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Design and Implementation of A Spectrum Sensing Algorithm for Cognitive Radio Networks Using Machine Learning Techniques

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Abstract

In cognitive radio networks, spectrum sensing in low SNR (signal-noise ratio) environments is regarded as a significant difficulty. Using well-known supervised learning approaches, the primary user detection is investigated in a noncooperating spectrum sensing framework. Additionally, the performance of the classifiers is assessed and the sensing data is analyzed. Learning is further complicated by the issue of data values missing from sensing data that should be present. In this study, we developed a supervised learning classification system based on the naïve bayes approach to forecast the missing values. This paper significantly advances the creation of frameworks based on machine learning that tackle the inherent issues in spectrum sensing. Three facets of spectrum sensing in cognitive radio are used in this research to recognize users in a channel or band. This thesis discusses spectrum sensing in Cognitive Radio Wireless Networks using MLP frameworks based on FFNN. Specifically, machine learning-based supervised and unsupervised spectrum sensing frameworks are defined to increase their efficiency. As a result, less sensing energy is used to estimate free channels, and spectrum usage can be enhanced. Thus, a spectrum predictor based on machine learning is created. Simulation studies have been conducted throughout this study to evaluate the approaches' overall performance and compare their outcomes with those of similar frameworks.

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Introduction

Government administrative organizations regulate the electromagnetic range dispensed to remote organizations and administrations in various countries around the world. The Telecom Administrative Power (TRAI) in India, the Government Correspondences Principles in the US, and the European Media transmission Norms Establishment (ETSI) in Europe are a couple of models. The undertaking of doling out range recurrence blocks to specific associations or organizations tumbles to these controlling bodies.[1] Concern concerning the static dispersion of the regular recurrence range has developed during the beyond a decade. As remote correspondence innovation creates from voice-just interchanges to information serious mixed media and intelligent administrations that are as of now generally utilized, this stress is additionally exacerbated by the developing longing for quicker information rates.[2, 11] A change in outlook from the past, order control strategy for recurrence circulation to dynamic range access has become fundamental to handle the issue of the range emergency hence delivered. Strangely, range inhabitance tests have uncovered that most of the apportioned ghostly groups are habitually underutilized in view of the current allotment method.

Cognitive Radio Technology

A new technology called Cognitive Radio (CR) can effectively address the increasing demand and limited wireless spectrum.[3] It is a wireless communication paradigm where an intelligent wireless system adapts its operating parameters based on information about the radio environment to guarantee dependable communication and effective spectrum usage. Cognitive radio systems have recently been taken into consideration by a number of IEEE 802 standards for wireless networks, counting IEEE 802.22 standard[4,12] and IEEE 802.18 norm. To actually use restricted transmission capacity, CR innovation grants unlicensed clients, otherwise called secondary users (SUs), to get to authorized range groups without adversely slowing down the help of authorized clients, otherwise called Primary users (PU).[16] For cognitive spectrum sharing, three primary approaches are being explored. These include interweave, overlay, and underlay approaches.[5] Under the overlay technique, the SUs and PUs coexist under the presumption that the SUs are aware of the PU's codebook and message. This data can be used to either dispense with or reduce the obstruction that the PU's transmission causes to the SU's multifaceted, high level sign handling strategies, such messy paper coding (DPC). The SUs can separate their transmission power and use a part of it to hand-off the PU's sign to the assigned essential collector to balance the obstruction that the SUs' transmissions cause to the Discharge. By doing this, the sign from the PU will be gotten with the proper SNR. The SUs can all the while speak with each other utilizing the leftover communicate power. In this manner, allowing SUs range access benefits both the Discharge and the SUs. The SUs can involve the authorized range in the underlay method without adversely obstructing PU correspondences.[14,17]

To do this, the SUs should ensure that impedance spillage to the essential clients stays under a healthy level. By utilizing a few recieving wires to redirect their pillars from the Discharge, the SUs can conquer the impedance requirement. The SUs may likewise utilize the spread range approach, which conveys the communicated signal over a huge data transmission with the goal that the power level is lower than the commotion floor. De-spreading may then be utilized to recuperate the signs at the SU collectors. It ought to be referenced that the SUs' transmissions might be limited to short-run correspondences in light of the fact that the underlay strategy's impedance limitation is to some degree extreme. Mental gadgets should be given both learning and thinking abilities to really know about the progressions in the exercises happening in their radio frequency (RF) climate.

