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An infrastructure-aided cooperative spectrum sensing scheme for vehicular ad hoc networks

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ABSTRACT

The Wireless Access in Vehicular Environments (WAVE) protocol stack has been recently defined to enable vehicular communication on the Dedicated Short Range Communication (DSRC) frequencies. Recent studies have demonstrated that the Control Channel (CCH) of the DSRC protocol on which all vehicular safety messages are sent might not provide sufficient spectrum for reliable exchange of safety information over congested urban scenarios. In this paper, we develop a scheme that calls for collecting spectrum sensing measurements by cars and then aggregating these measurements by Road Side Units (RSUs) to assess the state of the spectrum on road segments. We propose to opportunistically use the white spaces in the spectrum as an extension of the crowded Control Channel (CCH) for the next passing cars. A blind detector is applied and tested on the cars level, which takes advantage of their mobility to span a large area of the roads and deliver more accurate decisions in dynamic vehicular environments. To ensure homogeneity in the sensing samples among cars, we make the sensing rate of the cars dependent on their traveling speed. A fusion and decision algorithm is employed by Road Side Units (RSUs) to aggregate the individual sensing data and decide on the vacancy of the sensed frequency bands. The performance of the sensing and decision algorithms are evaluated and tested in various vehicular scenarios using the network simulator ns2. The obtained results prove the effectiveness of the system in detecting available ISM channels.

1. Introduction

Vehicular Ad Hoc Networks (VANETs) are distributed networks that allow car-to-car as well as car-to-infrastructure communication. Nodes in a VANET can share a whole range of information, from safety messages to application data, like multimedia file sharing. Modern cars are being equipped with a computing unit having a built-in transceiver, called On-Board Unit or OBU. On the infrastructure side, possible infrastructures include Road Side Units (RSUs), which are interconnected via a wired network or through the Internet by the use of high-bandwidth links. They are used to facilitate and control information sharing among the nodes. In 1999, 75 MHz of spectrum bandwidth was reserved for vehicular communication and now forms what is known as the Dedicated Short Range Communications (DSRCs) Spectrum at a center frequency of 5.9 GHz. Progressive attempts to standardize the communication along the whole protocol stack gave rise to several standards [18]. IEEE 802.11p was developed at the physical and lower MAC layers as an amendment to the preexisting IEEE 802.11 standard. It divides the spectrum into 7 channels of 10 MHz each, one of which (the center one) is the Control Channel (CCH), while the other six are Service Channels. Another protocol named Wireless Access in Vehicular Environments (WAVE) protocol covers all layers

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from the network till the application layers. Nodes in WAVE are synchronized to alternate between an SCH slot during which communication on one of the service channels is performed, and a CCH slot, during which all nodes switch to the common control channel.

In [26] and other publications, like [5], it has been proven that the control channel can suffer from severe contention under certain road scenarios. This problem has led researchers to search for innovative ways to solve this problem. Their primary aim was to improve the packet delivery ratio, along with other parameters crucial to the functioning of the VANET under contention, especially when important safety information is transmitted. The works in [19,10] exploited the use of TV channels to extend the spectrum used by network users. However, in practice, this solution is not practical when applied to vehicles in a highly mobile environment since it would require using a large and separate antenna (TV bands are in the MHz, as opposed to GHz for 802.11p). For this reason, we have proposed in our previous work [14] to apply cognitive radio concepts to VANET safety applications by exploiting the IEEE 802.11a outdoor channels centered around 5.8 GHz. Note that the extension of the licensed spectrum to bands outside the 5.9 GHz allocated spectrum but not directly adjacent to it was made possible through the use of Non-Contiguous Orthogonal Frequency-Division Multiplexing (NC-OFDM). The proposed system aimed at providing passing cars with spectrum availability information for the 802.11a channels. The RSU advised the cars about the free bands so they can cognitively use them when contention is inferred in the network [14]. It is therefore of crucial importance that the spectrum availability information be accurate to a certain extent so that cognitive users (also called secondary users) do not interfere with users who are initially intended to use this part of the spectrum (also called primary users). Examples of primary users of the ISM channels include passengers in cars who may be communicating with other passengers in WiFi ad hoc mode (i.e., without infrastructure), or trying to connect to the Internet via hotspots provided by shops and residences on sidewalks (although such a scenario is unlikely). In the simulations (Section 4), we model such scenarios using nodes (cars) of the vehicular network by supposing that a percentage of such nodes are primary users. Moreover, we assume that the probability of users located in cafes and restaurants along sidewalks interfering with WiFi communications on roads where cars are driven (especially major roads and highways) should be very low, which is why we did not consider such users in our experimental scenarios.

