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Effect of Spectrum Occupancy on the Performance of a Real Valued Neural Network Based Energy Detector

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***Abstract*— In this paper, a newly proposed Real Valued Neural Network (RVNN) based Energy Detector (ED) is presented for Cognitive Radio (CR) application. With little available on the performance of EDs in varying spectrum occupancy conditions, we provide a study to understand how occupancy variation affects the performance of a newly proposed RVNN based ED and other ED schemes. Other factors such as varying Signal to Noise Ratio (SNR) and model order values were also examined in this study and result analysis conducted using the Precision-detection statistics. Implication of results obtained indicate that the RVNN based ED would perform optimum in high occupancy and SNR conditions for a model order choice of $P = 20$. We also observed that the RVNN based ED would provide better precision performance characteristics over the Periodogram, Welch and Multitaper based ED schemes compared herein. Hence, the RVNN based ED suffices as a favourable choice for CR application even under varying occupancy conditions.**

Keywords- Artificial Neural Network; Cognitive Radio; Energy Detector; Spectrum Occupancy, Non-Parametric

I. INTRODUCTION

The Energy Detector (ED) scheme has been widely proposed as an optimum solution to the challenge of Spectrum Sensing (SS) in Cognitive Radio (CR) [1] – [3]. This can be attributed to its design and implementation simplicity, fast sensing capability and its semi-blind nature which provides an independence of the *a priori* knowledge of the Primary User (PU) waveform. However, it is known for its poor detection performance in low Signal-to-Noise Ratio (SNR) conditions and dependence on noise statistics. These drawbacks have recently driven several research efforts towards enhancing ED performance for CR application.

In an effort to improve poor ED performance in low SNR conditions, some works have proposed the use of co-operative spectrum sensing [4] – [6]. This approach is envisioned to solve challenges associated with low SNR conditions such as signal shadowing, fading and multipath effect. Detection performance has been shown to improve based on this approach; however, it introduces further complexity in the coordination of CR Secondary Nodes (SN) and increased cost of a third party Base Station or Fusion Center. Other works have proposed longer sensing time (large sample number) and a careful choice of threshold values to improve detection in low SNR [7]. However, these approaches tend to suffer from the snag of noise uncertainty which can overwhelm low powered PU signals. Also, the need for quick sensing in CR to prevent PU interference flouts the idea of long sensing time. Therefore, the invitation to develop a CR system capable of conducting local sensing at acceptable detection performance in low SNR condition and to possibly operate independent of noise fluctuations remains an open research area in CR.

Motivated by this challenge, in this paper, we present the idea of a new Real Valued Neural Network (RVNN) based ED which was developed from a two layered RVNN scheme proposed in Aibinu et.al [8]. We used the RVNN scheme to estimate the model coefficients of an Autoregressive (AR) system driven by white noise and then computed the Power Spectral Density (PSD) of the input process. We then extended the RVNN process to develop a new ED. This extension was further motivated by the fact that the RVNN scheme provides immunity to the challenge of spectral line splitting as compared to the Burg approach established in [8]. However, it remained unknown how well the RVNN based ED along with other ED schemes would perform in different spectrum occupancy conditions assuming the SNR was kept constant. To the best of our knowledge, such studies have not been performed even for other ED schemes, hence, the goal of this work. To achieve this, first, we present models for occupancy measurement and also for precision estimation. Then, different occupancy rates were simulated and precision responses of the different ED schemes observed accordingly. Implications of results obtained are presented in appropriate sections of this paper.

The rest of the paper is structured as follows: section II provides the description of the proposed RVNN based ED. Section III details the frequency occupancy and precision modelling while Section IV presents results and their implications. Then, conclusions are drawn in section VI.

II. REAL VALUED NEURAL NEWORK BASED ENERGY DETECTOR

The Real Valued Neural Network (RVNN) based Energy Detector (ED) was developed by observing that an Autoregressive (AR) system driven by white noise $x(n)$ is known to produce an output sequence $y(n)$ given as

$$y(n) = -\sum_{k=1}^{p} a_k y(n-k) + b_0 x(n) \tag{1}$$

where a_k, $1 \le k \le p$ and b_0 denotes the model coefficients, p is the model order. By taking the z-transform of (1) and rearranging the terms therein, the transfer function $H(z)$ of the AR-system can be obtained as

$$H(z) = \frac{Y(z)}{X(z)} = \frac{b_0}{1 + \sum_{k=1}^{p} a_k z^{-k}} \tag{2}$$

By assigning $b_0 = 1$, $z = e^{-jw}$ and taking the square of (2), we obtain the SNR as

$$SNR = \left| \frac{Y(jw)}{X(jw)} \right|^2 = \frac{1}{\left| 1 + \sum_{k=1}^{p} a_k e^{-jwk} \right|^2} \tag{3}$$

