RESEARCH ARTICLE

SAMRIDDHI Volume 14, Issue 3, 2022 Print ISSN: 2229-7111 Online ISSN: 2454-5767

Sensing and Sharing of Spectrum in Cooperative Cognitive Radio Vehicular Networks using K-tuned Classifiers and Fuzzy Logic

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Abstract

This paper aims to efficiently utilize the spectrum based on sensing and sharing optimal resources like relay and power on cooperative cognitive radio in a vehicular network. Resources are allocated in the V2V environment by considering the effect of the Doppler shift. Spectrum sensing is carried out using K-tuned Nearest Neighbors (KNN) algorithm, in which the K parameter is tuned to avoid misclassification-related problems that enhance the spectrum sensing. After sensing the status of the spectrum, a Fuzzy logic-based approach shares the spectrum with the help of optimized resources. Simulations are carried in different vehicle scenarios in terms of bit error rate and throughput.

Keywords: Cognitive, Cooperative Communication, Doppler shift, Fuzzy logic.

SAMRIDDHI : A Journal of Physical Sciences, Engineering and Technology (2022); DOI: 10.18090/samriddhi.v14i03.09

Introduction

Vehicle to Vehicle (V2V) communication is a part of the Intelligent Transport System (ITS) which assists vehicles in communicating with each other by providing information about the status of traffic and road conditions to the vehicle users[1,2] Apart from basic communication between vehicles, vehicle manufacturers now offer infotainment applications like video streaming and collision avoidance by warning drivers about dangers at intersections where the view of drivers is obstructed by buildings, trees, etc.[3-5] With more vehicles and new internet-enabled features, there arises a demand for more spectrum in IEEE 802.11p. V2V cannot solely depend on DSRC. Therefore, V2V makes use of cognitive radio (CR), an emerging technology that makes use of underutilized spectrum by sharing between primary users (PU) and secondary users (SU). CR helps to improve the spectrum sharing between PU and SU without affecting the performance of the primary user[6] Cooperative communication (CC) is a technique that helps the transmitter to sense and share spectrum effectively to the receiver with the help of relays through amplifying and forward (AF) and decode and forward (DF) methods. Resource allocation in a cooperative network is formulated to achieve an objective like maximizing the sum rate etc., by selecting an optimal relay, subcarrier, and power selection[7,8] Power allocation strategies like the Classic water-filling method and suboptimal two-step power allocation algorithm of subcarriers were proposed for optimal power allocation[9,10] Spectrum sensing is a technique by which vacant spectrum bands are sensed and allocated to secondary users without affecting the performance of the primary user.

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How to cite this article: Nyati S.U., Suralkar S.R., Bhadade U.S. (2022). Sensing and Sharing of Spectrum in Cooperative Cognitive Radio Vehicular Networks Using K-tuned Classifiers and Fuzzy Logic. SAMRIDDHI : A Journal of Physical Sciences, Engineering and Technology, 14(3), 302-306.

Source of support: Nil

Conflict of interest: None

The proposed strategy selects an optimized relay with the highest SNR by considering the effect of the Doppler shift. Power selection at the source and relays in CR are adjusted to power won't exceed a certain limit. The proposed strategy tunes the parameter k to avoid misclassification in the KNN algorithm. The rule-based fuzzy logic approach is carried out during spectrum sharing through an optimally selected relay by checking the subcarrier's energy and presence/absence.

Background

CR networks also use CSS (cooperative spectrum sensing). All of the research provided falls into two groups. The first kind is a two-step process. Step 1: Analyze data and find the PU signal using unsupervised machine-learning techniques. Using supervised machine-learning techniques, the model is trained in the second stage. In cognitive radio networks, spectrum sensing is a critical component. As a result of spectrum sensing, cognitive radio can learn about its surroundings and spectrum availability. Energy detection and matching filter detection are the most often utilized spectrum sensing technologies[11] A learning algorithm proposes a novel threshold expression model for cognitive radio spectrum sensing. The optimal decision threshold expression was redefined to limit the risk of choice mistakes. The suggested sensing system has greatly enhanced energy detection and matching filter-based spectrum sensing under low SNR situations[12] At the 40–60 SNR model, all four training features, and the Nesterov Accelerated Gradient optimizer, the optimum set of ANN hyperparameters may be acquired with a 0.0001 learning rate. The sample size can be adjusted to meet the application's system requirements. As a result of these factors, the suggested strategy outperforms the other three by around 60%. This study used only one PU and one SU. An intriguing issue for additional research is multi-PU and multi-SU studies, covering multi-pu channel selection.[13]