This brings us to the focus of the current paper, where the aim is to develop a robust sensing scheme that would: (1) allow the creation of accurate maps of the unlicensed ISM spectrum across the roads, (2) identify vacancies (also called white spaces) in those spectrum maps and (3) allow passing cars to use white spaces as cognitive extensions of the CCH. We propose a system where:

- The cognitive cars themselves are sensing nodes that use a blind detector. By doing so, we are taking advantage of their mobility so as to span a large area of the roads.
- The RSUs perform fusion and decision on the free ISM channels.
- The decision information is conveyed to the passing cars, enabling them to cognitively use the white spaces in the spectrum as extensions for the contended CCH.
- The approach is cooperative in nature since cars and RSUs work together to keep updated information on the state of the unlicensed spectrum on the roads, and to provide a viable extensions of the CCH.

We use the network simulator ns2 to show testing and evaluation of the performance of both sensing and decision algorithms, as well as the overhead incurred. Moreover, the performance of the blind detector is compared to that of the energy detector on a vehicle.

2. Related work

Several schemes have been proposed to perform sensing and manage the unlicensed spectrum for cognitive users in a Cognitive radio (CR) network [30,32]. The authors of [1] distinguish between different spectrum management functions: spectrum sensing, spectrum decision, spectrum sharing and finally spectrum mobility. In this paper, we focus mainly on the first two. Spectrum sensing can be either stand-alone or cooperative. The latter is of course much more effective in terms of accuracy since it combines information from several nodes to arrive to a decision, but such a scheme naturally incurs higher overhead. In [25], a cooperative spectrum sensing framework is described, where a coordination node (CN), normally an RSU or an elected car, performs the sensing on a continuous basis using energy detection. The CN receives requests on a predefined channel from regular cars that wish to communicate (secondary nodes: SNs), and sends them coordination instructions, specifying the free channels to use on a secondary-user basis. An SN that receives such instructions transmits pilot signals on the suggested channel C_i and sends a management signal to the intended recipient which must check if C_i is free in its area. If the channel is free, the two cars can communicate. The authors report that their proposed architecture is autonomous in the sense that cars, after receiving instructions from the CN, decide on the channel autonomously. However, and as was described above, the use of a free channel is still subject to the receiver finding it free on its end. In other words, the lack of coordination between the sender and the receiver in the initial selection of the free channel could result in scenarios where the channel selected by the sender may not be free in the intended receiver's area.

Obviously, a robust detector that delivers accurate decision in complicated vehicular scenarios will enhance the sensing performance. Accordingly, we replace the traditional energy detector (ED), which decides on the amount of energy collected, by a more sophisticated blind detector. Cognitive radio researchers proposed several spectrum sensing algorithms in the last decade. Some of those methods require a priori knowledge of noise and/or signal power information. Those include matched filter-based

sensing [8] and cyclostationarity-based sensing [27], relying on the full or partial knowledge of signal and noise levels. Similarly, the classical ED requires an estimate of the noise level in order to compare the ambient energy to a threshold dependent of the noise power level [29]. In a vehicular environment, however, the fast fading and model uncertainty problems could harm the performance of those detectors [31]. For this, a so-called blind detector that does not rely on any knowledge of the noise, signal or channel models will be more applicable to guarantee accurate individual sensing. Recently, the work in [20] proposed a blind detector to elude the model uncertainty problem by relying on advanced digital signal processing techniques to accomplish this.

On another level, cooperative sensing schemes can be either distributed or centralized. In the latter case, the sensed data is sent to a Fusion Center (equivalent to an RSU) to perform the decision. The work in [25] presents a hybrid scheme where, if no RSUs are present, a vehicle is used as a coordinating node, as was mentioned earlier. In [9], a distributed algorithm (CLICK) is described. There, the decision depends on quality metrics like the standard deviation of the channel as well as other parameters. However, the scheme in [12] is more successful when applied to inter-vehicular communication. To the best of our knowledge, that scheme is the closest to our present work considering all other reviewed works done on cognitive networks in vehicular communications. The scheme used is called CogV2V, which is a fully distributed and cooperative system. In that scheme, each car senses the spectrum for a time interval T_s and stores the samples as binary values in a Spectrum Availability Database (SADB) at the vehicle level. Then, after time T_b, the node performs an aggregation of the data in the SADB and broadcasts it to other cars within its spatial horizon. Spectrum information is hence shared among vehicles and each vehicle performs a decision based on its collected data as well as data from other cars. The algorithm of CogV2V requires frequent broadcasts, which could mean considerable overhead in an environment that is already contended. On the other hand, the aim of our research is to develop an approach that requires minimal data transmissions and computations at the vehicle level. To do so, we are interested in an RSU-based network architecture. The reason is that reliance on an infrastructure that is distributed and fixed in location provides higher accuracy of hypotheses concerning the spectrum availability since it aggregates information from all passing cars within fixed regions. Moreover, data stored at the RSU would have a temporal continuity (unlike moving nodes that would be forced to "start from scratch" every time a decision is taken due to high mobility).

