

NEURAL NETWORK BASED OPTIMUM RADAR TARGET DETECTION IN NON-GAUSSIAN NOISE.

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1. Abstract

Application of neural networks to radar target detection in non_gaussian noise environments is investigated. More specifically two new probabilistic neural networks, namely Gram-Charlier Neural Network (GCNN), and Gram-Charlier Probabilistic Neural Network (GPNN) are applied to radar detection problem. The performance of these detectors is evaluated and compared with Backpropagation and Bayesian classifiers by simulation for Gaussian, Weibull, and Lognormal noise environments.

2. Introduction

Radar detection problem can be represented as testing of two hypotheses H_0 and H_1 :

$$H_1 : x = s_i + n_i, \quad H_0 : x = n_i, \quad i=1,2,3,\dots,n \quad (1)$$

where x 's are samples of a received continuous waveform, s_i 's are samples of the signal and n_i 's are the samples of background noise. A maximum likelihood detector calculates a likelihood ratio $L(r)$ and compares it's to a threshold:

$$L(x) = \frac{f(x|H_1)}{f(x|H_0)} \underset{H_0}{\overset{H_1}{>}} th. \quad (2)$$

where x is the received samples and $f(x|H_1)$ is conditional density function of x given H_1 is true, and $f(x|H_0)$ is conditional density function of x given H_0 is true. For this paper the threshold is taken equal to one. Thus the following decision rule is applied:

$$H_1 \text{ is true} : f(x|H_1) > f(x|H_0) \quad (3)$$

$$H_0 \text{ is true} : f(x|H_0) > f(x|H_1).$$

Two performance measures are commonly used

$$p_d = \int_{th}^{\infty} f(X|H_1)dX \quad \text{and} \quad p_{fa} = \int_{th}^{\infty} f(X|H_0)dX, \quad (4)$$

where p_d is the probability of detection and p_{fa} is the probability of false alarm.

It is observed from equation (3) that in order to make a decision one has to calculate $f(x|H_1)$ and $f(x|H_0)$. A Probabilistic neural network based Bayesian classifier has been proposed by Specht [2]. Two new probabilistic neural networks, Gram-Charlier Neural Network (GCNN), and Gram-Charlier Probabilistic Neural Network (GPNN) [4] are proposed and applied here for implementation of a maximum likelihood detector described by equation (3). Performances of these detectors for radar target detection are evaluated by simulation. Also performance of these detectors are compared with those of Bayesian classifier and Backpropagation (BP) classifier [1] for Gaussian, Weibull, and Lognormal noise backgrounds.

3. Proposed Neural Network Architectures for Radar Target Detection

3.1. Gram-Charlier Neural Network GCNN (scalar sample case) [4]

The overall functional block diagram of GCNN classifier is shown in Figure 1. If it is needed to classify L classes $H_0, H_1, H_2, \dots, H_{L-1}$, then Figure 1 will consist of L subsections, one for each class. These subsections have the same architecture and function. As an example, one of the subsections is described in Figure 2. For class H_i , the first hidden layer in the i^{th} subsection adapts the weights w_{ik} to be equal to the corresponding coefficients c_i 's calculated using the input training samples belonging to class H_i . The nodes at the second hidden layer produce conditional density $f(x|H_i)$. The outputs of appropriate nodes of this layer for all classes are sent to the output layer for decision making.

3.2. Gram-Charlier Probabilistic Neural Network (GPNN) (scalar sample case) [4]

The overall architecture of GPNN is shown in Figure 3. If it is needed to classify L classes $H_0, H_1, H_2, \dots, H_{L-1}$ then Figure 3 consists of L separate subsections, one for each class. These subsections are similar in architecture and function and hence only one such subsection (e.g. the subsection for H_0) is shown in further details in Figure 4 and is described below. The outputs of appropriate nodes of this layer are added (at the nodes of the summation layer) to produce $f(x|H_0)$. For the radar target detection problem, there are only two classes H_0 and H_1 and hence only two subsections of Figure 4 are to be used.

4 Radar System Concept:

Block diagram of a general radar signal detection scheme is shown in Figure 5. One of the most important aspects for a radar system design is a radar waveform design. The Pulse Repetition-Frequency (prf) and carrier frequency determines the range and doppler ambiguities of a particular waveform. The radar waveform is designed to resolve the range and doppler ambiguities while detecting a target. Here a surveillance radar system is considered. The coherent pulse train waveform (Figure 6.) is almost always required for surveillance radars where a long detection range is desired and high clutter rejection is necessary.

