Identification of LPI Radar Signal Modulation using Bi-coherence Analysis and Artificial Neural Networks Techniques

L. Anjaneyulu, N.S.Murthy, N.V.S.N.Sarma
Department of ECE, National Institute of Technology, Warangal, AP, India
E-mail: anjan.lokam@gmail.com

Abstract : **This paper presents Higher Order Spectral Analysis (HOSA) and Artificial Neural Network techniques for identification of LPI (Low Probability of Intercept) Radar signal. Common Spectral analysis and conventional methods fail to detect low powered emissions of LPI Radars and even normal radars in noisy environments. This leads us to use Higher Order Spectral Analysis (HOSA) techniques (bi-spectrum, bi-coherence etc.,) enabling us to extract much more information from the same intercept and hence facilitating detection. Different types of radar waveforms used by LPI radars (e.g, pulse, LFM, phase coded using Barker code or Frank code etc.,) are simulated and then analyzed by bi-coherence analysis technique. An Artificial Neural Network (ANN) is trained on the results obtained by bi-coherence analysis, so that it will be able to detect and identify the LPI radar signal whose type is unknown when received. The results obtained clearly indicate the promising capability of the HOSA techniques to identify the type of LPI signal even with SNRs as low as –3 dB.**

I. Introduction

The important advantage of a LPI (Low Probability of Intercept) radar is to go undetected, while maintaining a strong battlefield awareness. Many users of Radar today are specifying LPI and LPID (Low Probability of Identification) as important tactical requirements. The term LPI is that property of a radar that, because of its low power, wide bandwidth, frequency variability, or other design attributes, makes it difficult for it to be detected by means of a passive intercept receiver. Many combined features help the LPI radar prevent its detection by modern intercept receivers. These features are centered on the antenna (antenna pattern and scan patterns) and the transmitter radiated waveform [1].

The LPI antenna must have a transmit radiation pattern with very low side lobes. The low side lobes in the transmit pattern reduce the possibility of an intercept receiver detecting the radio frequency (RF) emissions from the side lobe structures of the antenna pattern. A level of -20 dB is normally acceptable, but with LPI radar, ultra low side lobes are required (-45 dB).

Intercept receivers use a variety of strategies to identify radars based on their Angle of Arrival, Carrier Frequency, Scan Rate, Bandwidth, Modulation Period, Polarization etc., These properties of radiated waveforms make the radar susceptible to detection. Randomly altering one or more of these parameters can provide confusion to the intercept receivers.

II. LPI Radar Signals

LPI Radars use continuous wave (CW), wide bandwidth low power signals of the order of a few watts making its detection difficult. Conventional radar uses coherent pulse train and has independent control over range and Doppler resolution. In modulated CW signals, the average-to-peak power ratio is 1 or 100% duty cycle. This allows a considerably lower transmit power to maintain the same detection performance as the coherent pulse train, LPI radars use periodically modulated CW signals resulting in large bandwidths and smaller resolution cells . There are many modulation techniques that provide a wideband LPI CW transmit waveform. For the intercept receiver to demodulate the waveform, the particular modulation technique must be known (which is typically not the case)

The wideband CW techniques include:

1. Linear, nonlinear frequency modulation (FMCW)
2. Phase modulation (PSK, polyphase codes)
3. Frequency hopping (FSK), Costas sequence
4. Combined phase modulation and frequency hopping
5. Random signal modulation

A. Pulse Waveform

The Pulse is the most common form of radar signals. However they are also very susceptible to jamming due to their very predictable nature. In a simple pulse waveform, the amplitude and phase of the pulses do not vary with time. Due to the discontinuous pulses, we can get range information about the target. Similarly by aggregating a large number of pulses, we can obtain the Doppler information as well.

B. Linear FM (LFM)

This signal is used in FMCW radars. The signal amplitude is kept constant with a varying frequency. Due to this change in frequency, there is a continuous variation in phase.

C. Barker code

Bi-phase codes are widely used for pulse compression in radar systems. Barker codes are especially preferred in these applications because it achieves the best possible mainlobe to sidelobe ratio. Barker codes are the only known bi-phase codes with the smallest achievable side lobes. However, the longest known Barker code is of length 13.

