering technique. The performance is computed by using simulations.

General Terms
Passive Radar, Adaptive filtering, Gradient Adaptive Lattice (GAL)

Keywords
Least Mean Square (LMS), Cross Ambiguity Function (CAF), noise cancellation, Direct Path interference Cancellation (DPI), Doppler.

1. LITERATURE REVIEW
The bistatic radar idea comes in WW2 [1].The idea of commercial broadcast transmitters comes in 1980 [2] and in 1985, TV waveform was used and in 1999 Lockheed Martins's Silent Sentry was developed [3].

These radars allow the use of VHF and UHF part of RF spectrum that are attractive choices because of excellent coverage.[4] In 1999, Anderson et al, investigated different broadcast waveforms of opportunity for bistatic operations [5].In 2005 Griffiths et al. [6] analyzed analog and digital waveforms for bistatic approach. In 2005, Howland et al. [7] investigated the FM radio broadcast signals

DAB transmitter was also investigated by Griffiths et al [8]. In 2006, Kubica et al used GSM illuminator [9].In 2006, Thomas et al. [10] analyzed the ambiguity function of the DRM signals.

In 2007, another research was carried by Huang et al for the detection of moving target in FM broadcast-based passive radars via ambiguity function.[11] Griffiths et al gave a concept of using DRM (Digital Radio Mondiale) signals for HF passive bistatic radars [12]

The research on the illuminators of opportunity was further investigated by Howard et al in 2009.The research primarily focused on three sources: terrestrial TV transmitter, geosynchronous satellites and Global Navigation Satellite System (GNSS) [13] In 2010, Palmer et al analyzed the use of DVB-T signals in passive radar systems [14] in 2012, Kaeslin et al investigated that the Passive radars with Wi-Fi base stations as illuminators are best option for local area surveillance [15]

In 2013Martelli et al [16] presented architecture for PBR using FM radio as illuminator of opportunity.

Arroyo [17] investigated the OFDM signals for SAR imaging in 2012. In 2013, Pisane et al [18] investigated the target detection of air targets by signals from two or more illuminators of opportunity. In that work three automatic target recognition systems have been implemented.

The bistatic radar signal processing has always been an interesting area of work but this requires much more processing as compared to monostatic radars because there is no dedicated transmitter for its operation therefore there is no a priori knowledge of the signal being transmitted.

The use of FM signal is advantageous as because of its efficiency, noise immunity and larger bandwidth [22]

In the past a lot of work is done in this area. The work of Howland et al [7] dealt with the DPI cancellation using NLMS.

The work of Shentang Li et al [11] dealt with VSS approach.

However, the LMS approach to remove noise and DPI is accurate, easy to implement and less complex.

2. SYSTEM MODEL
For simplicity, it is assumed that there is only one aircraft reflection present and the transmitted signal is an FM radio signal as a signal of opportunity. The direct path signal will be reached at the receiver with some delay. The transmitted signal reflected by the aircraft will experience a Doppler shift and will be received at the receiver after some delay greater than direct path. There will also be some noise that will be added in the reflected signal. The receiver sees the sum of two signals and the noise that has been added in the system as well.

The signal received at the receiver can be mathematically written as:

$$sn\ (t) = m\ (t\text{-}T1) + m\ (t\text{-}T2)\ exp\ (2pifdt) + n\ (t) \qquad (1)$$

where m(t) is the reference signal and n(t) is a zero mean Gaussian noise. T1 and T2 are the delays associated with the direct path signal and the reflected signal. The exponential term is actually the echo reflected by the target.

2.1 Adaptive Filtering of Noise

The term n (t) is removed from the received signal and the filtered signal is then further processed for DPI removal.

The LMS approach depends on order of filter and the step size. [20] The step size parameter controls the convergence rate within its suitable range [21]

The LMS approach is used for the noise removal with step size 0.004 and filter order of 2.

