Radar Signal Detection In Non-Gaussian Noise Using RBF Neural Network

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Abstract— **In this paper, we suggest a neural network signal detector using radial basis function (RBF) network. We employ this RBF Neural detector to detect the presence or absence of a known signal corrupted by different Gaussian, non-Gaussian and impulsive noise components. In case of non-Gaussian noise, experimental results show that RBF network signal detector has significant improvement in performance characteristics. Detection capability is better than to those obtained with multilayer perceptrons (BP) and optimum matched filter (MF) detector. This signal detector is also tested on the simulated signals impacted by impulsive noise produced by atmospheric events and short lived echoes from meteor trains. Tested Results show, improved detection capability to impulsive noise compare to BP signal detector. It also show better performance as a function of signal-to-noise ratio compared to BP and MF.**

Index Terms— **Radial basis function neural network, non-Gaussian noise, impulsive noise, signal detection.**

I. INTRODUCTION

In radar, sonar and communication applications, ideal signals are usually contaminated with non-Gaussian noise. The radar performance can be degraded by impulsive noise interference such as environmental effects of atmospherics (lighting) and meteor train echoes. Lighting impulsive noise significantly reduces the signal detector performance about 25 percentage. Detection of known signals from noisy observations is an important area of statistical signal processing with direct applications in communications fields. General properties of neural networks include robustness and fault tolerance of the computational elements due to the massive parallesim. Also, adaptive neural networks that very with time are able to change with slowly time-varying signals, improving the non-Gaussian signal detection performance. Neural networks are nonparametric, making no assumptions about the underlying densities, which may provide more robustness and capability for detecting signals generated by nonlinear and non-Gaussian processes.

Optimum linear detectors, under the assumption of additive Gaussian noise are suggested in [1]. A class of locally optimum detectors are used in [2] under the assumptions of vanishingly small signal strength, large sample size and independent observation. Recently, neural networks have been extensively studied and suggested for applications in many areas of signal processing. Signal detection using neural network is a recent trend [3] - [6]. In [3] Watterson generalizes an optimum multilayer perceptron neural receiver for signal detection. To improve performance of the matched filter in the presence of impulsive noise, Lippmann and Beckman [4] employed a neural network as a preprocessor to reduce the influence of impulsive noise components. Michalopoulou it et al [5] trained a multilayer neural network to identify one of M orthogonal signals embedded in additive Gaussian noise. They showed that, for $M = 1$, operating characteristics of the neural detector were quite close to those obtained by using the optimum matched filter detector. Gandhi and Ramamurti [6], [7] has shown that the neural detector trained using BP algorithm gives near optimum performance. The performance of the neural detector using BP algorithm is better than the Matched Filter (MF) detector, used for detection of Gaussian and non-Gaussian noise. Michale Turley [10] suggested modifications to a known linear prediction missing data technique, and show that this technique is effective against HF radar impulsive interference. Barnum and Simpson [11] investigated a signal processing algorithm that increases radar sensitivity by 20 dB, after excising noise impulses, such as those caused by lighting at the receiver output.

In our previous work [12], [13] we suggest the signal detector for non-Gaussian cases such as Double exponential, Contaminated Gaussian and Cauchy noise components. In this work , we explore it further and propose a neural network detector using RBF network and we employ this neural detector to detect the presence or absence of a known signal corrupted by Gaussian, non-Gaussian and impulsive noise components. For many non-Gaussian noise distributions such as double exponential, Contaminated Gaussian, Cauchy and impulsive noise components. We found that RBF network signal detector performance is very close to that of MF and BP detector for Gaussian noise. While, we observed that in non-Gaussian and impulsive noise environments the RBF network signal detector show better performance

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characteristics and good detection capability compared to neural detector using BP.

II. Signal Detector and Statistics Preliminaries

Signal detection involves inferring from observational data whether or not a target signal is present. In general, the available observational data are the input to the detector and the output from the detector; these can have one of two possible values, either 1 or 0. The value "1" signifies the presence of the target signal and "0" signifies the absence of the target signal. Probability of detection P_d and the probability of false alarm P_{fa} are the two commonly used measures to assess performance of a signal detector [1] That is, P_d is defined as the probability of choosing H_1 given that H_1 is true, and P_{fa} is defined as the probability of choosing H_1 given that H_0 is true.