Another challenge in cooperative sensing is the fusion at the decision node. Functions like AND, OR, and k out of N rules are some hard combining methods mentioned in [2]. The authors in [18] use a linear-quadratic (LQ) fusion strategy that takes into account the correlation between nodes. In the system we propose, we try to minimize the correlation between individual samples by using a speed-dependent sensing operation at the car level. For this reason, a simple weighted averaging at the RSU level would be enough to provide an insight about the occupancy of the bands of interest. Each of the points mentioned above will be discussed in more detail in the following sections.

The rest of the paper is organized as follows. In Section 3, we describe our proposed system from the individual sensing at the car level up to the final decision after fusion at the RSU level. In Section 4, we present the results of a simulation done using the NS2 network simulation platform. Finally, we end the paper in Section 5 with concluding remarks and ideas for future works and extensions.

3. Proposed system

As was explained at the end of the introduction section, the proposed system aims to identify available ISM channels that may be used to extend the contended Control Channel of the 802.11p DSRC standard. Cars sense the ISM spectrum in regions where they are driven and send the measurements to nearby Road Side Units (RSUs) which in turn make decisions about the free channels in the sensed spectrum for future passing cars. As illustrated in Fig. 1, the proposed spectrum sensing system may serve as a block within a larger setup for mitigating the spectrum scarcity issue in the DSRC Control Channel (CCH) through the application of a cognitive radio approach. The proposed sensing scheme is shown in Fig. 1 as a collection of functions that include making measurements and storing them

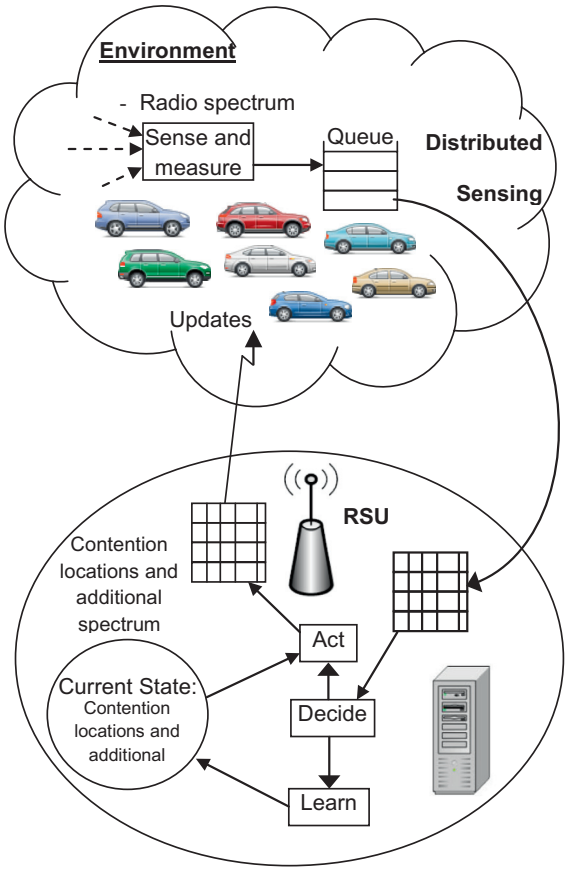

Fig. 1. Logical diagram of the proposed system.

in the car's database (upper part), and then sending the aggregated measurements to the RSU, where they are fused for decision making.

3.1. System overview

In our proposed scheme, the roads are divided into segments that we call cells. Fig. 2 illustrates the physical structure of our system. The side h of a cell is set to around 50 m, which is around half of the range of Wi-Fi. Most of the cells fall under the coverage area of a Road Side Unit (RSU), but there might be some cells that cannot communicate with any RSU due to an insufficient deployment of these units (non-overlapping ellipses in Fig. 2).

