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MACHINE LEARNING BASED SPECTRUM SENSING IN COGNITIVE VEHICULAR NETWORKS

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ABSTRACT

Increased demand for technology-driven and automated infrastructure that can address critical issues like passenger safety and traffic congestion has led to an exciting research and application area - Vehicular Adhoc Network (VANET). VANET enables vehicles to talk among them and also with fixed roadside infrastructure to support a myriad of potential life changing applications. The excitement surrounding VANET is not due to their application support or potential benefits but also because of the challenges like scarce spectrum, varied QoS requirements, poor connectivity, security issues etc., Cognitive Radio (CR), a technology that ensures efficient spectrum usage can be employed in VANET to address spectrum scarcity issue. Though several spectrum sensing algorithms have already been proposed, there is a need for an effective algorithm that has a significant impact on various sensing parameters like accuracy, delay and efficiency. Our focus in this paper is to provide a machine learning based sensing algorithm for CR VANETs implemented at physical layer that maximizes the spectral efficiency.

Keywords: VANET, QoS, cognitive radio, spectrum sensing, spectral efficiency.

INTRODUCTION

Advances in network connectivity, storage and processing capabilities are making possible new inter-vehicle systems with a wide-range of interesting applications. VANETs are developed as part of ITS to enhance road safety and traffic efficiency, provide internet access on the move by incorporating wireless technologies into transportation system. The main feature of VANET is that vehicles are provided with sophisticated equipment "On-Board Unit" (OBU), which allows vehicles to exchange messages among them via Vehicle-to-Vehicle (V2V) communication, and vehicles communicating with fixed road-side base stations via Vehicle-to-Infrastructure (V2I) communication. V2V and V2I evolution motivated the development of IEEE 802.11p standard, also called Dedicated Short-Range Communication (DSRC) standard. For the deployment of VANETs, FCC allocated 75MHz of spectrum in the 5.9 GHz which is categorized as a control channel (CCH) of 10MHz for critical safety applications, a group of six service channels (SCH) each of 10MHz for non-safety related applications and a 5MHz reserved channel for future use or as guard interval [1].

VANET, due its unique characteristics such as dynamic topology, high mobility of nodes and unreliable channel conditions pose many challenging research issues. Insufficient spectrum over congested scenarios is one of the major problems slacking up the deployment of VANET. The growing demand for spectrum, led to policies like Dynamic Spectrum Access (DSA) that provides opportunistic access to the channel. To realize DSA, Cognitive Radio (CR) technology which provides a tempting solution to spectral congestion issue has been proposed [2].

CR technology defines two types of users - licensed Primary Users (PUs) and unlicensed Secondary Users (SUs) enabling SUs to dynamically capture and access the unused licensed spectrum (also called Spectrum Holes) without causing interference to the PU activities. For this, SU must possess CR capabilities such as spectrum sensing, acquiring the knowledge, merging with the previous data and devising an optimal decision to exploit unused spectrum. This way CR technology tackles the conflict between spectrum under-utilization and spectrum scarcity.

COGNITIVE VEHICULAR NETWORK

With the growing demand for bandwidth resources to support emerging vehicular applications, 75MHz DSRC bandwidth is proved to be insufficient. This has a serious impact on the automotive industry. To address this, CR technology has been exploited in vehicular networks forming Cognitive Vehicular Networks. Inspite of several licensed spectrum bands which can be used for opportunistic access, FCC has proposed to use TV White Space (TVWS) for Vehicular Networks. CR allows the vehicular users to access the TV White Space and identify spectrum opportunities through spectrum sensing. The spectral holes detected are offered to VANET to utilize additional spectrum in case of increased vehicle traffic, thereby increasing the spectrum efficiency [3]. CR technology gets silent if the allotted 75MHz bandwidth is sufficient for the number of vehicles.

SPECTRUM SENSING TECHNIQUES

Spectrum sensing is the fundamental task in cognition cycle and is defined as the process of detecting the spectrum holes (vacant licensed bands or White spaces) in the local neighbourhood of CR. Sensing enables the SU to identify whether the PU is present or not, by detecting the presence of a receiver transmitted signal. This can be modelled as a simple binary hypothesis model, with a null hypothesis that defines channel free status and alternative hypothesis which represents the channel busy status.

H_0: y(n)=w(n); Primary user is inactive (1)

H_1: y(n)= x(n)+w(n); Primary user is active (2)

where *y(n)* - signal received at SU, *x(n)* - signal transmitted by PU, and *w(n)* - noise affecting the transmitted signal.