$$P_d = P(\wedge(\mathbf{X}(t)) > \eta/H_1) \tag{1}$$

and

$$P_{fa} = P(\wedge(\mathbf{X}(t)) > \eta/H_0) \tag{2}$$

Consider a data vector $\mathbf{X}(\mathbf{t}) = [x_1(t), x_2(t), ..., x_N(t)]^T$ as an input to the detector in Figure 1. Using the additive observational model, we have

$$\mathbf{X}(\mathbf{t}) = \mathbf{S}(\mathbf{t}) + \mathbf{C}(\mathbf{t}) \tag{3}$$

for the hypothesis that the target signal is present (denoted by H_1) and

$$\mathbf{X}(\mathbf{t}) = \mathbf{C}(\mathbf{t}) \tag{4}$$

for the hypothesis that the signal is absent (denoted by H_0), where $\mathbf{S}(\mathbf{t}) = [s_1(t), s_2(t), ..., s_N(t)]^T$ is the target signal vector and $\mathbf{C}(\mathbf{t}) = [c_1(t), c_2(t), ..., c_N(t)]^T$ is the noise vector. The likelihood ratio is defined by

$$\wedge(\mathbf{X}(\mathbf{t})) = \frac{P(\mathbf{X}(\mathbf{t})/H_1)}{P(\mathbf{X}(\mathbf{t})/H_0)} \tag{5}$$

where $P(\mathbf{X}(\mathbf{t})/H_1)$ and $P(\mathbf{X}(\mathbf{t})/H_0)$ are the jointly conditional probability density functions of $\mathbf{X}(\mathbf{t})$ under $H_1$and H_0, respectively. Denoting the decision threshold by η, we choose H_1 (the output of the detector is 1) if $\wedge(\mathbf{X}(\mathbf{t})) > \eta$; otherwise, we choose H_0 (the output of the detector is 0) [2]. The target $S(t)$ is known and that $C(t)$ is zero-mean, white, Gaussian noise vector, the likelihood ratio $\wedge(X(t))$ can be replaced by a sufficient statistic $Z(t)$ that is a linear combination of each component $x_i(t)$ of the input $X(t)$, that is,

$$Z(t) = \sum_{i=1}^{N} S_i(t) X_i(t) \tag{6}$$

above equation indicates that the sufficient statistic $Z(t)$ is the output of a matched filter of the target signal $\mathbf{S}(\mathbf{t})$. As a result, this detector is also called the matched filter detector.

In most of the cases, since the noise vector does not have a Gaussian probability density function, the likelihood ratio is a complicated nonlinear function of the input $\mathbf{X}(\mathbf{t})$, which makes it very difficult to design and realize the detectors. Although some simpler detectors such as locally optimum detectors have been designed for a specific non-Gaussian noise, their performance will greately degrade when the related assumptions are violated. With $f_N(x)$ as the marginal (symmetric) probability

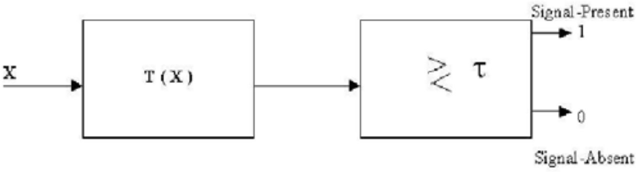

Figure 1. Block diagram of a signal detector.

density function (pdf) of $N_i, i = 1, 2, ..., n$, here we consider the following pdf's:

1) Gaussian pdf with $f_N(x) = e^{-x^2/2\sigma^2}/\sqrt{2\pi\sigma^2}$ and $E[N_i^2] = \sigma^2$.
2) Double exponential pdf with $f_N(x) = e^{-\|x\|/\sigma}/2\sigma$ and $E[N_i^2] = 2\sigma^2$.
3) Contaminated Gaussian pdf with $f_N(x) = (1 - \epsilon)e^{-x^2/2\sigma_0^2}/\sqrt{2\pi\sigma_0^2} + \epsilon e^{-x^2/2\sigma_1^2}/\sqrt{2\pi\sigma_1^2}$.
4) Cauchy pdf with $f_N(x) = \sigma/[\pi(\sigma^2 + x^2)]$ and $E[N_i^2] = \infty$.

where σ_0^2 is the nominal variance, $(\sigma_1^2 > \sigma_0^2)$ is contaminated variance, $0 \le \epsilon \le 1$ is the degree of contamination, and $E[N_i^2] = (1-\epsilon)\sigma_0^2 + \epsilon\sigma_1^2$. These non-Gaussian pdfs are commonly used to model impulsive noises. For the observation model, the test statistic $T(\mathbf{X}) = T_{LR}(\mathbf{X})$ of the *optimum* likelihood-ratio (LR) detector is given by

$$T_{LR}(\mathbf{X}) = \prod_{i=1}^{n} \frac{f_{X_i}(x_i|\theta > 0)}{f_{N_i}(x_i|\theta = 0)} \tag{7}$$

where $f_{X_i}(x_i)$ is the pdf of observation X_i. Often, the statistic T_{LR} depends of the unknown parameter θ, and therefore, the use of the LR detector is limited to some specific situations. The LR detector does, however, provide a useful performance upperbound to which other detectors are generally compared. In practice, the linear matched-filter (MF) detector is commonly employed because of its computational simplicity and UMP performance for detecting known signals in additive white Gaussian noise. Its test statistic is a linear combination of the N observations and is given by

$$T_{MF}(\mathbf{X}) = \sum_{i=1}^{n} S_i \mathbf{X}_i. \tag{8}$$

For the locally optimum detector, on the other hand, the test statistic $T_{LO}(\mathbf{X})$ is given by.