The basic pulse-train radar waveform consists of N medium-Pulse Repetition Frequency (prf) pulses, shown in Figure 6. Each coherent burst contains N_B sub pulses, and the radar's frequency and prf are changed from burst-to-burst. Training samples are obtained from the received burst data. The received data contains either a target or a noise. The detector based on either back-propagation, Bayesian, GPNN (scalar), or GCNN (scalar) where trained based on these training samples. After training, the neural network classifiers are ready to be used for target detection. The strength of the signal was varied to obtain training samples for SNR's of -10 dB to 25 dB. It should be mentioned that larger SNR indicates stronger or closer targets.

5. Discussion of simulation results

In the previous section radar system concept has been described. Performances of neural network based BP, Bayesian, GCNN, and GPNN detectors for radar target detection in Gaussian, Weibull, and Lognormal noise environments are presented in this section. Lognormal, and Weibull distributions are simulated for number of values of parameters (standard deviation σ and parameter α respectively). For each noise case, 6 pulses and the number of filler pulses are used. These noises and signals were synthetically generated and the training samples were obtained from these synthetic data for various SNR's. The training samples are generated from -10 to 25 dB signal to noise ratio with 100 samples for each 2 dB step. The BP, Bayesian, GCNN, and GPNN detectors are simulated and trained and tested using these training samples.

The simulation results are presented in Figures 7,8,9,10, and 11 and a summary comparison of the performance of the various detectors for probability of detection P_D of 0.9 is shown in Table 1.

From Figure 7, it appears that in Gaussian noise both GCNN and GPNN have higher P_D than both Bayesian and BP detectors for SNR above -2 dB. For Lognormal noise with $\sigma = 0.1$ (Figure 8), the GCNN and GPNN are outperformed by Bayesian and BP detectors for small SNR's, however as SNR goes above 5 dB, the GCNN and GPNN perform better than Bayesian and BP detectors. Similar results hold for Lognormal noise with $\sigma = 0.5$ (Figure 9). For Weibull noise with $\alpha = 0.5$ (Figure 10), The GCNN and GPNN were outperformed by Bayesian for low SNR's, however for higher SNR the GCNN and GPNN performed as well or better than Bayesian and BP detectors. The results for BP were not consistent (being higher for some α 's and lower for others). For Weibull noise with $\alpha \geq 1.0$ (Figure 11), the GCNN and GPNN either performed as well or better than Bayesian and BP detectors. Similar results are also evident from Table 1. However, it should be mentioned that under many conditions the P_D 's for Bayesian and BP detectors did not reach 0.9 where as the GCNN and GPNN always achieved $P_D = 0.9$ for resonable values of SNR.

Table 1.: Signal-to-Noise Ratio (SNR)'s equal for $P_D = 0.9$ GCNN, BP, and Bayesian detectors.

	SNR (dB)			
	GCNN	GPNN	BP	Bayesian
Gaussian	0	2.3	-	-
Lognormal ($\sigma = 0.1$)	4.9	4.9	6.0	6.0
Lognormal ($\sigma = 0.5$)	9.2	10.9	-	-
Weibull ($\alpha = 0.1$)	3.2	5.0	0.9	1.3
Weibull ($\alpha = 0.3$)	3.0	6.9	5.8	-
Weibull ($\alpha = 0.5$)	5.0	3.7	7.5	-
Weibull ($\alpha = 0.7$)	5.6	7.3	6.2	-
Weibull ($\alpha = 1.0$)	8.3	8.3	-	-
Weibull ($\alpha = 1.2$)	9.2	6.4	9.0	-
Weibull ($\alpha = 1.5$)	12.2	13.3	-	-
Weibull ($\alpha = 1.7$)	18.1	10.4	12.5	-
Weibull ($\alpha = 2.0$)	20.2	13.0	-	-

Note that '-' means P_D does not reach 0.9.

6. Conclusions

From the above results and discussion, it appears that both GCNN and GPNN provided high probability of detection for resonable values of SNR's. The Bayesian detector perform as well in some cases but did not perform well in many cases. The BP performed well in some of the cases, however

it's performance was not consistent and in some cases, probability of detection is very low (nearly equal to 0.5). Thus the GCNN and GPNN shows good promise as detectors in Gaussian and non-Gaussian noises like Weibull and Lognormal. Further evaluation of performances of these detectors are continuing.