To estimate the model coefficient a_k, we used a two layered Real Value Neural Network (RVNN) proposed in [8] as shown in Fig. 1. The output sequence of the RVNN system is obtained as

$$y(n) = \alpha \,\mathrm{F}\left(\sum_{l=1}^{M} w_{l1}\theta_l + h_{01} \right) \tag{4}$$

where M is the number of neurons in the hidden layer, w_{1l} represents the weight connecting node l in the hidden to output layer, h_{0l} is the bias term of the output neuron, θ_l denotes the output of the hidden node l and α the adaptive coefficient of the linear output activation function. The hidden node output θ_l is obtained as

$$\theta_l = \beta_l \,\mathrm{F}\left(\sum_{k=1}^{p} v_{kl}\, y(n-k) + g_{0l} \right) \tag{5}$$

where v_{kl} is the weight connecting input nodes k to hidden node l, g_{0l} is the bias of the hidden node and β_l is the adaptive coefficient of the hidden node linear activation

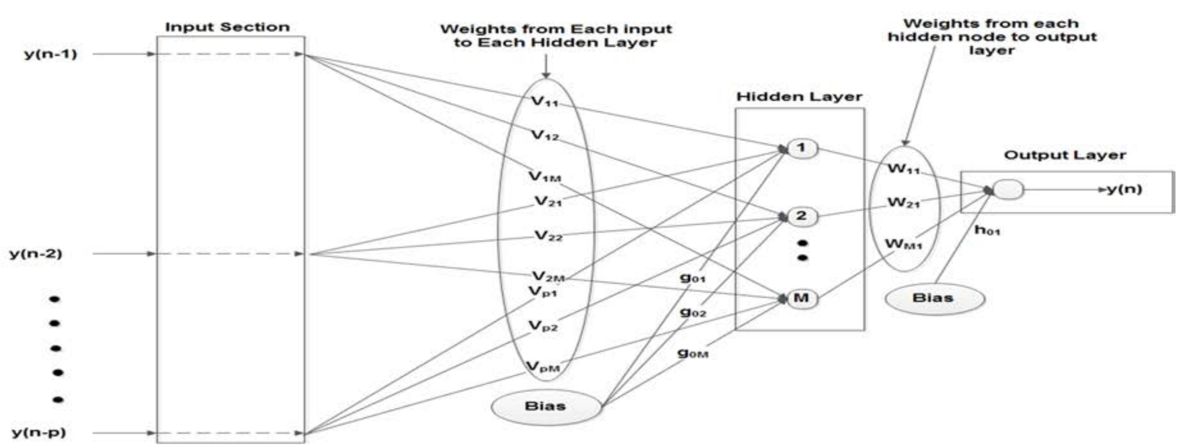

Fig. 1: RVNN Based AR Model Network Diagram

function. By using linear transfer activation functions in both hidden and output layer, i.e $\mathrm{F}(\bullet)$ is linear and substituting (5) into (4), the output sequence is obtained as

$$y(n)=\alpha\,\mathrm{F}\left(\sum_{l=1}^{M} w_{l1}\left(\beta_l\,\mathrm{F}\left(\sum_{k=1}^{p} v_{kl}\,y(n-k)+g_{0l}\right)\right)+h_{01}\right) \quad (6)$$

By rearranging terms in (6) and comparing with (2), the model coefficients a_k can be deduced as

$$a_k=\alpha\sum_{l=1}^{M} w_{l1}\beta_l v_{kl} \quad (7)$$

Thus, the AR model coefficients were estimated from the synaptic weights and the coefficients of the adaptive activation function of a properly trained two-layer RVNN. It was assumed that the model order p is known *a priori* and then the number of neurons in the hidden layer was determined by using the priori data length information at the input. By adhering to the necessary constraints provided in [8], an algorithm for the proposed RVNN system is given as follows:

1. Normalize the input data sequence to band-limit the acquired signal using either Z-score, Min-Max, sigmoidal or unitary data normalization techniques.
2. Format data using frame blocking and appropriate windowing of data sequence
3. Determine optimum number of neurons
4. Estimate model coefficient using (7).
5. Training of the RVNN system was realized using the Back Propagation (BP) supervised learning algorithm.