$$T_{LO}(\mathbf{X}) = -\sum_{i=1}^{n} s_i \frac{f_N'(\mathbf{X}_i)}{f_N(\mathbf{X}_i)} \tag{9}$$

where $f_N'(x) = df_N(x)/dx$. For f_N a Gaussian pdf, for instance, we have $T_{LO}(\mathbf{X}) = \sum_{i=1}^{n} s_i X_i = (T_{MF})$, whereas for a double exponential pdf, we have $T_{LO}(\mathbf{X}) = \sum_{i=1}^{n} s_i sgn(\mathbf{X}_i)$, where *sgn(a)* is the sign of x. For a non-Gaussian pdf, the statistic T_{LO} is generally a nonlinear function of $\mathbf{X}$ [6], [7], [14].

A. Radial Basis Function Networks

An alternative network to the backpropagation (BP) network for many applications of signal processing is the radial basis function (RBF) network, which has been proposed by different authors [15], [16], [17]. An RBF is a multidimentional function that depends on the distance between the input vector and a center vector. RBFs provide a powerful tool for multidimentional approximation or fitting that essentially does not suffer from the problem of proliferation of the adjustable parameters as the dimensionality of the problem increases [16]. Figure 2 shows the basic structure of the RBF neural network signal detector. If the input vector at time t be denoted by $\mathbf{X(t)} = [x_1(t), x_2(t), ..., x_N(t)]^T$ and the center vector of each hidden neuron be denoted by $\mathbf{C}_i$ for $(i = 1, 2, .., N)$. Then the output of each neuron in the hidden layer is

$$h_i(t) = f_i(\| \mathbf{X_t} - \mathbf{C}_i \|) \quad (10)$$

The connection between the hidden layer and output layer are weighted. Neuron of the output layer has a linear input-output relationship so that it performs simple summations. It has been shown experimentally that if a sufficient number of hidden neurons are used and the center vectors are suitably distributed in the input domain, then the RBF network is able to approximate a wide class of nonlinear multidimentional functions. Moreover, the choise of the nonlinearity of the RBF is not crucial for the approximation performance of the network. However, the approximation performance of an RBF network critically depends on the choice of the centers [9].

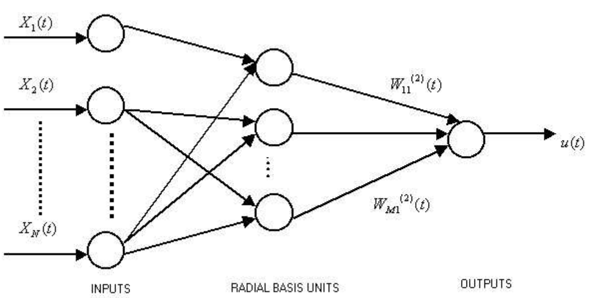

Figure 2. Schemetic of the basic RBF signal detector.

III. A RBF Neural Signal Detector

The structure of the signal detector based on an RBF network is shown in Figure 3 [9]. This neural network signal detector consists of three layers. The input layer has N number of neurons with a linear function. One hidden layer of K neurons with nonlinear transfer functions such as the Gaussian function. The output layer has only one neuron whose input-output relationship should be such that it approximates the two possible states. The two bias nodes are included as part of the network. A real-valued input x to a neuron of the hidden or output layer produces neural output $G(\mathbf{x})$, where $0 < G(\mathbf{x}) < 1$. The Gaussian function $G(\mathbf{x})$ that we choose here is $G(\mathbf{x}, \mathbf{x}_i) = exp(-1/2\sigma_i^2 \|\mathbf{x} - \mathbf{x_i}\|^2)$. The RBF neural network detector test statistic $T_{NN}(\mathbf{x})$ may now be expressed as,

$$T_{NN}(\mathbf{x}) = \sum_{i=1}^{K} w_i \varphi_i(\mathbf{x}) + w^{b_2} \quad (11)$$

where $\{\varphi_i(\mathbf{x}), i = 1, 2, 3, ..., K\}$ is a set of basis functions. The w_i constitutes a set of connection weights for the output layer. When using RBF the basis is

$$\varphi_i(\mathbf{x}) = G(\|\mathbf{x} - \Sigma \mathbf{t_i}\|^2) + w_i^{b_1}, i = 1, 2, 3, ..., K \quad (12)$$