The multi-step machine learning model for spectrum sensing. The first stage uses K-means to find the PU. In the second phase, support vector machines or other classifiers assign the previous step's classes to the new input data. A benefit of machine learning is that it can handle complicated models quickly[14] Next-generation communication systems need better data transmission rates and hence more bandwidth. To receive the best available channel, SUs must perceive a wider range of radio frequency ranges. So, wideband spectrum sensing is used to suggest certain ideas[15] Analytical models for hard and soft fusion are used in spectrum sensing for cognitive radios using SVM. It appears from the numbers that the approaches investigated can assess the state of various Sus channels. The suggested NN-ELM strategy outperforms existing machine learning models and the best MRC combiner technique, according to the RoC curve and AUC metrics. Accordingly, we evaluated the proposed method's computational efficiency to several popular machine learning techniques. The training time required by the recommended method is less than that required by other techniques. So the detection/training time trade-off has been improved. A similar method may be used for mobile or non-stationary Pus.[16]

This paper focuses on the corporative cognitive radio communication technology in the vehicular network focuses on the spectrum sensing based on the shared mechanism using a K-tuned classification methodology and fuzzy logic mechanism.

Spectrum Sensing through K-tuned Classifier and Resource Allocation in Cognitive Radio Vehicular Network

System Model

Consider a Cognitive radio network where the Primary user coexists with the secondary user. CR network consists of M secondary users who sense and reports the energy level conditions to a fusion center. The fusion center decides the number of free subcarriers based on the energy level report. Primary users in the network are indexed by secondary users indexed by $M = 1,2,\ldots m$ N relays and S_l subcarriers. Let S_l indicate the state of the Primary user D_m when primary users are in one state $D_m = 1$ else 0. Figure 1 shows the architecture of the proposed system.

Energy Vector Model

Our proposed system senses the spectrum using K-tuned Nearest Neighbors (KNN) with Energy-based detection. The energy detector measures the energy of the received signal by comparing the result to a threshold value. Let the time duration be τ , and the bandwidth be denoted as τ the energy detector takes signal samples τ. Let y be the signal sample taken by SU

$$Y_m = \sum_{m=1}^{M} D_m \, h_{l,m} \, X_l(i) + N_m(i)$$ ....(1)

Where $h_{l,m}$ denotes the channel gain from PU l to SU. l be the status of the channel. l Does PU transmit the signal l. $N_m(l)$ Is the AWGN noise at SU $Z = Z_1, \cdots, Z_N)^T$. The secondary users transmit the message with estimated energy levels to the fusion center, and the fusion center generates an energy vector given as ($Z = Z_1, \cdots, Z_N)^T$ .Let $\bar{Z} = \{z^{(1)}, \ldots\ldots z^{(L)}\}$ be the training energy vector, and subcarrier availability for each training vector is $\Delta(x, y)$. These training vectors are fed into the classifier for training. The KNN classification technique is based on the maximum voting pattern of neighbors. Let $\Delta(x, y)$ is the distance between the energy vector x and y.

The performance of a classifier depends on the K value. KNN with small K values is sensitive to noise data. If the K value is increased, it invites unnecessary classification. A traditional KNN classifier selects K without any rules. Small, moderate, or big K values yield different results; therefore, we introduce a method to regulate the selection Y to mitigate the effects of miss classification. Select closest points Y and divide Y closest points into Y clusters. $K = N/Y$ Pair can be defined as $K = N/Y$. The test data is classified into occupied or unoccupied subcarriers through the KNN classifier algorithm.