The sensing procedure at each vehicle goes as follows: periodically, each vehicle stops transmitting and/or receiving data to sense on a set of M channels from the ISM bands of interest during the Service Channels (SCH) slots. The vehicle uses a blind detector that goes over the channels successively and reports the availability of each. As in [12], the temporary spectrum availability information is stored in local Spectrum Availability Databases (SADB), but to suit our architecture, we will differentiate between the Vehicle SADB's (VSADB), which contains the direct results of the sensing procedure in a vehicle, and the Central SADB's (CSADB) residing in the RSU, which stores the aggregated information sent by the vehicles within the coverage area of the particular RSU. The two hypotheses model (where H_0 signifies absence of a nearby primary user and H_1 means its presence) is used for the decision process. The accumulated content of the VSADBs is used to create decisions based on the local sensing data for the current cell. A decision for the current cell is taken by the car whenever the vehicle leaves this cell. This decision is directly sent to the RSU it can communicate with (if any) on one of the six Service Channels. Whenever possible, the data is piggybacked on outgoing packets to save on bandwidth consumption. Once this is done, the VSADB is cleared and is filled again. The RSU sporadically receives information from the vehicles, stores them in its CSADB and performs fusion to provide the next passing vehicles with an assigned channel in the ISM bands to be cognitively used, and hence communicate more reliably.

3.2. Spectrum sensing at the vehicle level

3.2.1. Collection of individual samples

Since dynamic spectrum allocation will potentially occur only for the CCH, the vehicles can freely sense the spectrum during the SCH time slots. They can hence detect the presence of primary users outside the cognitive VANET (abbreviated as CVANET) with no risk of mistakenly identifying an outsider when it is in fact a current cognitive user transmitting on one of the ISM channels. During the SCH time slots, each vehicle undertakes the collection of samples for the set of the M ISM bands (if busy receiving data

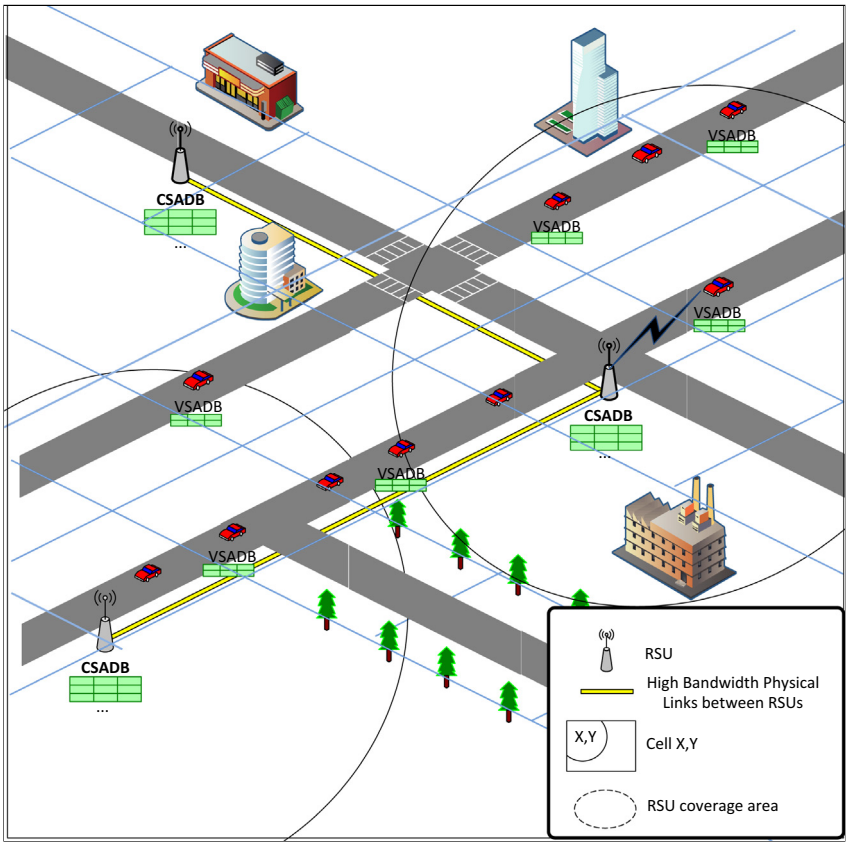

Fig. 2. Illustration of the proposed architecture's environment.

Initialize:

a) Acquire n data samples from the spectrum sensing interval formed by N_s samples.
b) Set l the number of OMP iterations and M the number of delays τ ($\tau = 1 \ldots M$).