where $\mathbf{t}_i = [\mathbf{t}_{i1}, \mathbf{t}_{i2}, ..., \mathbf{t}_{iN}]^T$ with $\mathbf{t}_i$ as unknown centers to be determined. Σ is a symmetric positive definite weighting matrix of size $N\mathbf{x}N$. $G(.)$ represents a multivariate Gaussian distribution with mean vector $\mathbf{t}_i$ and covariance matrix Σ. By using above equations we redefine $T_{NN}(\mathbf{x})$ as

$$T_{NN}(\mathbf{x}) = \sum_{i=1}^{K} w_i G(\mathbf{x}, \mathbf{t}_i) = \sum_{i=1}^{K} w_i G(\|\mathbf{x} - \mathbf{t}_i\|). \quad (13)$$

We determine the set of weights $\mathbf{w} = [w_1, w_2, ..., w_k]^T$ and the set $\mathbf{t}$ of vectors $\mathbf{t}_i$ of centers such that the cost functional,

$$\xi(\mathbf{W}, \mathbf{t}) = \sum_{i=1}^{M} (d_i - \sum_{j=1}^{K} w_j G(\|\mathbf{x}_i - t_j\|))^2 \quad (14)$$

where $\{\varphi_i(\mathbf{x}), i = 1, 2, 3, ..., M\}$ is a new set of basis functions. The first term on the right hand side of the equation may be expressed as the squared Euclidean norm $\|\mathbf{d} - G\mathbf{W}\|^2$, where $\mathbf{d} = [d_1, d_2, d_3, ..., d_M]^T$ and $\mathbf{W} = [w_1, w_2, w_3, ..., w_K]$ [8].

$$G = \begin{bmatrix} G(\mathbf{X}_1, t_1) & G(\mathbf{X}_1, t_2) & \cdots & G(\mathbf{X}_1, t_K) \\ G(\mathbf{X}_2, t_1) & G(\mathbf{X}_2, t_2) & \cdots & G(\mathbf{X}_2, t_K) \\ G(\mathbf{X}_3, t_1) & G(\mathbf{X}_3, t_2) & \cdots & G(\mathbf{X}_3, t_K) \\ \vdots & \vdots & \ddots & \vdots \\ G(\mathbf{X}_N, t_1) & G(\mathbf{X}_N, t_2) & \cdots & G(\mathbf{X}_N, t_K) \end{bmatrix}$$

$$\mathbf{W} = [w_1, w_2, w_3, ..., w_K].$$

The first step in the learning procedure is to define the instantaneous value of the the cost function.

$$\xi = 1/2 \sum_{\imath=1}^{K} e_i^2 \quad (15)$$

where K is the size of the training sample used to do the learning, and e_i is the error signal defined by

$$e_i = d_i - F(\mathbf{X_i})$$

$$e_i = d_i - \sum_{\imath=1}^{K} w_i G(\| \mathbf{X_i} - t_i \|) \qquad (16)$$

We assume $\Sigma = diag[\sigma_1, \sigma_2, ..., \sigma_N]$. Σ is to be minimized with respect to the parameters w_i, t_i, and σ_i^{-1}. The cost function ξ is convex with respect to the linear parameters w_i, but non convex with respect to the centers $\mathbf{t}_i$ and matrix σ_i^{-1}. The search for the optimum values of $\mathbf{t}_i$ and σ_i^{-1} may get stuck at a local minimum in parameter space. The different learning-parameters assigned updated values to $\mathbf{w}_i$, t_i, and σ_i^{-1}.

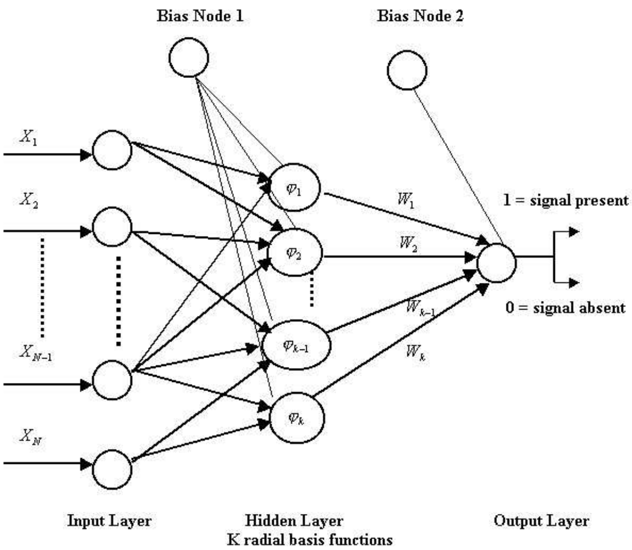

Figure 3. Signal detector based on the RBF.

