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Spectrum Sensing – An Approach to Improve Resource Allocation in 5G Using Improved Energy Detector Algorithm

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Abstract: With the rapid development in wireless communication, the need for high performance network architecture is evident. Also with the increase in the wireless terminals the complete allocation of spectrum is the need of the hour. Spectrum sensing is one of the techniques of discussion and could be a possible solution to the resource allocation to the user equipments (UE) using the new radio spectrum in 5G. The resource to the user equipment in 5G needs to be dynamically allocated and since the system uses IoT, cloud and Artificial Intelligence (AI) to store and predict the position of User Equipment, energy detector (ED) with adaptive sampling is proposed to suit the requirements. In this technique the environment is set up with sampling points assuming the presence of user equipments. To evaluate the proposed system the SNR is calculated at points where UE are present and not present using ED. When the SNR decreases the number of sampling points can be increased to maintain the SNR. The proposed system is carried out in Matlab.

Keywords—*5G, CNN, Energy detection Spectrum sensing, SNR, ,LSTM*

I. Introduction

In the mobile networks from 2G to 5G the deployment of base stations have been connections oriented. The mobile operators have been constrained to obtain a considerable performance from the network and inflexibility to fulfil the spectrum to the UE by adding the physical resource blocks (PRBs). Setting up PRB is a complex task. Also, complexity in processing the received signal is time consuming. with the ever-increasing diffusion of smart pervasive systems has brought to attention on the need to optimally manage liable energy as well as the request for more general intelligent functionalities.5G is associated with content delivery and IoT with prediction services in AI. IoT represent one of the fastest technologies in the field of communication where the main challenge is gathering data streams. Therefore flexibility and reconfigurability of the mobile network gets the prime importance. The challenge in these networks are i) heterogeneity in the resources ii) widely distributed UE and iii) the energy or the capability of the UE. In this paper resource allocation to the UE and the capability of the UE is determined.

The high densities place heavy demands on energy consumption for sampling the received signal. The perception of adaptive sampling mechanism is the need to be able to detect samples' correlations in the area under consideration. It means that many of the UE may not need to sample at a given moment in order to achieve a desired level of accuracy. a decentralized network mechanism for adaptive sampling called as USAC(Utility Based Sensing and Communication)[10] is proposed. This mechanism works with two protocols, one for sensing the environment and the other for communication. The sensing algorithm uses a linear regression method which is run to determine the next predicted data with some bounded error called as confidence interval (CI). If the next observed data falls outside the CI, the UE sets the sampling rate to the maximum rate in order to integrate this phase change. if data falls within the CI, it means the UE has to reduce its sampling rate. This method results in allowing the UE to reduce the sampling rate to obtain a better energy efficiency. Therefore, the technique discussed imply that they are opportunistic access of the spectrum without any PRB present as an intermediate. If primary user (PU) reuses the same frequency spectrum the secondary user(SU) will exit the spectrum. To maintain the throughput to SU while protecting the PU is another predicament. Therefore spectrum sensing (SS) with adaptive sampling is used to provide fairness in allocation of spectrum to both PU and SU.

Among the various SS schemes, the performance evaluation /improvement can be carried out using matched filtering detector [12], energy detector (ED) [13], cyclostationary feature detector (CFD) [14]. The matched filtering detector

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is an optimal detector if the current state of PU is known. The cyclostationary feature detector, first checks upon the existence of the PU. Due to presence of background noise the stochastic technique can be used to low SNR cases and it has high complexity in computations. The Energy detector (ED) mechanism is based on the amount of energy available for comparison with the threshold that is preset. This provides a good performance in allocation of the spectrum to the UE with low complexity in computations and lesser interference. In this paper ED is considered for resource allocation to the UE. Although the ED suffers the influence of noise, improved energy detector algorithm proposed in this paper provides clarity to the noise involved.