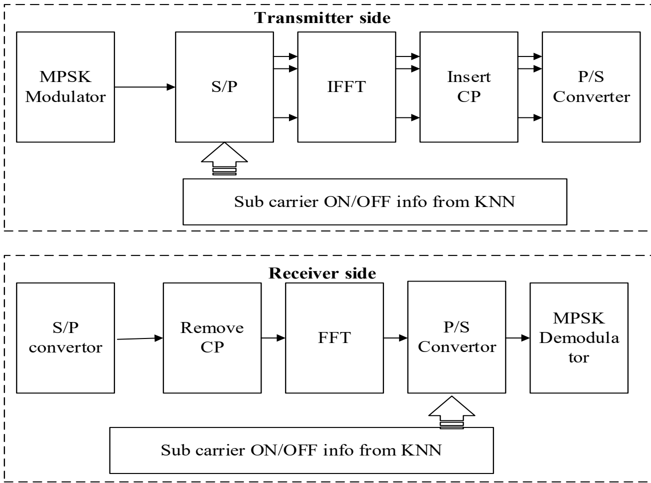

Figure 1. Proposed Cooperative Cognitive Radio vehicular network

Resource Allocation in Cooperative Cognitive Radio

Problem Formulation

The resource allocation objective in cooperative cognitive radio is to efficiently share the spectrum between primary and secondary users. Let the nth relay power on ith sub-carrier $P_{d,i}$. The amplified signal is transmitted by letting the power of the relay to the destination be $P_{d,i}$. The relay amplifying factor for CR transmission is given as

$$\beta_{n,i} = \sqrt{P_{ndi}} / |H_{sn,i}|^2 P_{sn,i} + \sigma_n^2 + \sum_{l=1}^{L} J_{\ln,i} \quad \text{...(2)}$$

Where $J_{\ln,i}$ is the AWGN noise generated $J_{\ln,i}$ is the interference generated by $R_{n,i}=\{0,1$ PU at the destination. The relay section decision is taken as $R_{n,i} = \{0,1\}$ Total interference introduced by CR source, and relay transmission can be expressed as

$$I_{sp} = \sum_{l=1}^{L} \sum_{n=1}^{N} \sum_{i=1}^{N} R_{n,i} |H_{s,i}|^2 P_{sn,i} \quad \text{................................(3)}$$

$$I_{rp} = \sum_{l=1}^{L} \sum_{n=1}^{N} \sum_{i=1}^{N} R_{n,i} |H_{h,i}|^2 P_{d,i} \quad \text{...................................(4)}$$

The resource allocation is stated as follows $Maximize \sum_{i=1}^{N} \sum_{n=1}^{N} R_{n,i} = 1/2 \log_2 (1 + \gamma_{n,i})$ subject to

$$C2: \quad \sum_{i=1}^{N} R_{n,i} P_{d,i} \le P_N \quad \forall n$$

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$$C3: \quad I_{p} \le I_{h}$$

$$C5: \quad \sum_{n=1}^{N} R_{n,i} = 1 \quad \forall i$$

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$$P_{n,i} \ge 0 \ \forall \ n,i \quad P_{sn,i} \ge 0 \ \forall \ n,i$$

$$P_{d,i} \ge 0 \ \forall \ n,i \quad P_{d,i} \ge 0 \ \forall \ n,i$$

$C1$And $C1$ are the power at the source and relays. $C1$ is the maximum permissible interference to the PU pair. $C1$ And $C2$ are the transmit power constraints at the source and the relay. $C4$ And $C4$ are the total interference threshold for the CR source and the relay.

Relay and Power Selection in Cooperative Cognitive Radio

The optimal relays are needed to be selected; the SNR of the relays are calculated. The proposed system selects a relay working in half-duplex mode. A threshold SNR value is selected from the relay node that produces the least SNR for a higher Doppler shift. Each of the SNR measured between relay and source-destination nodes is compared with the threshold SNR. The highest SNR produced by the relay is selected because even though there is a relay near the proximity of the SU pair, the velocity of the vehicles also affects the SNR.