The MSE (Mean Square Error) criterion is used for noise removal. [19]

The weight updating equation is as follows:

$$w(n+1) = w(n) + \mu e(n)\, x(n) \qquad (2)$$

In this approach the weights are adjusted in accordance with the filter output.

2.2 Adaptive Filtering of DPI

The noiseless signal is then further processed for DPI removal. For this case the GAL algorithm [19] is used which orthogonalizes the input signal and the orthogonalized sequence is passed through an adaptive filter that filters out the DPI.

For this an LMS approach is used for updating the weights.

The filter length of 20 is appropriate for the DPI removal.

For Lattice Predictor:

$\xi_{m-1}=a$

$k_m(0)=0$

$f_0(m)=b_0(m)=u(n)$, (u(n)=lattice predictor input)

(For prediction order m=1,2….. and time step n=1,2…..)

$€_{m-1}(n)=\beta €_{m-1}(n-1)+(1-\beta)(|f_{m-1}(n)|^2 + |b_{m-1}(n-1)|^2)$

$f_m(n)=f_{m-1}(n)+k_m b_{m-1}(n-1)$

$b_m(n)=b_{m-1}(n-1)+ k_m f_{m-1}(n)$

$k\hat{}_m(n)=k\hat{}_m(n-1)- \hat{u} / €_{m-1}(n)(f^*_{m-1}(n)b_m(n)+b_{m-1}(n-1)f^*_m(n))$

The $f_m(n)$ and $b_m(n)$ are forward and backward prediction errors.

For Estimator:

The weights are updated using the LMS approach that uses orthogonalized sequence (output of predictor) as input to estimate the echo.

2.3 CAF Calculation

The signal obtained after signal processing of the received signal gives the actual echo that is reflected by the target.

This echo signal is correlated with the reference signal to calculate CAF.

The CAF calculation is done using the summation method.

$$CAF(T, k) = \sum_{n=0}^{N-1} [\, s_1(n) s_2^*(n-T)]\, e^{-j2pik/N} \qquad (3)$$

The other methods reduces the computation by applying various filters like fine mode, fine mode generic and fine mode frequency domain filter can also be used but the direct summation method is highly accurate [24].

3. RESULTS

In this section, the simulation results will be presented

3.1 Noise Cancellation

The Fig.3.1 (a) shows the signal that is actually received by the receiver. This signal contains the received signal corrupted by DPI that has been added in the signal as well.

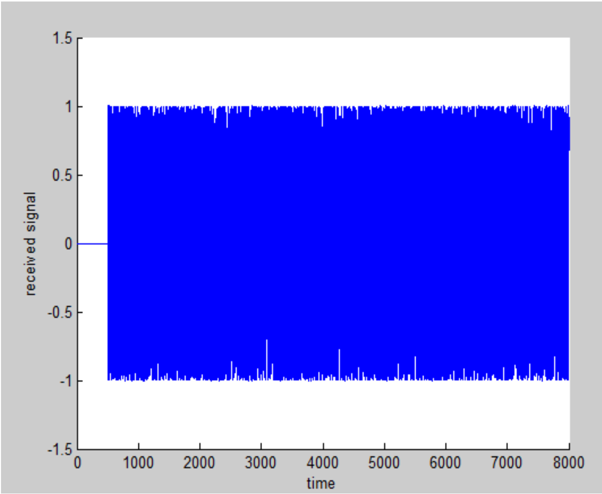

Figure 3.1(a): Received Signal

The Fig.3.1 (b) shows the noisy received signal. In the received signal the DPI and noise signals are embedded and needs to be removed before calculating the Doppler.