II. System Model

In traditional ED the threshold and the sampling points are fixed. The proposed algorithm is an adaptive Energy Detector method where the adaptive sampling of spectrum is carried out. This paper provides a theoretical derivation of SNR for adaptive ED and how the SNR can be maintained

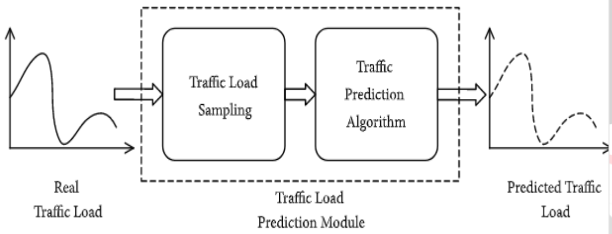

Fig 1.General framework for adaptive sampling

The Fig1 depicts a general frame work for traffic load sampling further leading to apply the Adaptive ED algorithm.

When the detected signal is obtained it is first segmented. This signal is given to the SNR estimation block- with the convolution neural network (CNN) and Long short term memory block which is a recurrent neural network capable of learning order dependence in a sequence of prediction problems. The block diagram of the system model is as shown in Fig 2

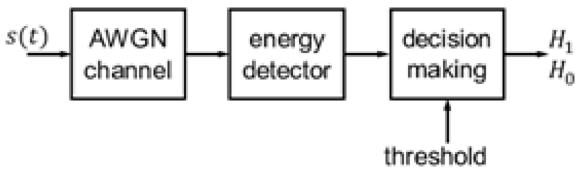

Fig 2.Block Diagram of the System Model

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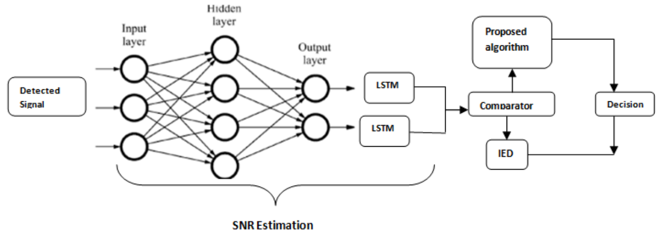

Fig 3. System Model

The traditional Spectrum Sensing can be denoted by the following mathematical model.

Let us assume that H1 represents the presence of the primary user (PU) and H0 represents the absence of the PU. When PU is active, the sampling signal received by the SU can be represented as,

$y(n) = s_n + x_n$ -------------------------(1)

And when PU does not exist

$y(n) = x_n$ ------------------------------(2)

Where s_n is the signal of PU with the mean 0 and variance σs^2 and x_n is the additive white Gaussian noise with mean 0 and variance σx^2. Also if τ is the sampling slot and N is the sampling point and

$N = \tau$ fs is then the received energy can be represented as

$T(y) = \frac{1}{N}\sum_{n=1}^{n}|y(n)|^2$--------------(3)

The function T(y) is the probability density function (PDF) and is a Chi-square distribution with the degree of freedom of 2N in the complex-valued case[22].The probability for false alarm and the corresponding detection probability of ED can be, denoted as $P_f = P(H1|H0)$

$P_f = Q\left[\left(\frac{\bar{\varepsilon}_i}{\sigma^2_{x-i}} - 1\right)\sqrt{N}\right]$------------------(4)

Where, σ^2_{s-i} is the power of the signal in PU, $\bar{\varepsilon}_i$ is sensing threshold and σ^2_{x-i} is the power of noise.

And $Q(x) = 1-\Phi(x)$, where Q(x) is a complementary inverse function of $\Phi(x)$.

$Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{\frac{-t^2}{2}}\,dt$-------------------(5)

The detection probability can be given as Pd and is represented as,

$Pd = P(H1|H1) = Q\left[\left(\frac{\bar{\varepsilon}_i}{\sigma^2_{x-i}} - \gamma - 1\right)\sqrt{\frac{N}{2\gamma+1}}\right]$ -------------(6)

and $\gamma = \frac{\sigma^2_{s-i}}{\sigma^2_{x-i}}$ represents the received SNR.

Considering both the false alarm probability and the detector probability, the optimization objective Fi can be represented as,

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$F_i = P_{f-i} + P_{d-i} = Q\left[\left(\frac{\overline{\varepsilon_i}}{\sigma^2_{x-i}} - 1\right)\sqrt{N}\right] + Q\left[\left(\frac{\overline{\varepsilon_i}}{\sigma^2_{x-i}} - \gamma - 1\right)\sqrt{\frac{N}{2\gamma+1}}\right]$

--------(7)

and 1- P_{d-I} is the missed detection.