7. REFERENCES

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4. M. Kim, and M. Arozullah,' Generalized Probabilistic Neural Network Based Classifiers', submitted to the IEEE International Joint Conference on Neural Networks to be held in Baltimore, June 1992.

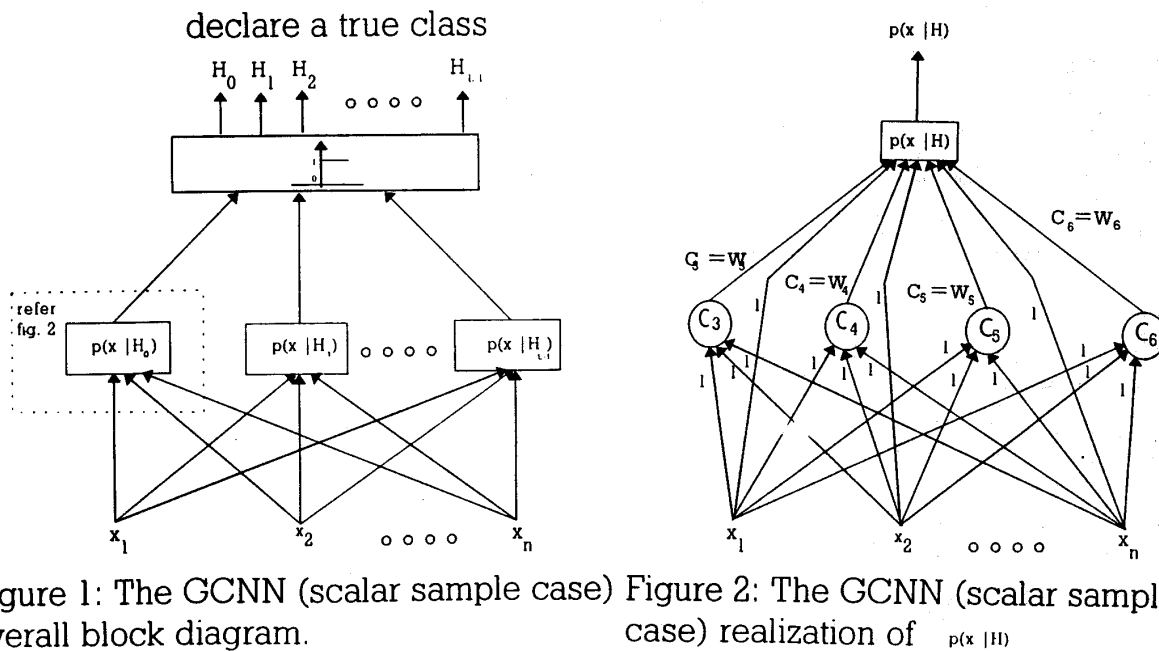


Figure 1: The GCNN (scalar sample case) overall block diagram. Figure 2: The GCNN (scalar sample case) realization of $p(x | H)$

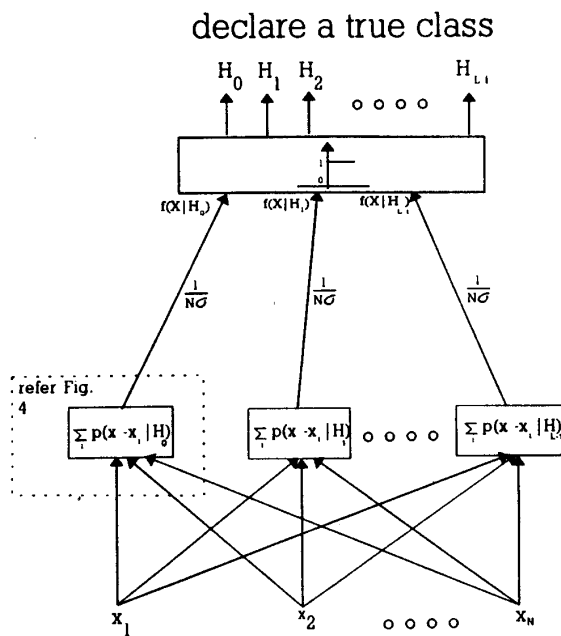


Figure 3: The GPNN (scalar sample case) overall block diagram.