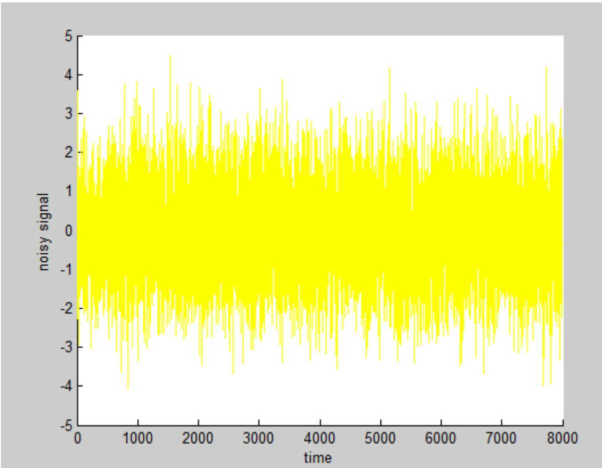

Figure 3.1(b): Noisy Received Signal

In order to estimate the actual received signal the noise embedded in the received signal is removed.

For this the LMS algorithm is used that removes the noise from the received signal with great accuracy .The Fig. 3.1(c) shows the filtered signal obtained after adaptive filtering.

The filtered signal is a good approximation of the received signal. The noise components are found in the initial samples.

However, the noise quickly falls which shows that the LMS has fast convergence.

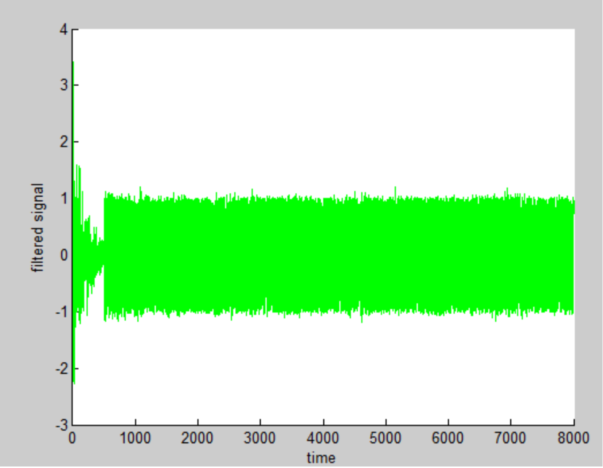

Figure 3.1(c): Filtered Signal

The criteria to compare the received signal with the filtered signal was the Mean Square Error criteria that is actually the square of the difference between the filtered and originally (noiseless) received signal.

The comparison between the noiseless (received) signal and the filtered signal is done using MSE. The Fig. 3.3(d) shows that the MSE falls to zero which shows that the noise has been removed accurately.

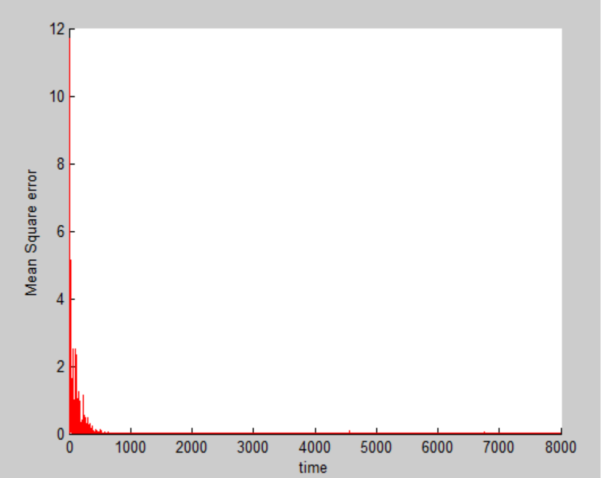

Figure 3.1 (d): Mean Square Error

The SNR of received signal before filtration was -3.2491 and after filtration it becomes 14.3208.