D. Frank Code

Codes that use any harmonically related phases based on a certain fundamental phase increment are called poly-phase codes. Frank code is a very popular poly-phase code. In this case, a single pulse of width τ' is divided into N equal groups; each group is subsequently divided into other sub-pulses each of width $\Delta\tau$. Therefore, the total number of sub-pulses within each pulse is N^2, and the compression ratio is $\zeta = N^2$. A Frank code of N^2 sub-pulses is referred to as an N-phase Frank code with fundamental phase increment $\Delta\varphi$.= 360 /N

E. Costas Code

The Costas code is a type of Stepped Frequency Waveform. In SFW, a relatively long pulse of length τ is divided into N sub-pulses, each of width τ_1 ($\tau' = N\,\tau_1$). Each group of sub-pulses is called a burst. Within each burst the frequency is increased by Δf from one sub-pulse to the next. The overall burst bandwidth is $N\Delta f$.

F. P4 Code

P4 (poly-phase 4)This code is derived by converting a linear-frequency modulation waveform to base band using a local oscillator on one end of the frequency sweep and sampling the I and Q video at the Nyquist rate. With this frequency, the phases of successive samples for an N bit code are

$$\phi_i = \left[\frac{\pi(i-1)^2}{N}\right] - \pi(i-1), \text{ here i=1, 2,..., } N$$

III. Implementation Details

A. Simulation of LPI Radar Signals and calculation of Ambiguity function

For testing the algorithms of HOSA, a large database of sample LPI waveforms is required. These waveforms are simulated with the facility to customize the waveforms and to vary various parameters and for adding noise. Autocorrelation, Ambiguity functions [2],[3] can be calculated for the LPI waveforms generated. A Graphical User Interface (GUI) for simulation of LPI radar signals has been developed. The GUI allows choosing one of many preset signals, or defining a new signal through its amplitude, phase and frequency vectors. With this GUI the following types of ideal signals can be generated. All these waveforms can be modified in terms of Amplitude, Phase, Frequency, Number of Bits, Max. Doppler shift for ambiguity plot, Max Delay, No. of positive Doppler shifts etc.,

1. Pulse
2. Linear FM
3. Barker 13
4. Costas
5. Frank
6. P4

Pulse is also included here to test for no modulation (phase / frequency) cases.

B. Bi-Coherence analysis technique

The radar ambiguity function [2],[3] for the signal is defined as the modulus squared of its 2-D correlation function. The data of the ambiguity function is processed by the Bi-coherence analysis algorithm [4] to extract the useful information from the signal using. The algorithms [5] use 128 point FFT. The flow chart for the bi-coherence computation is shown in Figure 1. The Bi-coherence images (2D plots) produced are unique for each LPI signal and serve as a signature. An experienced operator can quickly identify the type of modulation by looking at these plots. Figure 2 shows the bi-coherence plots of all the signals.

C. Artificial Neural Networks for LPI identification.

The LPI waveform signatures generated by the HOSA algorithms are used to train a Multi-layer Feed Forward Neural Network with back-propagation for automatic identification and classification of the analyzed waveforms. The Network architecture is shown in figure 3. Table.1 shows the identification ability of ANN with Bi-coherence signatures as input to the trained network. The values in the table indicate the confidence level with the algorithm identifies a signal. For example, the 3rd row of the table shows that when the Costas signal is loaded (as unknown), the network correctly identifies the LPI signal as Costas as an output by producing the largest output value of **0.9426** at that node. Table.2 shows the identification ability of ANN even with addition noise e.g., Frank signal.

IV. Conclusion

Higher order spectral analysis of the signals clearly demarcates one signal from the other even if noise levels are made greater than the signal. A multilayer feed forward neural network with supervised back-propagation training algorithm is used. After training, the network identifies the modulation types immediately when applied with the inputs. The neural network based on bi-spectrum analysis gives an excellent performance with very low level SNR of zero dB and even lower. This system would be very efficient in identifying LPI radar signals.

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[4] C.L. Nikias and A.P.Petropulu., *Higher Order Spectral Analysis*, PTR Printice Hall, New Jersey, 1993

[5] Ananthram Swami, Jerry M. Mendel and Chrysostomos L. (Max) Nikias., *Higher-Order Spectral Analysis Toolbox for use with MATLAB*