Spectrum sensing techniques can be categorized into non-cooperative and cooperative [4]. Of all the techniques, energy detection technique is the most popular and easiest sensing technique that can be employed in cognitive radio networks [5]. It is a common method used for the detection of unknown signals.

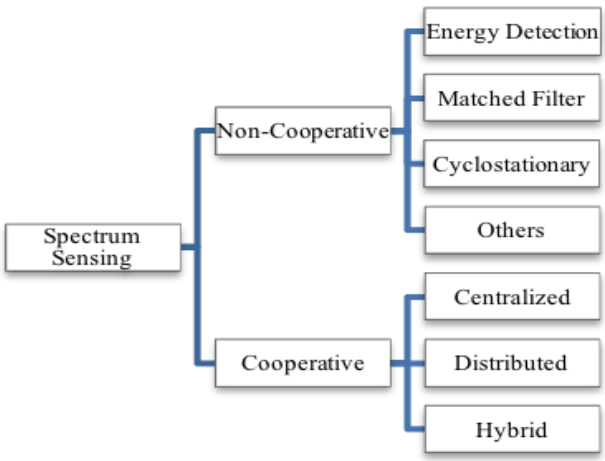

Figure-1. Categories of spectrum sensing techniques.

ENERGY DETECTION TECHNIQUE

Energy detection method is employed as the sensing scheme. The signal transmitted by the PU propagates in free space and reaches the SUs in the network through direct paths and reflected paths. Meanwhile, the signal strength is attenuated due to fading and noise is also introduced into the signal.

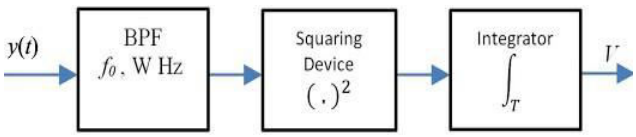

Figure-2. Block diagram of energy detection approach.

The received signal is passed through a BPF to filter out the frequency components of permitted range. The output of the band pass filter is given to a squaring device and then passed through the integrator which is used to determine the energy in a particular observation interval.

Fusion Rules

In order to improve the sensing performance, an efficient fusion technique is needed to make the global decision on the channel availability status.

AND, OR and Majority fusion techniques are used to take a final decision by applying a logic on the received data from SUs and transmit back the global decision about spectrum availability to the SUs.

AND rule: The spectrum is assumed to be available if one SU declares the absence of a primary user in the channel.

OR rule: The spectrum is assumed to be available if all the SUs declares the PU absence.

Majority rule (K out of M rule): As the name suggests, this technique is based on the majority of the individual decisions given by the SUs. If the result from at least greater than half of the number of SUs is of one hypothesis, then that particular hypothesis is made as the final decision.

PROPOSED MODEL

In our work, a machine learning based sensing technique for Cognitive Vehicular Network is proposed to improve the sensing efficiency by optimizing the sensing parameters such as probability of detection, misdetection and false alarm.

Probability of detection (P_d): This measures the ability of the receiver to detect the PU status accurately.

Probability of misdetection (P_{md}): Finds the channel to be free when busy. With the increase in P_{md}, there will be an increase in the interference to the PU.

Probability of false alarm (P_f): Detects the channel to be busy when free. The increase in P_f value reduces the throughput.

Therefore, for reliable sensing performance, the value of P_d must be high and values of P_f and P_{md} must be made low.

We considered 'N' SUs in a highway scenario that continuously sense the spectrum and report to the fusion centre through the dedicated channel. The SUs transmits information about the Received Signal Strength Indicator (RSSI) to the fusion centre in the form of beacon signals. SUs are assumed to be close to the PU and outside the range of other PUs. The 'N' SUs on the considered highway scenario moves in one direction.

On its roadside, PU base station exists, and on the other side, the fusion centre exists. The SUs moves with random speeds. A total of 200 movements of SUs are considered throughout the execution cycle of the program. At each instant, each SU in the network evaluates RSSI and transmits it to the fusion centre which then applies the collective data to ML model (Weighted-KNN) and decides the presence/absence of PU.

Weighted K- Nearest Neighbour (W-KNN)

The role of Machine Learning techniques in Cognitive Vehicular network scenario is significant especially in Spectrum sensing [6,7]. The Weighted KNN is a modified version of KNN technique. The concept of W-KNN is to give more weight to the points which are nearby and less weight to the points which are far off.