Numerous qualities and arrangements, for example, send power, coding plan, tweak plot, detecting calculation, correspondence convention, detecting strategy, and so on, should be changed simultaneously in remote correspondence, and dynamic range access specifically. The solo characterization calculations can be arranged as parametric or non-parametric and don't need marked preparing information.[6, 13] The execution of solo learning may not need earlier information on the climate's attributes, making it simpler to recognize signals independently in new radio conditions. Conversely, administered and semi-managed methods can regularly be utilized in natural or known conditions. The fact that these learning strategies have been used to address numerous classification-related data mining issues is very intriguing. They are thought to be equally capable of being effectively transformed into algorithms that offer answers to our spectrum sensing issue.

Overview of proposed Framework

There were numerous difficulties encountered when gathering sensor data in our indoor experimental setting. The most important factor among these difficulties that might directly affect our research was the values that were missing from the data set where they should have been. We could see that at some point in time, some characteristic values changed significantly.[7, 8]. This might be because of the surroundings in which the trials were conducted. In order to carry out our classification, we previously threw away the values. In actuality, however, it renders the dataset incomplete, which may affect the learning model. Therefore, the learning model may be impacted by these missing variables, which could reduce the likelihood of detection. Therefore, it became crucial to understand how to forecast those missing variables. It is commonly accepted that predicting missing values is a component of the data purification stage that is carried out prior to data mining or any additional analysis. Our suggested approach to missing value prediction is limited to a single numerically valued characteristic. Since power is the primary attribute in our data set, we are concentrating on it here. It is discovered that this power attribute's distribution behaves normally. Using a suggested discretization approach based on the normal distribution, our suggested methodology first converts the missing value problem into a classification problem.

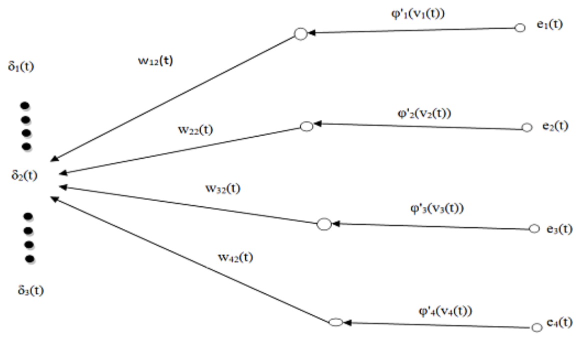

Fig. 1: Backward pass of BP algorithm

After that, a classification algorithm is used to forecast the values. Three components make up the suggested approach: prediction, classification, and discretization.

System Model and Assumptions

Assuming a finite number of channels, "N," and a single SU. The secondary user functions according to time slots, meaning that time is separated into slots with a duration of "T." Every channel is either busy (i.e., with primary activities) or available (i.e., no primary activities) during each time slot. With a probability of pi, every channel in every slot is devoid of primary radio activity.We make the assumption that a channel's current state—whether it be busy or free—is unrelated to both its prior condition and the states of other channels in that slot. We also take into account the fact that fading effects cause the signal to interference plus noise ratio (SINR) to fluctuate randomly for every slot in a channel. It is assumed that the SINR random variable follows an arbitrary distribution and is i.i.d. across various slots and channels. The transmission rate that can be achieved depends on the instantaneous SINR on the channel if the secondary user chooses to send on a channel that is detected as free ci. The SINR of the channel ci is mapped into the resulting transmission rate by the function F (SINRi), which is a monotonically increasing function.[9]

We presume that there are no errors in the sensing process. As there is no prior information on the channel state, the secondary users sense the "N" channels sequentially in the following order: {O1, O2, O3, O4........ ON } The time spent sensing the channels and the transmission rate the user receives in the selected channel are related to the efficiency of a certain sensing sequence. The time needed to sense each channel is represented by the variable τ. The secondary user conducts the channel sensing ci+1, which is the subsequent channel in the sensing phase, if the channel ci is detected as busy.