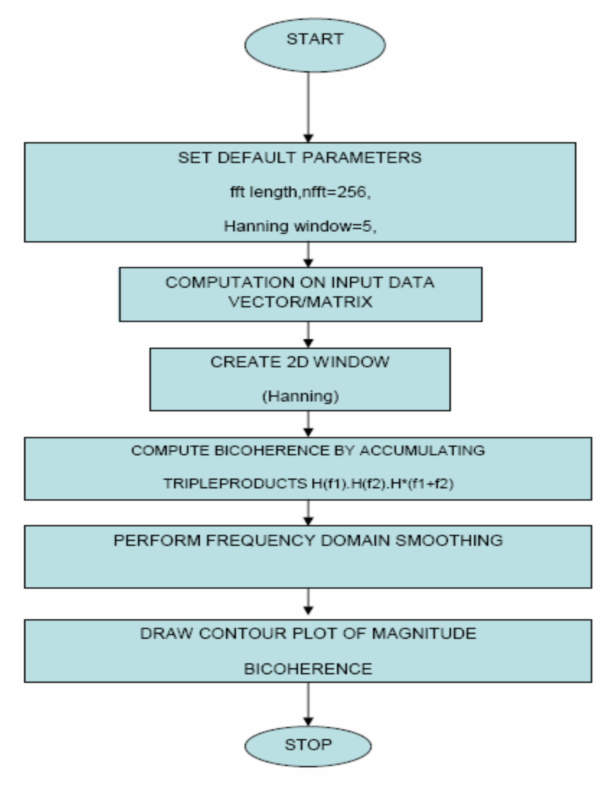


Fig. 1 Flow chart of bi-coherence computation

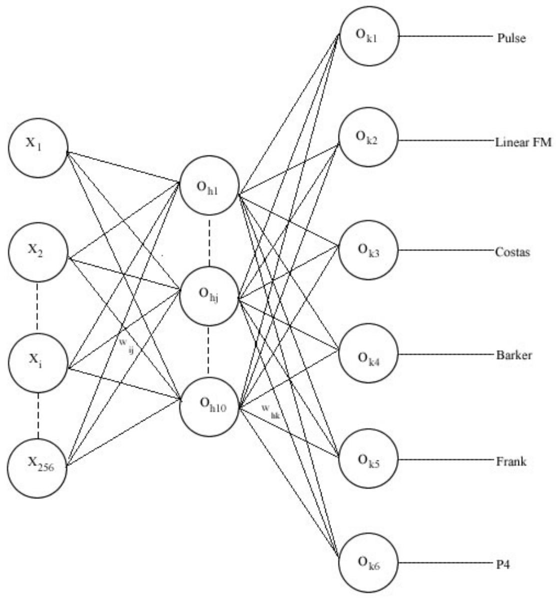
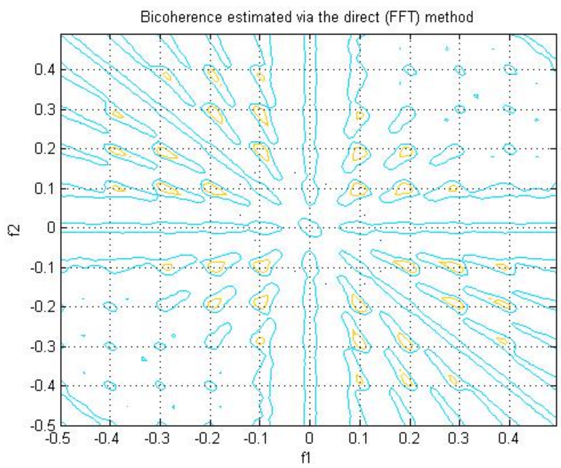
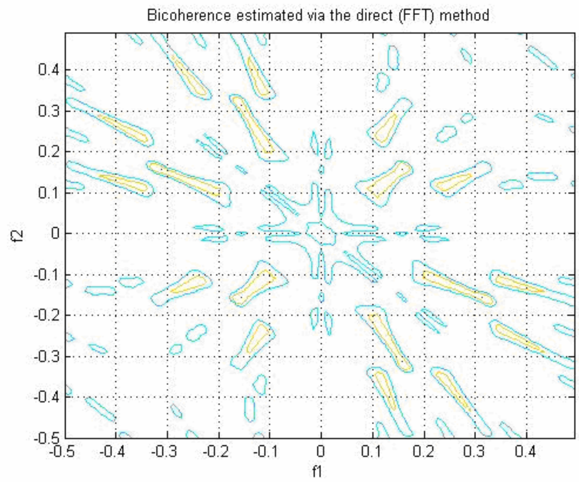


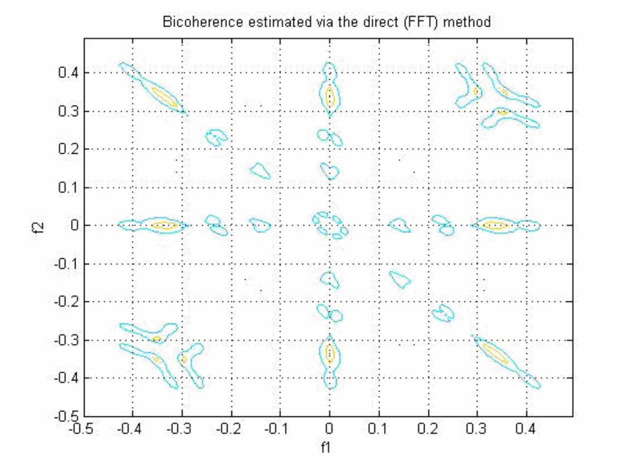
Fig.3 Multi-Layer Feed Forward Neural Network