Now, by using the above described algorithm, we further extended to develop an RVNN based Energy Detector (ED) scheme. This was achieved by generating the Power Spectral Density (PSD) using (3) and introducing a detector system as shown in Fig. 2. A simple Analogue-Digital-Converter (ADC) was utilized for digitization, the Fast Fourier Transform (FFT) was used for frequency response estimation, the transfer function estimator block was realized using the frequency response vector obtained from appropriate adaptive filtering of the FFT samples, a simple square law device was used for squaring and the detector analyzer was realized using empirically deduced thresholds. Then, the newly proposed RVNN based ED was analysed for its response to different frequency occupancy values and compared with other ED schemes in similar conditions.

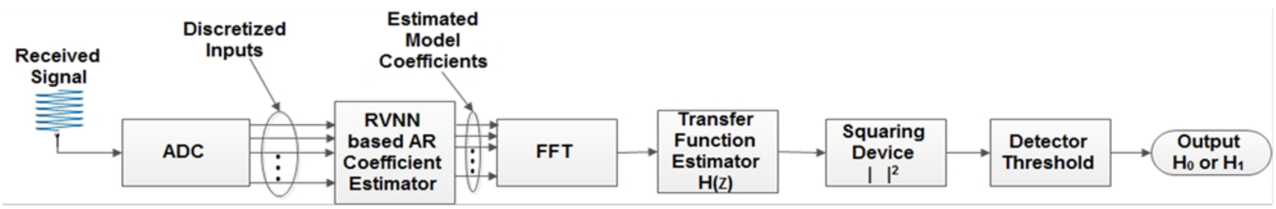

Fig.2: Proposed RVNN based ED for CR application

III. FREQUENCY OCCUPANCY AND PRECISION MODELLING

By frequency occupancy, we refer to the probability that the received signal energy is greater than a threshold value within a specified spectrum [9]. This is synonymous to the probability of detecting a signal within a defined spectrum. To estimate occupancy, let us denote the scanned spectrum as Δf, E_n be the measured PSD per n sample $\forall n=1,2,...,N$, where N is the total number of samples within Δf and V_T be the threshold. Now, for a sampling frequency $f_s=2\times\Delta f$, let S_n denote a function obtained as

$$S_n=\begin{cases}1 & \text{for } E_n\geq V_T\\ 0 & \text{for } E_n<V_T\end{cases} \qquad \text{for all } n=1,2,...,N \quad (8)$$

Consequently, the frequency occupancy percentage can be obtained as

$$O_c=\left(\frac{1}{N}\sum_{n=0}^{N-1} S_n\right)\times 100\% \quad (9)$$

We can easily observe that (9) is synonymous to the detection probability, hence, different occupancy percentages can be simulated and performance analysis achieved using the Precision-detection curves of the RVNN based ED. This analytical approach provides insight into how much effect a densely or sparsely populated band would have on the performance of the RVNN based ED and other ED schemes.

To further motivate the choice of precision-detection analysis over the use of the Receiver Operating Characteristic (ROC), it must be noted that the ROC curve provides no information on the effect of frequency occupancy on the performance of an Energy Detector (ED). This can be understood by considering the confusion matrix of Fig. 3 and observing that the ROC depends strictly on the probability of false alarm P_{FA} and detection P_D and not on a combination of both. Hence, it does not change even when the ratio of signal to noise samples changes as the case maybe in occupancy studies. Therefore, to study the effect of occupancy on the detector performance, the use of precision is suggested which provides a cross-interaction between signal and noise samples.

Hence, by using the number of samples obtained in a certain spectrum sweep, let us establish the probability of detection P_D and false alarm P_{FA} as

$$P_D = \frac{TS}{SN} \tag{10}$$

$$P_{FA} = \frac{FS}{NN} \tag{11}$$

where SN denotes the total number of signal samples and NN denotes the total number of noise samples while other abbreviations can be deduced from Fig. 3. Precision Pc is thus defined as [10]

$$Pc = \frac{TS}{TS + FS} \tag{12}$$

Hypothesized Class \ True Class	Signal	Noise
Signal	True Signal (TS)	False Signal (FS)
Noise	False Noise (FN)	True Noise (TN)
	SN	NN