RBF networks with supervised learning were able to exceed substantially the performance of multilayer perceptrons [8]. After updating at the end of an epoch, the training is continued for the next epoch and it continues until the maximum error among all K training patterns is reduced to a prespecified level.

IV. Experimental Results and Performance Evaluations

Neural weights are obtained by training the network at 10-dB SNR using $\theta = \sqrt{10}$ and $E[N_i^2] = 1$. During simulation, the threshold τ_{NN} is set to 0.5, and the bias weight w^{b_2} value that gives a P_{fa} value in the range $0.001 - 1$. For each w^{b_2} value that gives a P_{fa} value in the above range, the corresponding P_d value are also simulated. These P_d values are plotted against the corresponding P_{fa} values to obtain the receiver operating characteristics. Of course, for a given P_{fa} value, larger P_d value implies a better signal detection at that P_{fa}. The 10-dB-SNR-trained neural network is tested in the 5-dB and 10-dB SNR environment. This latter experiment is carried out to study the neural detector's sensitivity to the training SNR. To achieve 5-dB SNR environment, we keep θ at $\sqrt{10}$ and sufficiently increase the noise variance $E[N_i^2]$.

A. Performance in Gaussian Noise (Constant Signal, 10 dB

Performance characteristics of neural detectors using RBF, MLP and MF detectors are presented in Figure 4 for Gaussian noise. The RBF and MLP neural detectors are trained using the constant signal and ramp signal with SNR = 10 dB. And then both neural detectors and match filter detector are tested with 10-dB SNR inputs.

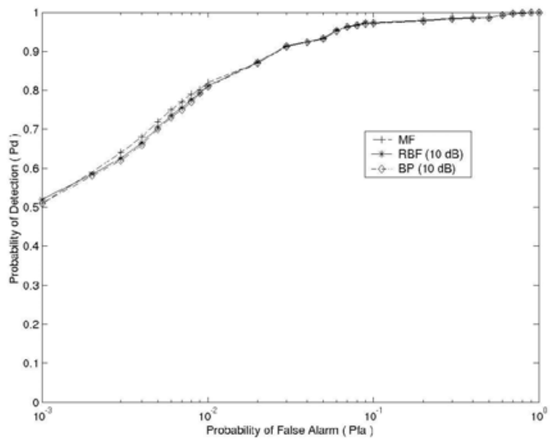

Figure 4. Performance in Gaussian Noise (Constant Signal,10 dB).

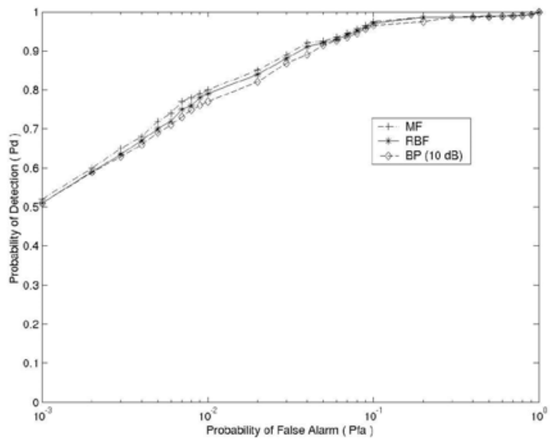

Figure 5. Performance in Gaussian Noise (Ramp Signal, 10 dB).

B. Performance in Gaussian Noise (Ramp Signal,10 dB)

For gaussian noise, the receiver operating characteristics of neural detectors as well as matched filter detectors are presented in Figure 5. In this case, RBF and MLP neural detectors are trained using the ramp signal with SNR = 10 dB. All detectors are then tested with 10-dB SNR inputs. In both Constant and Ramp Signal cases, the RBF and MLP neural detectors performance is very close to that of the MF detector.

V. Testing of Signal Detector in Non-Gaussian Noise

In this work, we consider the classical problem of detecting known signals in *non-Gaussian* noise. Performance characteristics of RBF and MLP neural detectors are presented at small false alarm probabilities (in the range 10^{-3} to 10^{0}) that are of typical practical interest.

A. Performance in Double Exponential Noise (Ramp Signal)

Here we, illustrates performance comparisons of the LR, MF, LO, and neural detectors using RBF and MLP for ramp signal embedded in additive double exponential noise. Figures 6 and 7 show the comparison for a 10-dB-SNR-trained neural detectors operating in the 10-dB and 5-dB SNR environment. In this testing, the signal detector using RBF network continues to provide performance improvement, compare to MLP neural, MF and LO signal detectors.