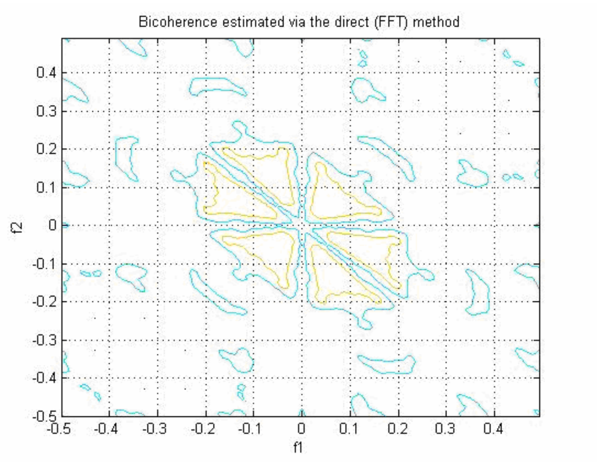
2 (a) Pulse



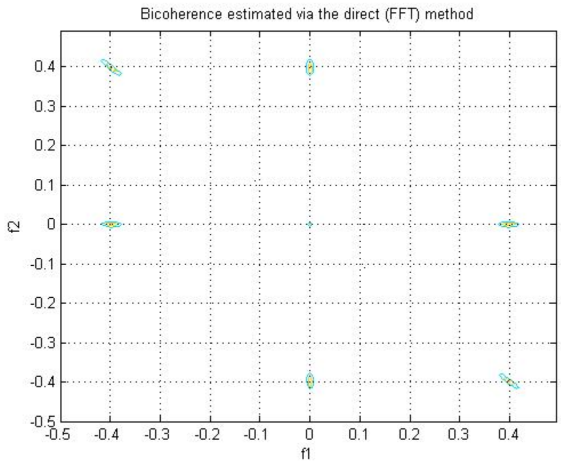
2(b) LFM



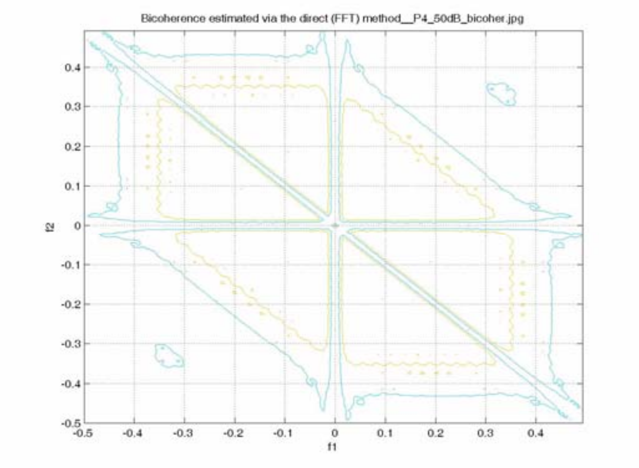
2(c) Costas



2 (d) Frank (N=16)



2 (e) Barker 13



2(f) P4 (N=8)

Fig 2. Bi-coherence plots of all the signals

Table 1. Bi-coherence based Neural Network Output

Output / Input	Pulse	Linear FM	Costas	Barker	Frank	P4
Pulse	**0.9843**	0.0011	0.0000	0.0006	0.0000	0.0035
Linear FM	0.0000	**0.9875**	0.0014	0.0000	0.0001	0.0010
Costas	0.0033	0.0051	**0.9426**	0.0428	0.0034	0.0000
Barker	0.0000	0.0000	0.0453	**0.9254**	0.0004	0.0000
Frank	0.0000	0.0143	0.0376	0.0312	**0.8891**	0.0045
P4	0.0527	0.0045	0.0203	0.0201	0.0010	**0.9875**

Table 2. Effect of Noise on Bi-coherence based Neural Network Output

Output / Input	Pulse	Linear FM	Barker	Costas	Frank	P4
Frank: 10dB SNR	0.0000	0.0000	0.0000	0.0000	**0.7946**	0.0112
Frank: 0 dB SNR	0.0000	0.0000	0.0000	0.0000	**0.5676**	0.0021
Frank: -3 dB SNR	0.0000	0.0000	0.0000	0.0000	**0.4806**	0.0034