Consider an energy vector y* of size L. The weighted distance of each test vector is found from all the training energy vectors and the training vectors are arranged in the ascending order of their distances.

The 'K' training energy vectors from the top are selected as neighbors by the KNN classifier. Let Φ (y*, y) be the neighbour set of y* between y.

The class of y* is found by categorizing the 'K' number of neighbors among channel available and unavailable classes.
The number of neighbours in the channel available class (x = 1) and the channel class unavailable (x = -1) is defined as

$$\nu(x; y^*, y) = |\{l = 1,...,L | x(l) = x, y(l) \in \Phi(y^*, y')\}| \quad (3)$$

The y* is categorized as the channel unavailable class (i.e., x = −1) if and only if

$$\frac{v(-1; y*, y\prime)}{v(1; y*, y')} \geq \Phi \quad (4)$$

Here, Φ is constant which controls the trade-off between probability of false alarm and probability of misdetection. KNN adopts a weighted distance measure.

Each component of energy vector is weighted by a factor denoted by ω_n and is calculated by drawing a ROC curve using the nth components of the training energy vectors (i.e., $y_n^{(1)}$, …. $y_n^{(L)}$) and the corresponding channel availability (i.e., $x_n^{(1)}$, … , $x_n^{(L)}$)).
Therefore, ω_n is equal to the curve of the area under ROC of the nth component of energy vectors.
The Euclidean distance is given as:

$$\Delta(x, y) = \sum_{n=1}^{N} \{\omega_n (x_n - y_n)\}^2$$

and the city block distance is gives as:

$$\Delta(x, y) = \sum_{n=1}^{N} |\omega_n (x_n - y_n)|$$

NOTE: If K value is fixed and training energy vectors approach infinity, then all K neighbours converge to y*. Therefore, the label of each of K-nearest- neighbours is random variable that takes the value of 'x' with probability Pr [A = x | Y= y *].

If the value of K increases, the proportion of the label of each neighbour approaches Bayesian a posteriori probability [8]. Thus, the probability of error of KNN classifier approaches the Bayesian classifier as K value increases. Generally, the number of training energy vectors is limited and there is a need to increase the efficiency by reducing errors. Hence, there is a need to select a fair value of K to satisfy our requirements.

Initially to get the data, we need a network scenario for simulation. We need to select the number of nodes and run the simulation for 200 frames by changing the PU activityfor every frame. Then energy is evaluated at each node by using the energy detection method. The energies are stored as features and the corresponding PU activity is used as the label and these when combined form the training data.

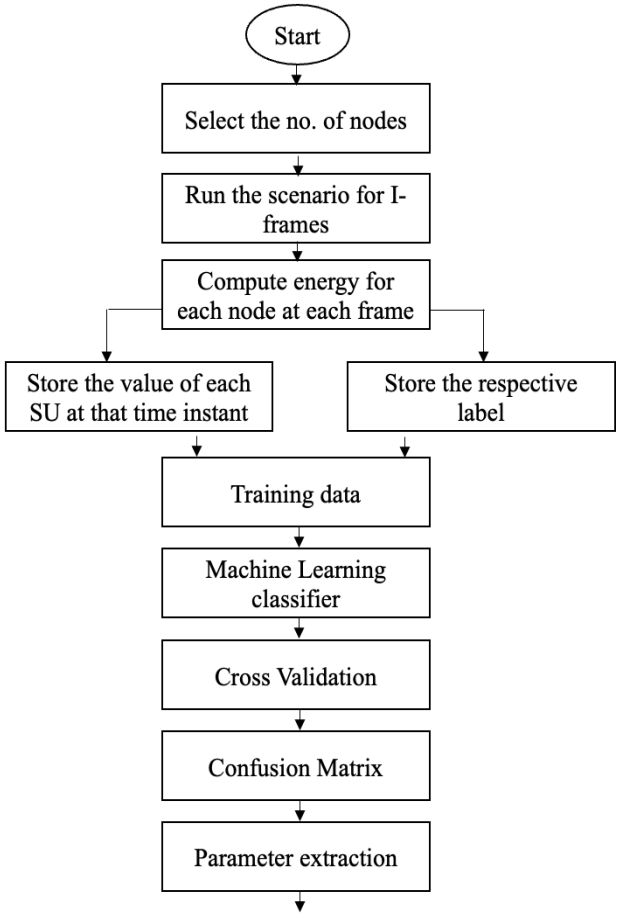

Figure-3. Flow chart.