A simple power allocation method is proposed in this section. The power allocation should not exceed maximum transmit power constraints, therefore transmit power of the cognitive source is allocated as

$$P_{s,i} = \begin{cases} P_{s,i}^T, & f \ \sum_{i=1}^{N} P_{s,i} \le P_S \\ \min(P_{s,i}^T, P_s / N) & otherwise \end{cases} \quad \text{..............................(5)}$$

Similarly, at the relay, power is allocated as

$$P_{n,i} = \begin{cases} P_{n,i}^T, & f \ \sum_{i \in D_n}^{T} P_{n,i}^{\text{int}} \le P_n \\ \min(P_{n,i}^T, P_n / n_s) & otherwise \end{cases} \quad \text{...(6)}$$

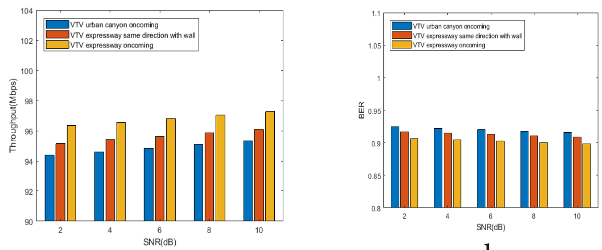
D_n It is the set of subcarriers used by nth relay and D_n is the number of subcarriers in the set D_n .

Spectrum Sharing by Fuzzy Logic

Once the Subcarriers are classified into occupied and unoccupied based on their energy using KNN, Fuzzy logic is used to share the subcarriers between the primary and secondary users. The rule-based decision-making system considers input as a subcarrier, energy of the PU and SU, SNR generated from relays. Based on the input conditions, the rule-based IF-THEN clause allocates the subcarrier to primary and secondary users based on the following observations. The subcarrier is allocated to PU only if the subcarrier is on, the SNR of the relay is higher, and energy is above the threshold of the primary user. Similarly, the sub-carrier is allocated to SU only when the subcarrier is off, the SNR of the relay is higher, and energy is below the threshold of the primary user. The subcarrier is not allocated to PU and SU under a condition where subcarrier is on/off, SNR is lower/higher, and energy is above the threshold of PU,

Experimental Results and Performance Evaluation

The experimental analysis is carried on MATLAB. The parameter setting for the proposed system is given as follows. The cell radius is 200m, in which 4 PU and 4 SU are selected. Let the bandwidth be 12MHz.The number of the optimal relay



a b

Figure 2: (a) Throughput performance (b) BER performance under various vehicular scenarios Proposed and existing system[17]

is four selected from 10 relays. The maximum interference permitted to PU is $5*10^{-5}$ W. The channel model is Nagakami. The vehicular scenarios for the simulation are V2V Expressway Oncoming, V2V Urban Canyon, and V2V expressway same direction as the wall.

Throughput and Bit error rate (BER) are the two metrics taken into account for evaluating the performance of the proposed approach. We consider three roads with varying doppler shifts to analyze the system's throughput.

The throughput performance of the cognitive radio under three different scenarios from the Figure 2 (a) proves that the proposed system has achieved a higher throughput even in the scenarios where the Doppler shift is high. With increasing SNR, throughput in various scenarios shows a significant improvement in its performance. Throughput performance is higher in this case than urban canyon since scattering is only due to the mobility of vehicles. Figure 2 (b) presents the BER performance. The bit error rate performance shows that an increase in SNR can generate a lesser BER. In each scenario, the decrease in bit error rate varies according to the scatters in the scenario. This shows that our proposed approach can reduce scattering effects with the help of cooperative communication.

Conclusion

The proposed strategy has introduced a sensing and sharing scheme based on cooperative communication in cognitive radio. Resource allocation in work has concentrated on selecting an optimized relay by considering the impact of the Doppler shift. Further, to enhance the sensing capability of cognitive radio, we have used the KNN algorithm. Finally, through a fuzzy logic-based approach, the spectrum is shared between primary and secondary users. Simulations results show that the cooperative cognitive radio throughput of the system has increased to an extent under different speeds and various scattering effects. The proposed strategy successfully provides better results in terms of bit error rate, throughput, and mean square error by selecting an optimized resource allocation.

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