III. SPECTRUM SENSING WITH ADAPTIVE SAMPLING METHOD

In the ED the $\overline{\varepsilon_i}$, varies adaptively w r t the noise in the background for a fixed value of the sampling points N.

Therefore we have,

$Q\left[\left(\frac{\overline{\varepsilon_1}}{\sigma^2_{x1-i}} - 1\right)\sqrt{N}\right] = Q\left[\left(\frac{\overline{\varepsilon_2}}{\sigma^2_{x2-i}} - 1\right)\sqrt{N}\right] = Q^{-1}(\overline{P_f})$------(8)

Here $\overline{\varepsilon_1}$ and $\overline{\varepsilon_2}$ are the thresholds at 2 different instances and $\overline{\varepsilon_1} < \overline{\varepsilon_2}$. σ^2_{x1-i} and σ^2_{x2-i} are the corresponding noise powers which can be defined as

$K = \frac{\overline{\varepsilon_1}}{\sigma^2_{x1-i}} = \frac{\overline{\varepsilon_2}}{\sigma^2_{x1-i}}$ where the value of K is less than 1.

If σ^2_{x-i} varies from σ^2_{x1-i} to σ^2_{x2-i} where the latter being at a higher value, the Fi can be maintained constant for an increasing sampling points N for a fixed false alarm probability.

$\left[\left(\frac{\overline{\varepsilon_1}}{\sigma^2_{x1-i}} - \gamma_1 - 1\right)\sqrt{\frac{N_{i-1}}{2\gamma_1+1}}\right] = \left[\left(\frac{\overline{\varepsilon_1}}{\sigma^2_{x2-i}} - \gamma_2 - 1\right)\sqrt{\frac{N_{i-1}}{2\gamma_2+1}}\right]$

where γ_1 and γ_2 are the corresponding SNR.

To maintain the performance of detection of signal $N_{i-1} = N_{i-2}$.

Pd can be maintained by increasing N when the environment becomes worse. At the same time, due to the increase in N, the Pf will be smaller than before.

For a given value of γ, σ^2_{x-i} , σ^2_{s-i} and $\overline{\varepsilon_1}$, the constraint value of Ni can be made constant when $N_{min} < N < N_{max}$. The value of N_{max} and N_{min} can be defined as

$N_{min} = \left\{\left(\frac{Q^{-1}(\overline{P_{f-i}})}{\frac{\overline{\varepsilon_1}}{\sigma^2_x}}\right)^2 . \left(\frac{\sqrt{2\gamma_i+1}\,Q^{-1}(\overline{P_{d-i}})}{\frac{\overline{\varepsilon_1}}{\sigma^2_x} - \gamma_i - 1}\right)^2\right\}$ and $N_{max} = fsT_0$

where T_0 is represented as the maximum sampling interval.

If σ^2_{x-i} varies from σ^2_{x1-i} to σ^2_{x2-i} ($\sigma^2_{x1-i} < \sigma^2_{x2-i}$), the sensing performance can be maintained and even improved when $N_{min} \le N1 \le N \le N_{max}$ for the fixed false alarm probability, where N1 denotes the minimum point that can keep Pd constant. This is the condition for improved energy detector.

Also, with the above mathematical model we can conclude that if SNR in the environment decreases, the detection performance can be maintained by increasing the sampling point. The trade off in this is if the sampling point is increased, the system tends to become more complex and the time taken for computation is also high. It has to be optimized after this processing using CNN and LSTM prediction algorithms. Here is where the Improved Energy detection (IED) algorithm as explained earlier by equation plays an important role.

Using the above mathematical modeling, the SNR can be estimated.

In the proposed system, the accuracy of SNR evaluation strictly influences the sensing performance. The SNR estimation is carried based on CNN and LSTM network[24]. The SNR estimation is divided into two parts, the CNN module and the LSTM module. The CNN module extracts the features of the segmented signal to form the feature vector. The output feature of the CNN module is input to the LSTM module. The feature of each short sequence is fused in the fully connected layer. After the fully connected layer, the evaluated SNR is obtained.