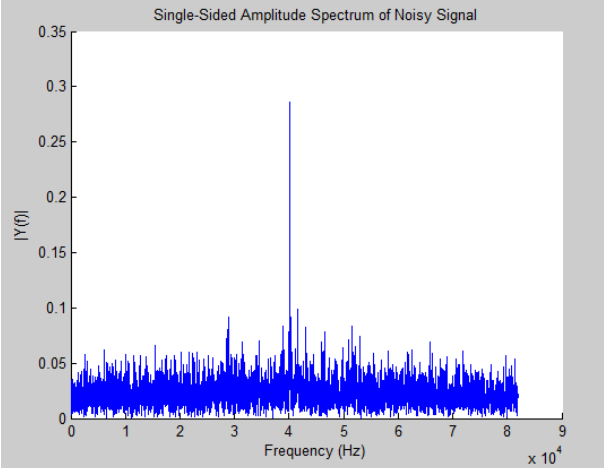

Figure 3.1 (e): Spectrum of Noisy signal

The frequency spectrum of the noisy signal in Fig.3.1 (e) shows that the noise is spread throughout the spectrum.

This can be seen by observing the frequency spectrum of the received signal shown in Fig. 3.1(f).

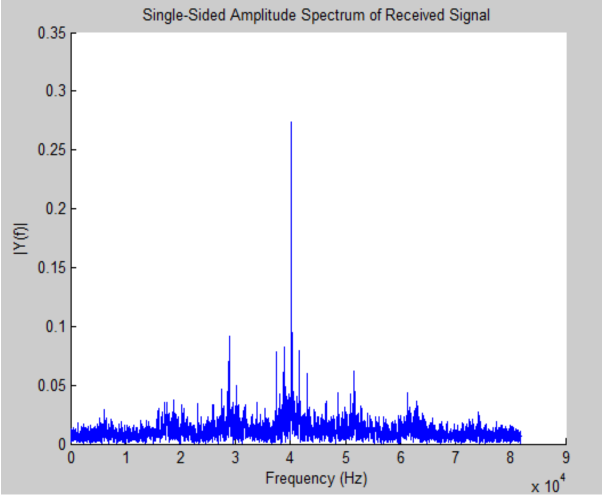

Figure 3.1 (f): Spectrum of Echo signal

However, the frequency spectrum of the filtered signal is a very good and close approximation of the noiseless received signal.

The spectrum of the filtered signal is shown in Fig. 3.1(g).

The spectrum of noisy signal in Fig. 3.1(e) compared to the spectrum of filtered signal in Fig. 3.1(f) shows the accuracy of the proposed filter.

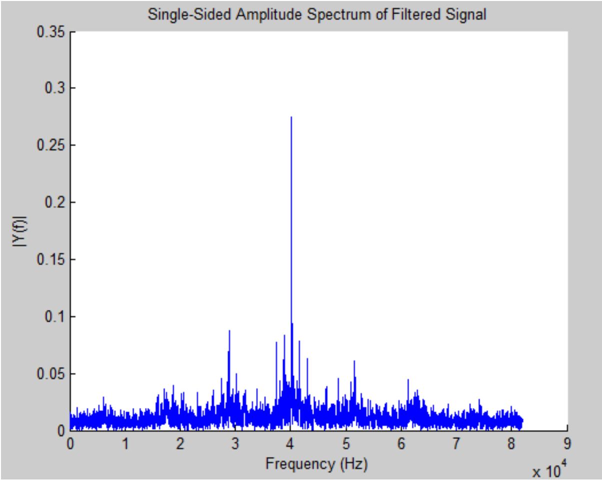

Figure 3.1 (g): Spectrum of filtered signal

3.2 Direct Path Interference Cancellation

The actual echo and the estimated echo are shown in Fig. 3.2(a) and 3.2(b) respectively.

The actual echo is the product of the delayed version of transmitted signal and Doppler that exists due to the motion of target.