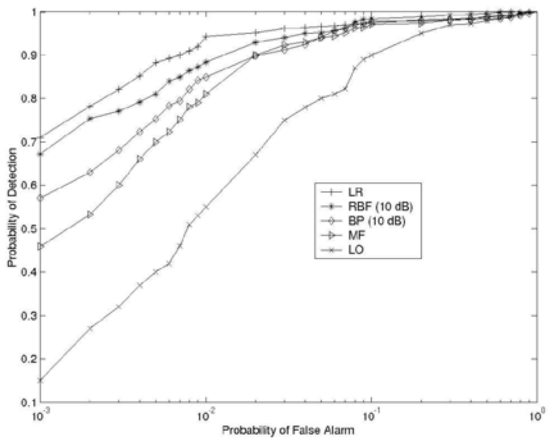

Figure 6. Performance comparison in double exponential noise (Ramp Signal , 10 dB).

B. Performance in Contaminated Gaussian Noise (Ramp Signal)

The same experiment is repeated for the ramp signal embedded in contaminated Gaussian noise with parameters $\epsilon = 0.2, \sigma_0^2 = 0.25$ and $\sigma_1^2 = 4$. Figures 8 and 9 show the comparison for a 10-dB-SNR-trained neural detectors operated in the 10-dB-SNR and 5-dB-SNR environment respectively. In all cases, we see that both MF and LO detectors perform similarly and that the neural detector using RBF network clearly provides the best detection performance compare to MLP neural detector.

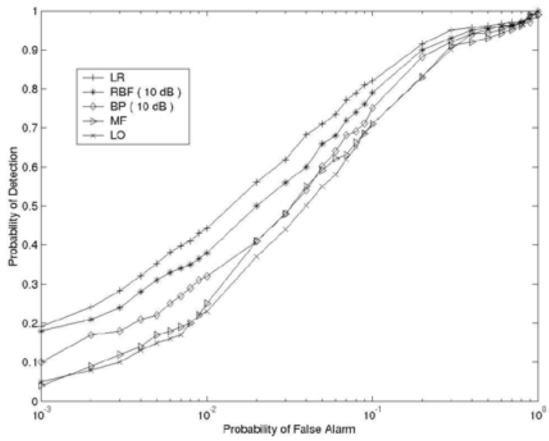

Figure 7. Performance comparison in double exponential noise (Ramp Signal , 5 dB).

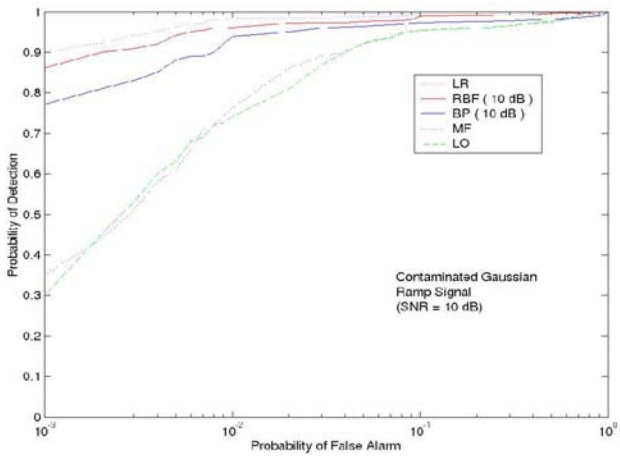

Figure 8. Performance comparison in contaminated Gaussian noise (Ramp Signal, 10 dB).

C. Performance in Cauchy Noise (Constant and Triangular Signal)

In this case, we are not consider SNR as the random variable is not finite in Cauchy noise. Here, we consider the signal energy $= 250$ and $\sigma = 1.0$ of the Cauchy pdf. Performance of detector are illustrated in Figures 10 and 11. We observe that the neural detector using RBF outperforms compare to other detectors. But for relatively high P_{fa} values its performance decreases compare to the matched filter and locally optimum detectors.

VI. Testing of Signal Detector in Impulsive and Mixed Noise

In this work, the performance of signal detector is tested with signal corrupted by impulsive interferences such as environmental effects of atmospherics (lighting) and meteor train echoes. These interferences raise noise level, there by reducing target to noise power ratios. The segment or segments of data that are corrupted depend on both the environmental distribution of the impulsive bust duration, frequency and energy, and radar waveform

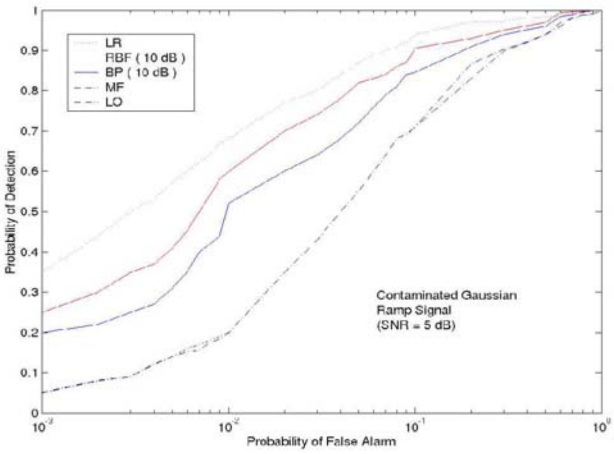

Figure 9. Performance comparison in contaminated Gaussian noise (Ramp Signal, 5 dB).