The observed frequency band is assessed and found to be busy if it satisfies any of the three conditions as given below:

1. The energy of the received signal is higher than the threshold.

2. The energy of the received signal is lower than the threshold.

Both the average energy and the last energy of the received signal are seen to be higher than the threshold.

IV. SIMULATION RESULTS

The relation between detection threshold, optimal SUs and SNR is shown in the Fig. 4. It is evident from this, as the SNR increases the optimal SUs decreases for a given detection threshold and also as the detection threshold increases the optimal SUs increases for a given SNR value.

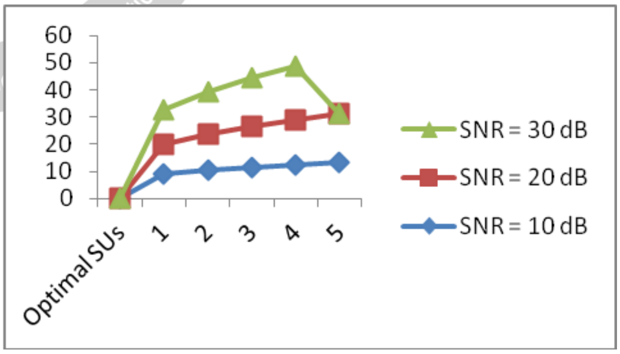

Fig 5.SNR vs Optimal SUs

The optimal number of cooperative SUs verses detection threshold for SNR=10dB,20dB,30dB is shown in the Fig. 5. It is evident from this that as the SNR increases, the optimal number of cooperative SUs increases for a given detection threshold and also as the detection threshold increases, the optimal number of cooperative SUs decreases with SNR. Therefore the optimal number of SUs is calculated based on SNR or detection threshold according to the required applications of the users.

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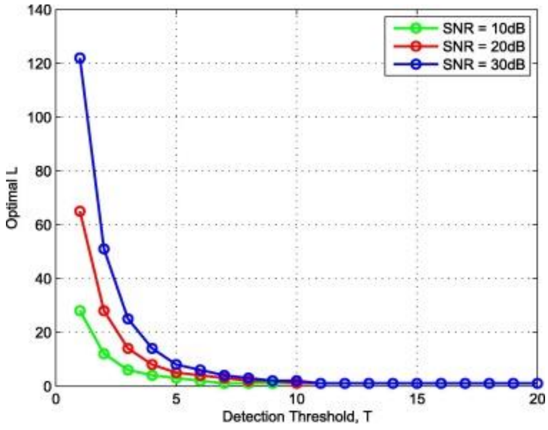

Fig 4.SNR vs Optimal L

The Fig 6. depicts the traditional ED and the ED after optimizing using the CNNLSTM combination.

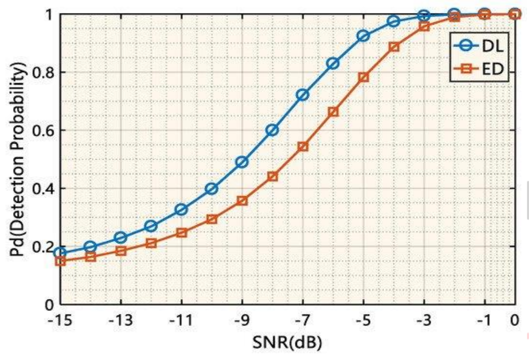

Fig 6. Graph denoting Traditional ED and improved ED with CNNLSTM algorithm

V. Conclusion

Improved Energy Detector method is proposed in this paper. From the simulation results obtained it is found that the optimal number of SUs is calculated based on SNR or detection threshold according to the required applications of the users. The system complexity can be reduced in the agreed range of frequency and the accuracy of the system in detecting a SU can be improved using the proposed method. Also, the system complexity can be reduced within the agreed range of detection. In this paper, an adaptive sampling scheme is proposed to balance the sensing accuracy in real time. Te sampling adaptively changes w r t the SNR. This greatly improves the sensing accuracy in the low-SNR cases. In other cases, IED is considered to SS, which improves the sensing accuracy without forfeiting the complexity.

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