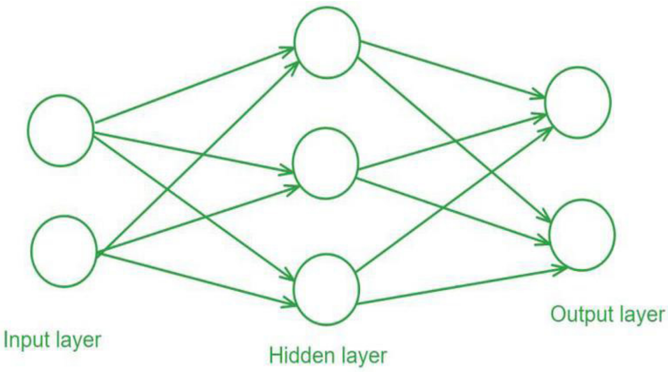

Fig. 2: architecture of FFNN

Here, the multilayer perceptron is used by the feed forward neural network-based predictor to forecast the channel status for the upcoming slot. An input layer, a hidden layer, and an output layer make up this multilayer structure network.[10, 15]

Neurons in each buried layer are primarily responsible for the calculation. These neurons conduct the non-linear transform on the sum and compute the adaptive weights. Adaptive weights are used to connect neurons in various levels. The total number of inputs determines the FFNN network's order. There are two layers, depending on our model. There are twenty neurons in the first layer and twenty-five in the second.. There is only one neuron in the output layer. Here, the nonlinear transformations are carried out using the straightforward Sigmoid activation function. The kth layer neuron j's output, represented by , can be written as

$$y_j^k = \frac{1}{1+\exp(v_j^k)}$$

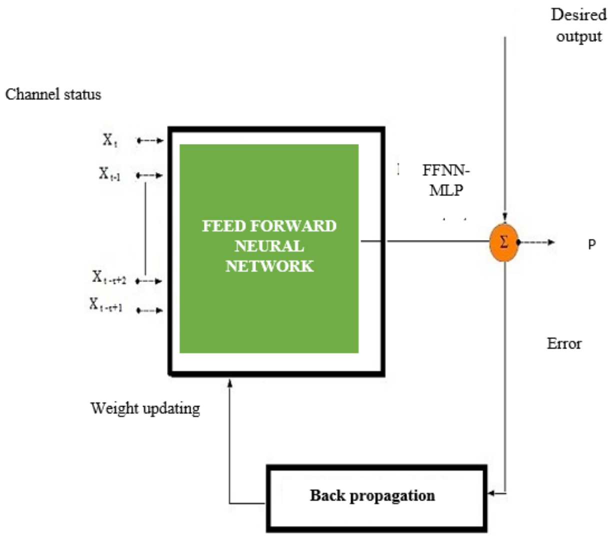

Fig. 3: Overall architecture

Figure 2 shows the fundamental plan of the CR organization. It shows that the essential organization and the CR network are the two fundamental sorts of organizations. The essential organization is any sizable authorized network that has the restrictive right to utilize specific recurrence groups. The expression "essential organization base station" and "Discharge" indicate the base station and different essential organization hubs, individually.

For the secondary user to use the channel in the absence of the original transmission, the likelihood of detection is a crucial metric. Additionally, in low SNR conditions, it enables the secondary user to determine whether the channel is suitable for the secondary broadcast.

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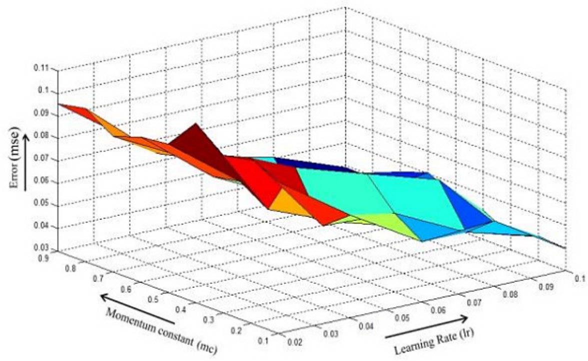
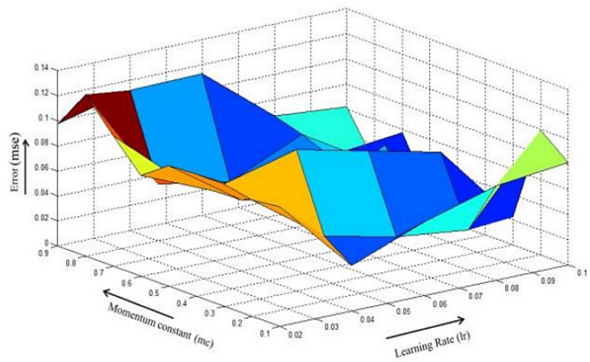


(a)



(b)

Fig. 4: Surface plot for error obtained for the pruned network

SIMULATION RESULTS

The predictor's performance is assessed in the presence of stationary traffic. The average inter-arrival rate and the principal user traffic intensity did not alter over time in each simulated scenario with stationary traffic conditions.