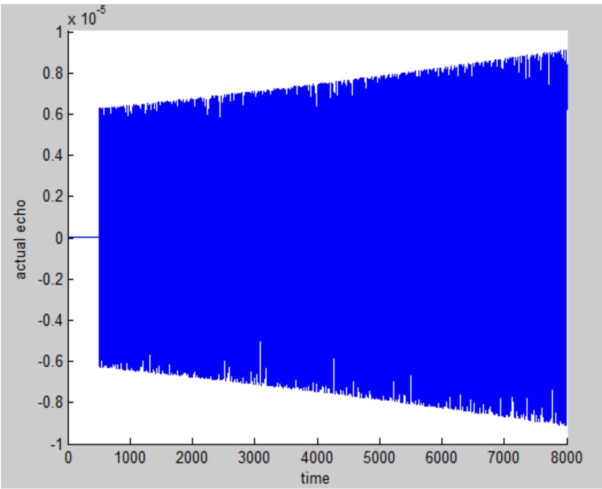

Figure 3.2(a) Actual Echo

The next task is to remove the DPI from the filtered signal. The DPI removal using the GAL and LMS jointly, proved to be efficient as the DPI is removed with efficiency using this approach.

The Fig. 3.2(b) shows the estimated echo that has been obtained after filtering. Some noise components can be observed at the initial samples but the filtered signal contains zero noise in the later samples.

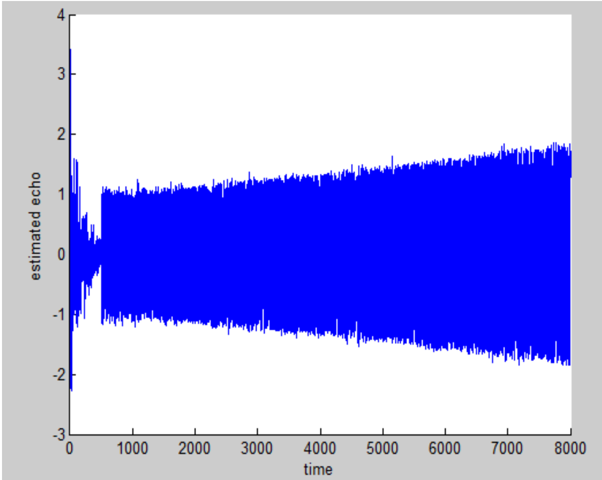

Figure 3.2 (b): Estimated Echo

3.3 CAF Calculation

Using equation (2) CAF is calculated by the summation method. [24]

Table 1.CAF Calculation for various fd

fd	CAF
-0.00001	0.0033
-0.000009	0.0031
-0.000008	0.0027
-0.000007	0.0028
-0.000006	0.0030
-0.000005	0.0033
-0.000004	0.0034
-0.000003	0.0034
-0.000002	0.0038
-0.000001	0.0037
0	0.0038
0.000001	0.0042
0.000002	0.0045
0.000003	0.0045
0.000004	0.0044
0.000005	0.0046
0.000006	0.0051
0.000007	0.0052
0.000008	0.0051
0.000009	0.0054
0.00001	0.0059

The actual value of the fd is obtained at the maximum CAF.

This is done using the summation method that increases complexity but gives accurate results.

4. CONCLUSION

The noise cancellation with LMS has given remarkable results as this algorithm is easy to implement, accurate and computationally efficient.

Using GAL for DPI was much desirable as this algorithm orthogonalizes the input and helps in predicting the values of the DPI.
The orthogonalized input is then fed in to updating algorithm in which the algorithm being used was the LMS as it converges faster.

The LMS algorithm used is actually a variation of the original algorithm in which the co efficient updating equation is altered in such a way that the weight values are updated gradually with a small decrement applied to it.
This approach has given accurate results with little error and the DPI is removed with accuracy.

The CAF calculation is done with summation method. However, this approach is computationally complex as it requires two loops and multiplication processes for T and fd but this method is the most accurate method.

This idea can be further extended using other methods of interference removal i.e. recursive least square. The CAF calculation using efficient CAF approaches using various filters that could provide accuracy, efficiency and less complexity at the same time can be done in future for further extension of the proposed system.

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