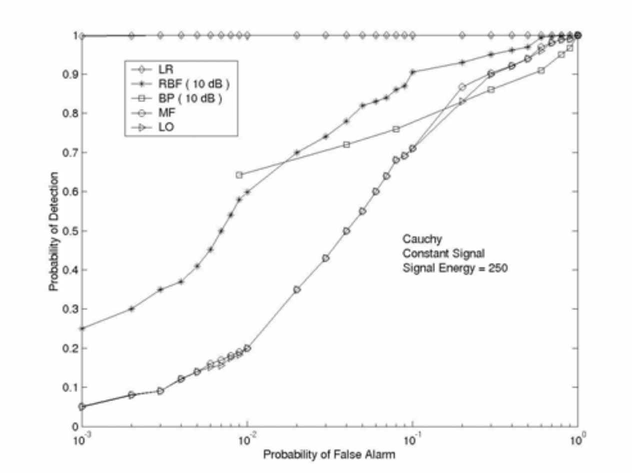

Figure 10. Performance in Cauchy Noise (Constant Signal).

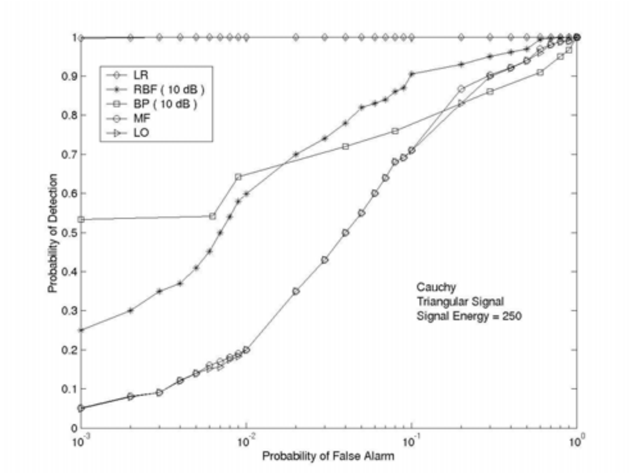

Figure 11. Performance in Cauchy Noise (Triangular Signal).

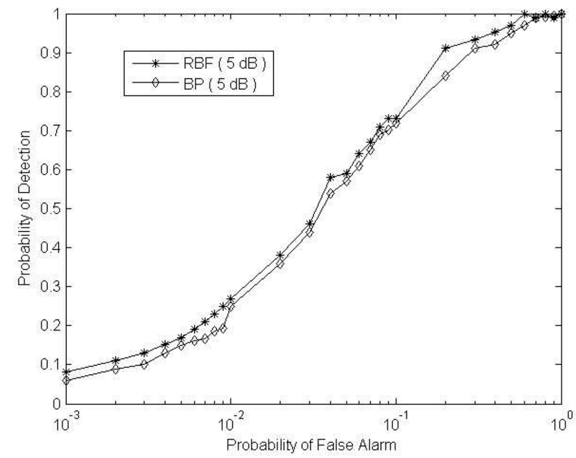

Figure 12. Performance in Impulsive Noise, (5dB SNR, while testing).

parameters of coherent integration time, carrier frequency and pulse repetition frequency. The median environmental noise factor is 20 to 60 dB larger than the receiver noise figure, depending on frequency, season,and time of day. When thunderstorms are present in the radar coverage, the average noise level created by lighting discharges increases relative to predicitions by as much as 20 dB on individual radar dwells. We generated the impulsive noise which increases the average noise level by 20 to 25 dB. In noise model, we considered the prominent lighting impulses, including both cloud-to-cloud and cloud-to-ground electrical discharges, that occur within 1-or 2-hop coverage by the radar (nominal ranges of 500 to 3000 nmi), will be received by the associated electrical storms. Lighting impulse rates of one per second to one per 5 seconds are typical during active stroms, and the physics of lighting indicates total impulse durations lasting 200 to 400 ms. In this testing, the signal detector using RBF network continues to provide performance improvement, compare to MLP neural signal detectors. It is show in Figures 12 and 13.