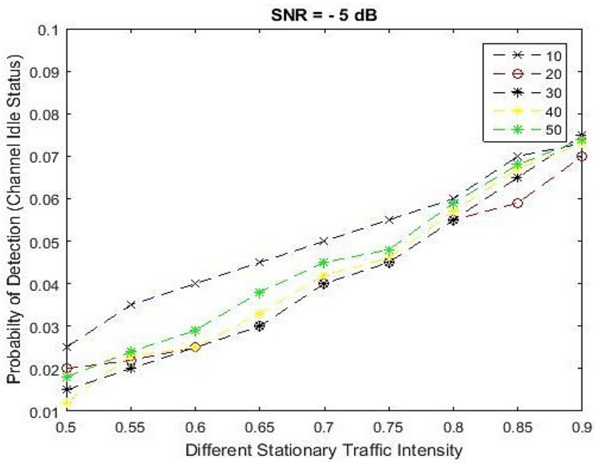


Fig. 5: Results for SNR = -5dB

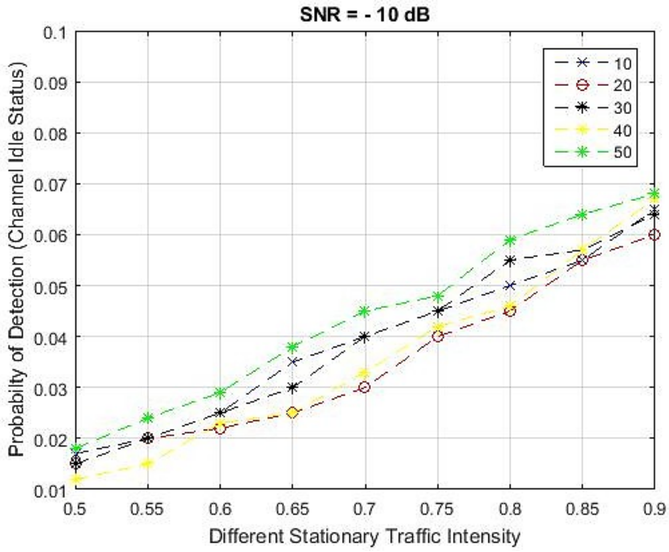


Fig. 6: Results for SNR = -10 dB

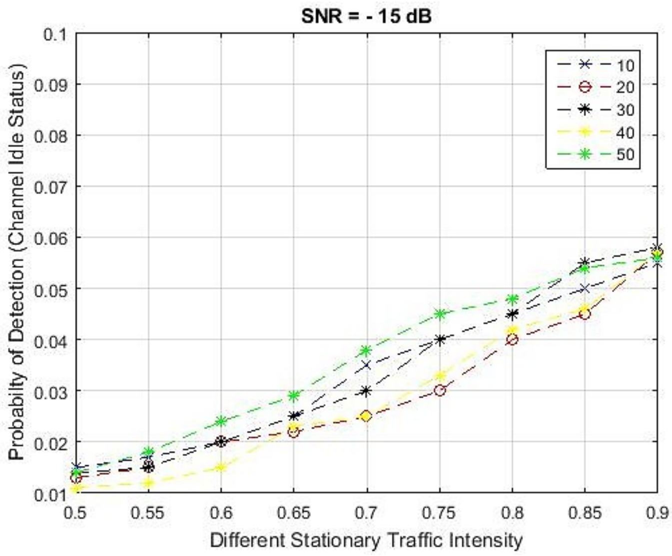


Fig. 7: Results for SNR = -15 dB

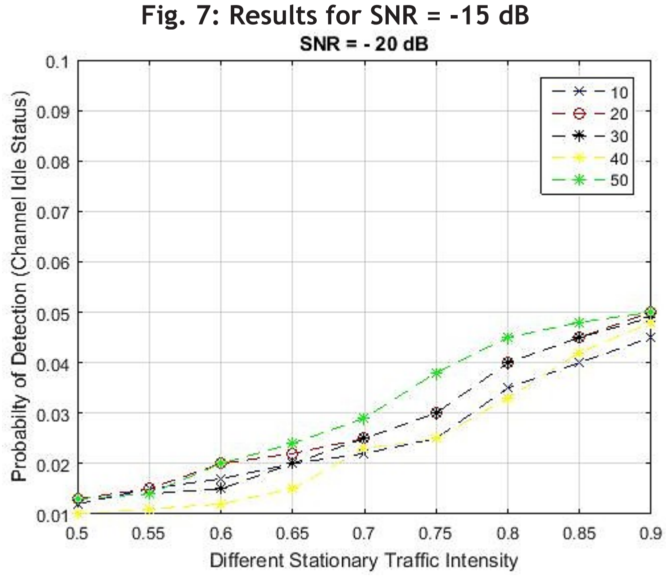
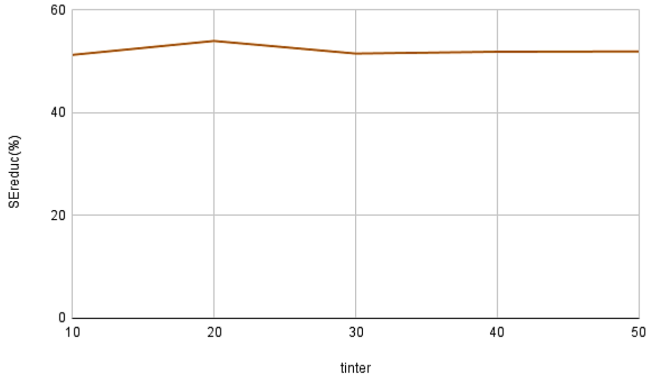
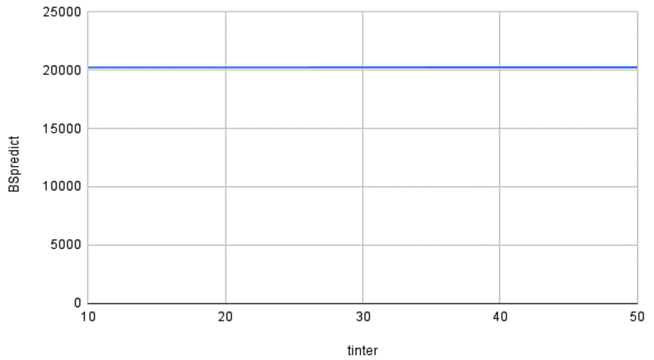


Fig. 8: Results for SNR = -20 dB

The predictor's performance is displayed in Figures 5-8 under various traffic intensity and low SNR situations. As can be shown, the likelihood of detecting a free channel varies with probability estimate and is larger than when the noise level drops. This is because the detection of the channel idle status is impacted by random noise that attempts to overlap the signal. When the slot is expected to be busy during sensing, the sensing operation is not carried out, saving sensing energy.



(a)



(b)

Fig. 9: Sensing Energy reduction

Predicting the channel status in cognitive radio networks can reduce sensing energy use and enhance overall spectrum usage. One of the biggest challenges is predicting the channel status at low SNR. Here, a channel predictor based on FFNN is created. The cognitive radio network's primary users' channel utilization statistics are unknown beforehand. Several simulations are used to demonstrate the performance analysis. The suggested channel status prediction methodology is used to assess the reduction of sensing energy.

Conclusion:

We might construe from this study that different AI methods can be utilized to address different range detecting issues in mental radio organizations. In order to address some of the issues pertaining to individual sensors in low SNR (signal noise ratio) environments, many learning techniques have been put forth and studied. Spectrum sensing studies and several machine learning techniques were carried out in an indoor laboratory setting, yielding a respectably satisfactory outcome. Additionally, a hierarchical architecture with multiple classes is suggested, which investigates signal type detection, another essential component of sensing in cognitive radio networks. The framework's performance is indicated by the accuracy, sensitivity, and specificity. Furthermore, a new method based on reinforcement learning has been created to improve the sensing mechanism by addressing the channel sensing order. Lastly, a spectrum prediction method based on FFNN is offered, which can reduce the energy used for sensing. The performance of the suggested methods has been assessed for inquiry using comparison curves, the F1 measure, the likelihood of detection, and the chance of false alarm. In conclusion, machine learning approaches can be utilized to handle a variety of spectrum sensing problems, including identifying signals with low signal strength, classifying channel sensing order, and reducing energy consumption to improve spectrum utilization.

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