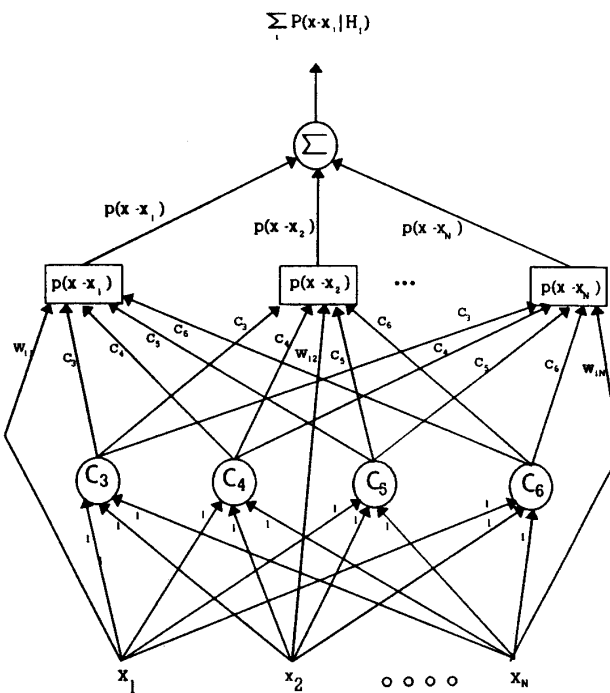


Figure 4: The GPNN (scalar sample case) realization of $\sum p(x \cdot x_i | H_i)$

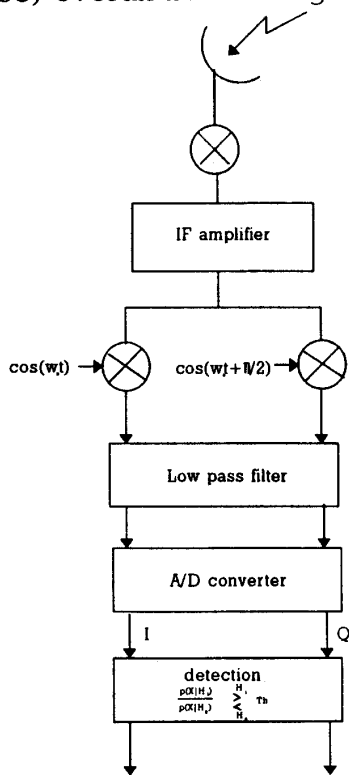


Figure 5: Radar Receiver Block Diagram.

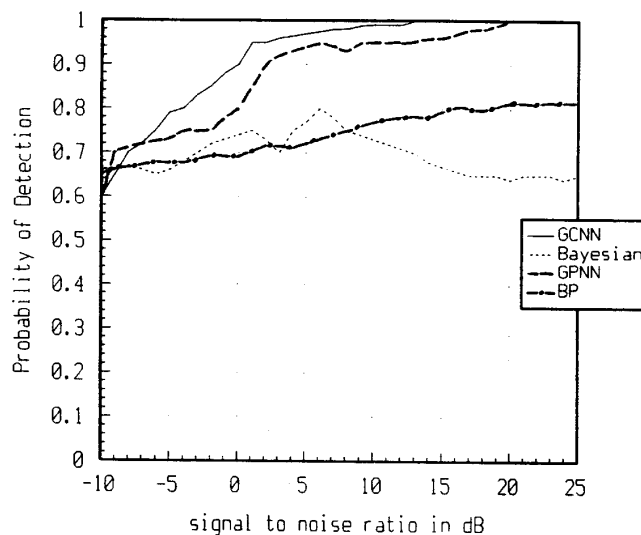


Figure 7: Performances of NNs for target detection in Gaussian noise (scalar case).