Fig. 3: A Confusion Matrix for Signal and Noise Detection

With an applicable metric defined in (12), we then simulated several sinusoids $s(n)$ operating at different sub-carrier frequencies using

$$s(n) = \sum_{i=1}^{Q} A_i \sin 2\pi f_i n \tag{13}$$

where A_i and f_i denote the different sub-carrier amplitudes and frequencies respectively and n the time indexes. Each individual sub-carrier frequency was observed to occupy a 5Hz bandwidth resulting from the increased variance or band leakage caused by the choice of the RVNN model order. We further ensured that the SNR for each sub-carrier was kept constant throughout all experiments at $SNR = 10dB$ as observed in Fig. 4A – Fig. 4D; the spectrum span was set at $\Delta f = 100Hz$, total number of samples $N = 250$, RVNN model order was chosen as $p = 30$ and $Q = 19$ denotes the total number of sub-carrier frequencies used to occupy the 100Hz band. We simulated different occupancy values by switching off the respective number of sub-carriers Q within the 100Hz spectrum band and their respective PSD were obtained using the RVNN based ED as shown in Fig. 4A – Fig. 4D

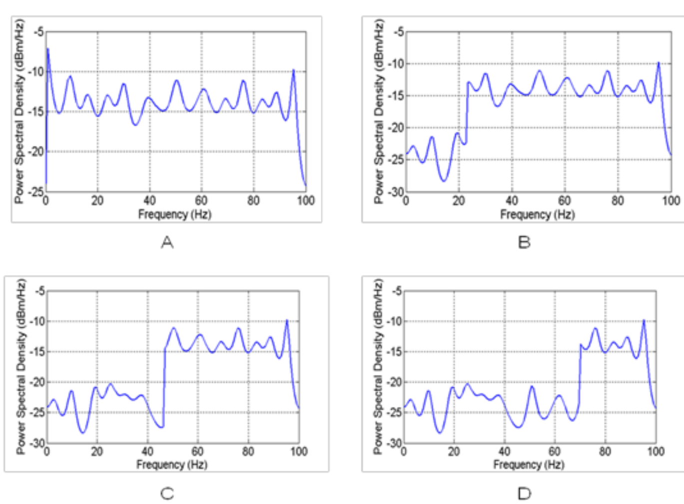

Fig. 4: PSD estimated using the RVNN based ED for different occupancies as follows: (A) 95% Occupancy (B) 70% Occupancy (C) 50% Occupancy (D) 25% Occupancy

IV. RESULTS AND ANALYSIS

The performance of the RVNN based ED was examined and results shown in Fig. 5 for different occupancy values for a constant high SNR condition of 10dB and total number of samples N = 250. It was observed as expected that performance was best for occupancy of 95%. A 50% reduction in precision performance was observed for an occupancy drop from 95% to 25%. Hence, it was easily concluded that the RVNN based ED provides optimum performance when utilized in highly occupied spectrums.

Analysis was conducted and results shown in Fig. 6 to examine the RVNN based ED performance in varying SNR conditions for a constant occupancy of 50%. It was also observed as expected that precision performance degrades with drop in SNR. Particularly, a 60% reduction in precision was observed for a change in SNR from 10dB to 1dB. This result reveals that RVNN based ED would be best utilized in high SNR conditions to ensure high precision-detection performance.

Further analysis was conducted to examine the performance of the RVNN based ED for varying model order values as shown in Fig. 7. Best performance was observed at a low model order $P = 20$ and this was attributed to the increased averaging and lower noise variance experienced at this model value. However, it must be noted that spectrum estimation accuracy and resolution is lower at this value than higher values. Hence, the choice of $P = 20$ was chosen for RVNN based ED as a candidate operating value for CR application.

Finally, we conducted a comparative analysis between the RVNN based ED and other non-parametric ED schemes, particularly, the Periodogram, Welch and Multitaper based ED. This was conducted for high and low SNR conditions and results obtained are shown in Figs. 8 – 9 respectively. It was easily observed that the RVNN based ED performed better than other examined techniques with a 10% precision gain over the Multitaper based scheme while the Simple Periodogram scheme performed least in the comparative exercise.

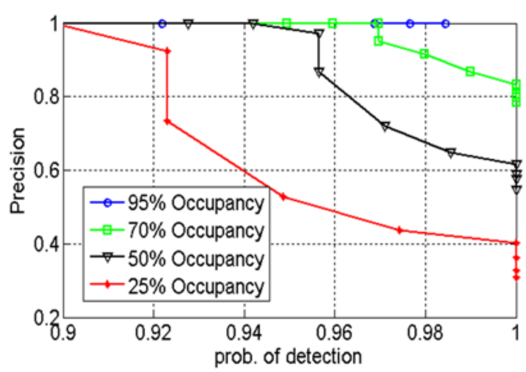

Fig. 5: Relationship between the Precision-Detection performances of RVNN based ED in varying occupancy conditions.