VII. Detection Performance as a Function of SNR (Ramp Signal)

Here we try to study the behavior of MF, LO and RBF, MLP neural detector's for fixed $E[N_i^2]$ and varying θ values. The noise variance is set to unity during training and testing. Here, we consider the case of contaminated Gaussian noise distribution with $\epsilon = 0.2$, $\sigma_0^2 = 0.25$ and $\sigma_1^2 = 4$, as before. The neural detectors are trained using the ramp signal at 0, 10 and 15-dB SNR. During testing, we adjust the bias weight in both the neural detector's to ensure that the neural detector's operation at $P_{fa} = 0.001$. We set $E[N_i^2]$ to unity and vary θ for SNR values between 0-15 dB. These probability of detection values are plotted in Figures 14,15 and 16 as a function of SNR. The neural detector using RBF network clearly yields superior performance characteristics in all three cases.

VIII. Conclusion

In this paper radial basis function network is proposed for known signal detection in Gaussian, non-Gaussian and impulsive noise. Neural detector using radial basis

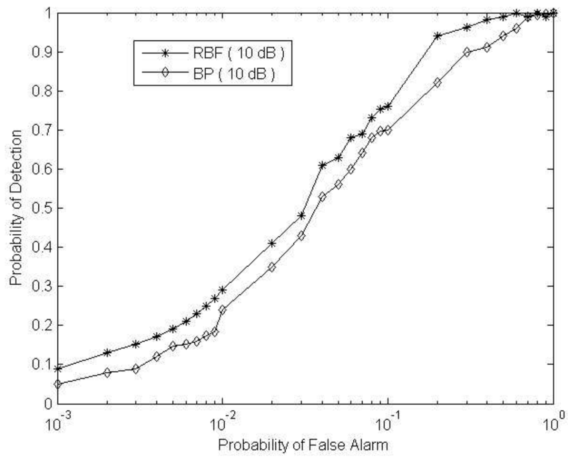

Figure 13. Performance in Impulsive Noise, (10dB SNR, while testing).

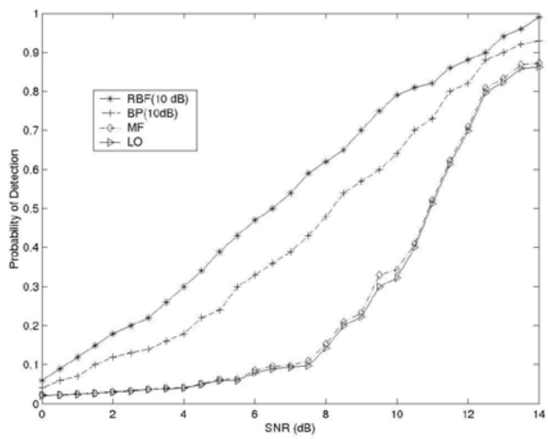

Figure 15. Detection Performance as a Function of SNR (NN Trained at 10 dB SNR).

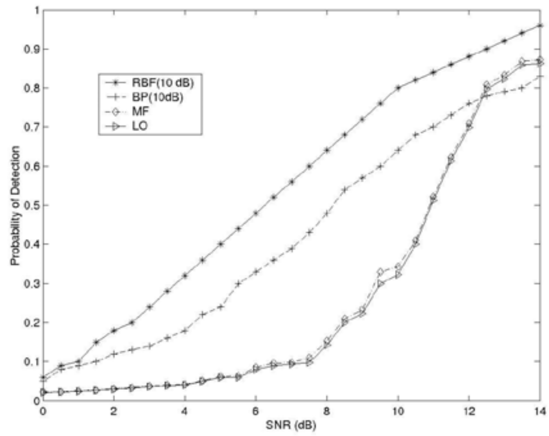

Figure 14. Detection Performance as a Function of SNR (NN Trained at 0 dB SNR).

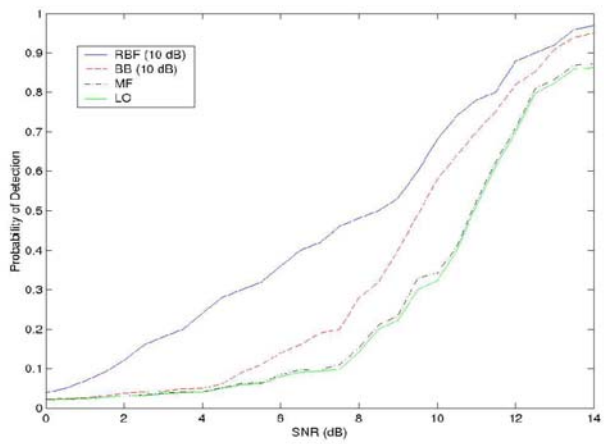

Figure 16. Detection Performance as a Function of SNR (NN Trained at 15 dB SNR).

function network show better performance characteristics for many non-Gaussian noise distributions such as double exponential, contaminated Gaussian, Cauchy and Impulsive noise. We observed that in non-Gaussian noise environments the RBF neural network signal detector show good detection capability compared to neural detector using multilayer perceptron (BP) and conventional signal detectors. It also show better performance as a function of signal-to-noise ratio compare to BP and MF detector.

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