CLASSIFICATION LEARNER

The tool used for simulating the scenario mentioned is MATLAB 2019a.The energies detected by the SUs are stored as features and the PU activity are stored in the form of states (0 or 1) which are termed as labels. The MATLAB has a machine learning tool called as classification learner which tales both variables and files for inputs. It automatically separates the features and labels. When data is fed to the classification learner tool, we need to mention the validation type and number of folds. So, set the validation as cross validation and the number of folds to 5. As KNN is being implemented, we need to mention the K value from the advanced settings. Set K to 10. Then train the machine using the "TRAIN" option. We obtain outputs such as probability of detection, probability of misdetection and false alarm.
The overall simulation is divided into two modules and includes several steps in each module.

Module-1(Cognitive vehicular network scenario creation)

Step 1: Choose background where vehicles (treated as nodes in VANET) can move. We choose X and Y axes with some spacing on it (axes are needed so that we can place PUs, RSUs, and SUs on it).

Step 2: Place PUs, RSUs, and SUs on the background. In the scenario, primary users (PUs) and Roadside Units (RSUs) are fixed while Secondary Users (SUs) position varies continuously and the numbers of SUs vary from 5 to 50.

Step 3: Consider the no. of SUs (N) at the beginning of each loop and give movement with maximum speed up to 40 Kmph at the junction.

Step 4: We considered the signal for PU such that it is ON (represents busy for some period of time) and OFF (represents idle in next period of time) and modulated this signal using AM technique.

Step 5: The SUs start to move on the road for 100 iterations with a speed which increases gradually or remain constant which resemblances real time road network.

Step 6: As the SUs move through the road, the Received Signal Strength Indication (RSSI) by the SU is affected by multi path reflections and attenuations.

Step 7: So, the RSSI is not constant always and therefore each SU has its own threshold (set as described above) based on the distance it is from the PU base station.

Step 8: The movement of SUs is varied always in 100 iterations throughout the program for number of vehicles from 5 to 50 in increments of 5.

Module-2 (Spectrum sensing in CR VANET using ML)

Step 1: Run the scenario assumed by initializing the number of SUs.

Step 2: The values of the energies observed by the SUs are collected into an excel sheetalong with the PU activity called as features and label.

Step 3: Open classification learner tool and select new session from the excel sheet saved.

Step 4: Select the type of verification as cross validation and number of folds as 10.

Step 5: Click on train by selecting the model as Weighted KNN model.

Step 6: Observe the confusion matrix and calculate P_d, P_f, P_{md}.

Step 7: Repeat the above steps by varying the number of nodes.

RESULTS

The network scenario created can be observed in the following figure. The blue dots represent SUs and the triangle represents PU base station. The movement of nodes can be interpreted from the figure below and at each instant RSSI is calculated at each node at each instant of time.

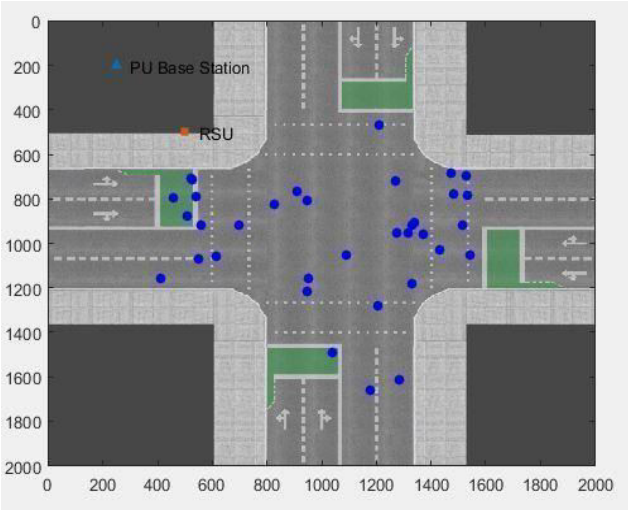

Figure-4. Network scenario.