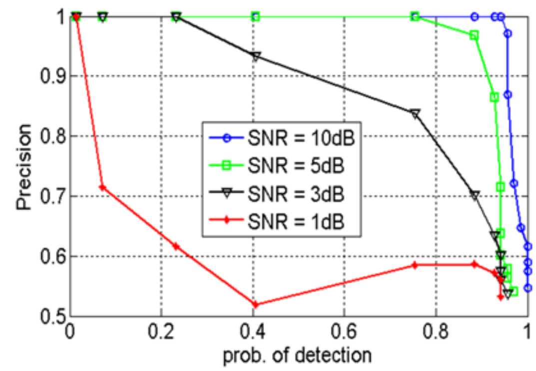

Fig. 6: Precision Performance of RVNN based ED in varying SNR conditions at constant N = 250 and 50% Occupancy rate

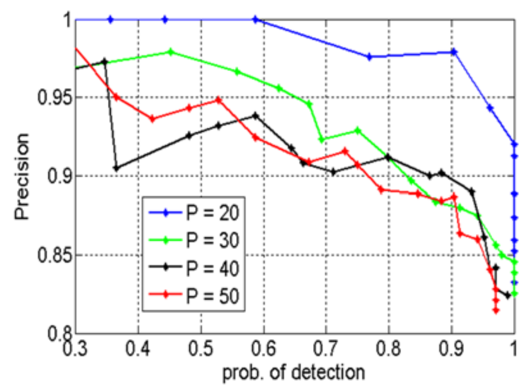

Fig. 7: Precision Performance of RVNN based ED for varying model order at constant SNR = 3dB, N = 250 and 50% Occupancy rate.

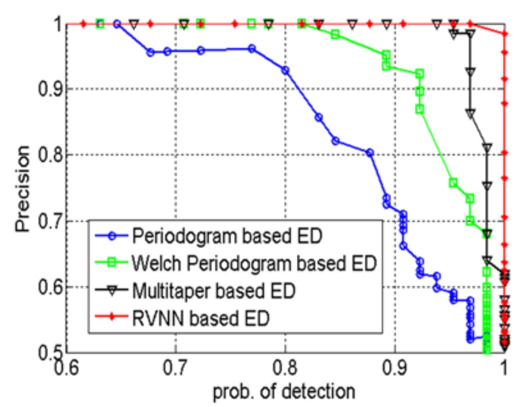

Fig. 8: Comparative Precision Performance of RVNN based ED with other Energy Detector Schemes in high SNR = 10dB, P = 20, constant N = 250 and 50% Occupancy rate

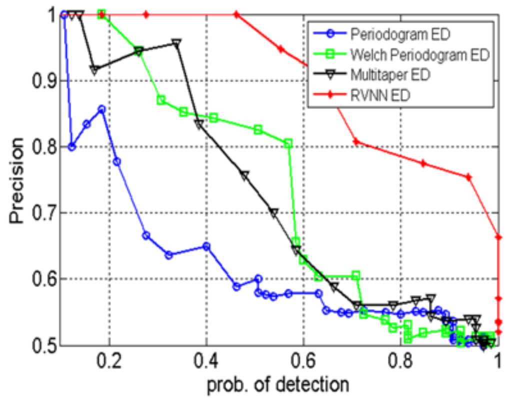

Fig. 9: Comparative Precision Performance of RVNN based ED with other Energy Detector Schemes in Low SNR = 2dB, P = 20, constant N = 250 and 50% Occupancy rate

V. CONCLUSION

In this paper, a study of the effect of frequency occupancy on the performance of a newly proposed Real Valued Neural Network (RVNN) Based Energy Detector (ED) and other ED schemes has been presented. The RVNN based ED was developed from a two layered RVNN scheme used to estimate the model coefficients of an Autoregressive (AR) system. The transfer function of the RVNN-AR system was estimated to generate appropriate Power Spectral Densities (PSD) and further extended to develop the ED. Several frequency occupancy statistics were simulated and subjected to the RVNN based ED to investigate its performance characteristics. Furthermore, comparative analysis was conducted with other ED schemes like the Periodogram (PD), Welch Periodogram (WP) and the Multitaper (MT). By using precision estimate as the comparative performance metric, results obtained revealed that the RVNN based ED performs optimum in high SNR and occupancy conditions at model order $P = 20$. Furthermore, it was observed that the RVNN based ED performed better than the PD, WP and MT schemes in both low and high SNR conditions. However, we note that the complexity demands of the RVNN based ED remains an open area for future investigations as compared to other ED schemes examined in this work.

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