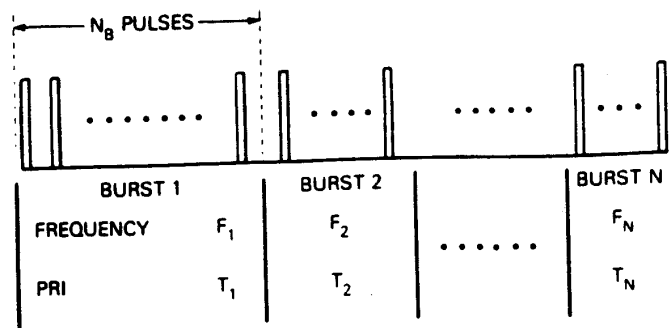


Fig. 6 — Medium PRF waveform

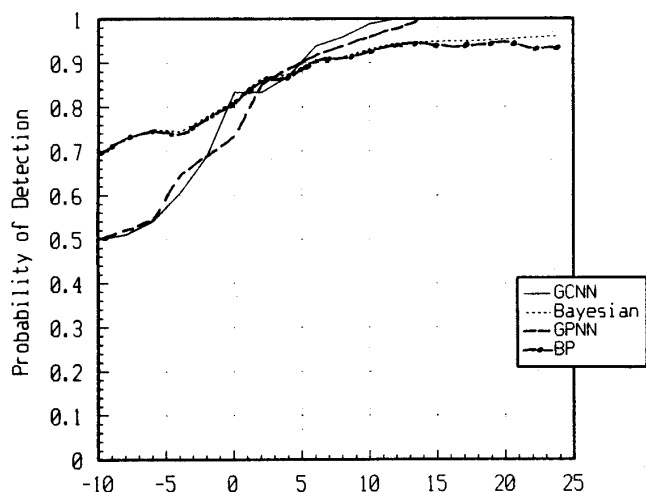


Figure 8: Performances of NNs for target detection in Lognormal noise ($\sigma=0.1$) case. (scalar case).

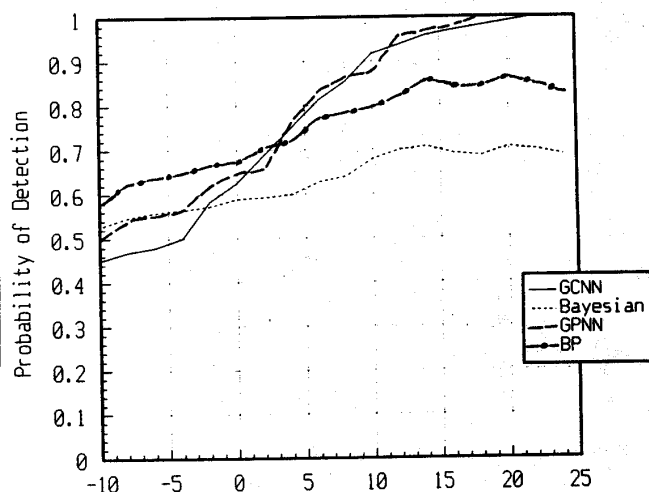


Figure 9: Performances of NNs for target detection in Lognormal noise ($\sigma=0.5$) case. (scalar case).

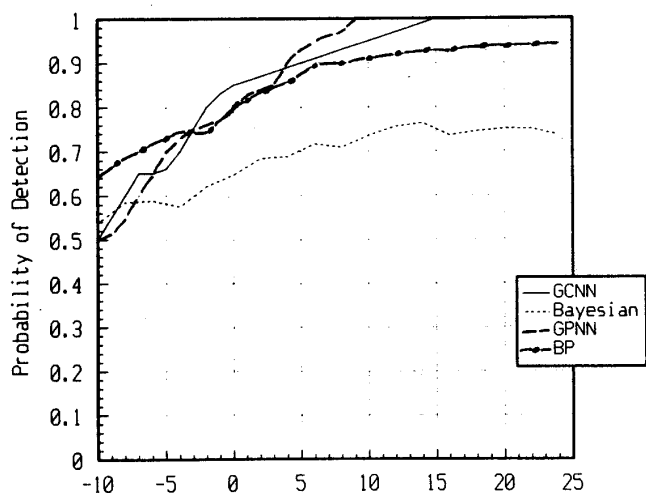


Figure 10: Performances of NNs for target detection in Weibull noise ($\alpha=0.5$) case. (scalar case).

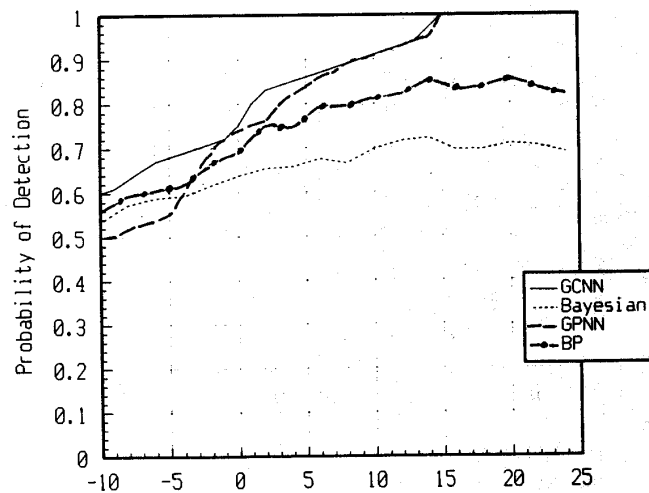


Figure 11: Performances of NNs for target detection in Weibull noise ($\alpha=1.0$) case. (scalar case).