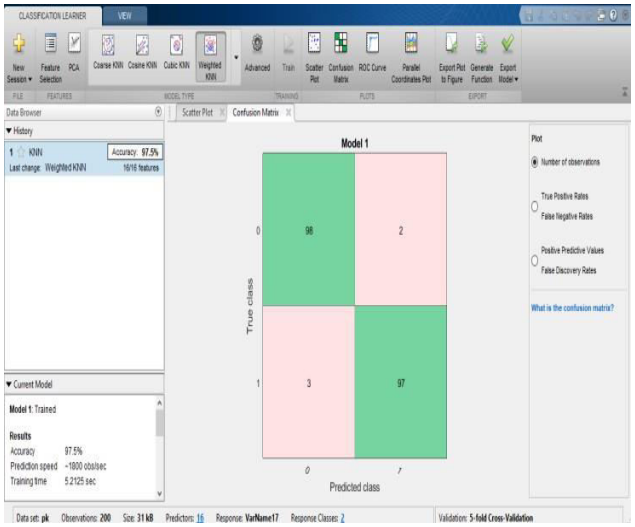

Figure-5. Confusion matrix.

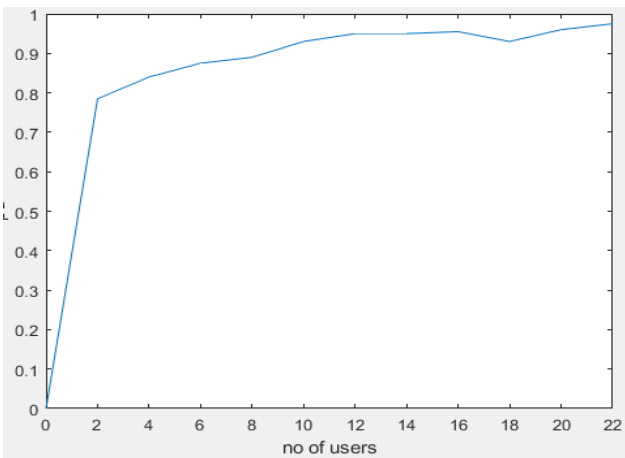

Figure-6. P_d Vs No. of SUs.

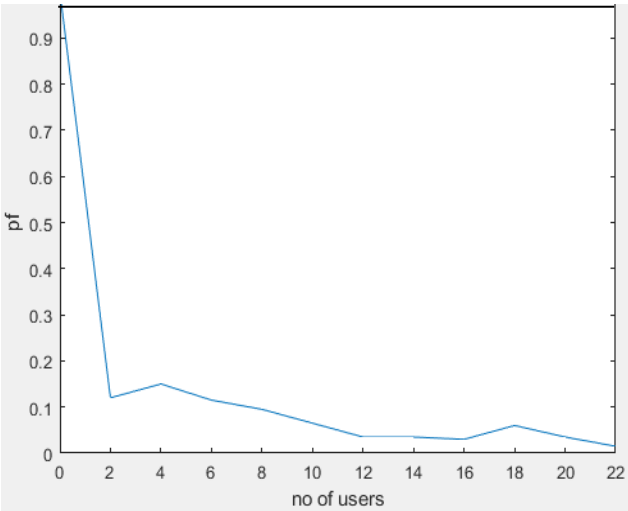

Figure-7. P_f Vs No. of SUs.

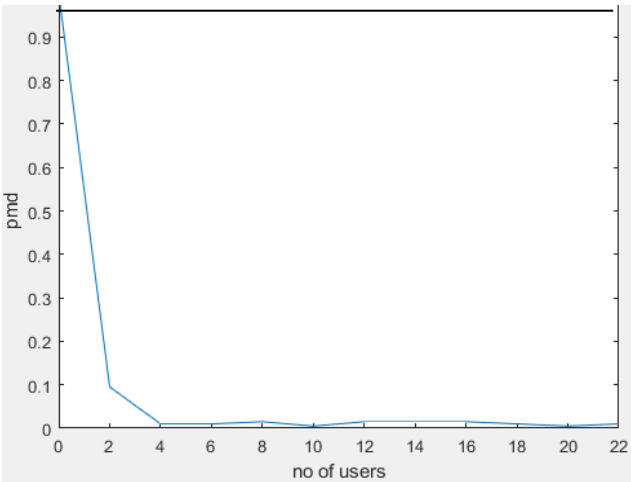

Figure-8. P_{md} Vs No. of SUs.

CONCLUSIONS

In the proposed work, spectral scarcity is addressed using Cognitive Radio technology and Machine Learning techniques. In dense vehicular regions, the 75 MHz bandwidth allotted is never sufficient and is utilized for high priority messages and is always busy and cannot be assigned to other vehicles requiring spectrum. This is solved using cooperative spectrum sensing that improves the detection performance by exploiting the spectral holes in TV band. The detection performance is evaluated by calculating probability of detection, misdetection and false alarm against varied number of vehicles participating in the spectrum sensing.

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