For M different values of τ:

a) Calculate autocorrelation vector $\overline{f}_\tau$:

$$\overline{f}_\tau = [f_\tau(0), f_\tau(1), \ldots, f_\tau(N_s - 1)]^T \text{ where } f_\tau = y(t)y(t+\tau)$$

b) Calculate the elements of the matrix $A(n,N_s)$ performing the IDFT transform:

$$a_{pq} = e^{2i\pi(p-1)(q-1)/N_s}$$

c) Estimate the cyclic autocorrelation vector $\overline{r}_\tau$ by solving:

$$A\overline{r}_\tau = \overline{f}_\tau$$

and using an iterative optimization technique called Orthogonal Matching Pursuit (OMP) [11] that delivers an approximated solution $\hat{r}_\tau$

d) Run the OMP algorithm l times.
e) Calculate the symmetry index for this value of τ, by ignoring the first amplitude that corresponds to the first iteration of OMP, and measuring the mean value of the abscissa of the remaining (l-1) non zero elements in $\hat{r}_\tau$

$$IND_{SYM}^{\tau} = \frac{1}{l-1}\sum_{i=1}^{n}(\hat{r}_\tau)_i$$

End For

Equivalent decision:

a) Compute the equivalent index resulting from M symmetry indexes with different values of τ

$$IND_{SYM}^{EQU} = \sum_{i=1}^{M} IND_{SYM}^{\tau,i}$$

b) Calculate the final output of the algorithm:

$$Output = \begin{cases} 0 \text{ if } IND_{SYM}^{EQU} = 0 : H_0 \\ 1 \text{ if } IND_{SYM}^{EQU} > 0 : H_1 \end{cases}$$

Fig. 3. Steps of the SP-CAF algorithm. (See above-mentioned reference for further information.)

on its input buffer, it stops its communication). These samples are accumulated in VSADB entries, called *SAE*s (Spectrum Availability Entries) in the following format, similar to [12]: ⟨*Sample*, *X*, *Y*, *Chan*, *Output*, *Time*⟩, where *X*, *Y* are the cell identifiers in the urban grid, *Chan* is the Channel ID, and *Output* is a binary value coming from the spectrum sensing algorithm (1 for occupied; 0 for unoccupied).

CVANETs typically use an energy detection approach for sensing, also known as radiometer, since it is a non-coherent and simple detector [6,7]. However, its efficiency degrades rapidly in low SNR environments and under noise uncertainty conditions. For this reason, we propose in this paper to enhance the spectrum sensing at the vehicle level by using the SP-CAF algorithm, which was proposed in [20] and elaborated in [22], as an efficient and blind spectrum sensing algorithm. This algorithm, based on the symmetry property of the cyclic autocorrelation function (SP-CAF), is adapted in this work to operate with the high frequency bands of 802.11a and 802.11p. Moreover, the sensing rate is derived (see next section) to produce a tradeoff between efficiency (small sample set size) and effectiveness (large enough number of samples for reliable detection).

Energy detection (ED) simply applies a threshold on the collected energy of the received signal. The threshold is used to decide on whether a licensed user is present or not:

$$\text{Output} = \begin{cases} 0 & \text{if } P_f < P_{th} : \quad H_0 \\ 1 & \text{if } P_f \geqslant P_{th} : \quad H_1 \end{cases}$$

where P_f is the measured power, and P_{th} is a threshold value.

On the other hand, detection based on the symmetry property of the cyclic autocorrelation function works by blindly extracting the periodicity feature induced in telecommunications signals. In practice, transmitters modulate signals by coupling the base band signal with sine wave carriers, repeating spreading, pulse trains, cyclic prefixes or hopping sequences which induce periodicity in the statistics, mean and autocorrelation of the resulted signals. This built-in periodicity is known as the cyclostationarity feature of modulated signals and can be extracted and analyzed using Fourier analysis. In CR networks, detecting this feature leads to a differentiation between primary users and random noise [28].

The SP-CAF algorithm estimates the cyclic autocorrelation function (CAF) of the received signal by using compressed sensing tools that guarantee a relatively small sensing time. Then, an analysis of the accurate estimation of the CAF function of the received signal leads to the decision. If the CAF function has a symmetry feature, a positive decision on the presence of the licensed user is taken. It is

proven that this detector can outperform the radiometer with a reasonable computation complexity [20]. As described in Fig. 3, which summarizes the main steps of the algorithm, the SP-CAF detector alleviates the complexity of cyclostationarity-based algorithms by studying $n < N$ samples using the compressed sensing technique. It also benefits from the sparseness property of the CAF function to estimate the cyclic autocorrelation vector through an iterative optimization technique (OMP). It was shown that $l = 3$ iterations of OMP are sufficient to decide on the symmetry of the vector. The blindness property of this detector relies on its simple test statistics that check the symmetry of the estimated vector without using any noise, signal or channel models. Such a property is very suitable for vehicles' transceivers since the fast changing environment prevents the cognitive receiver from accurately estimating a model of the wireless environment.

3.2.2. Sensing rate

The rate at which the vehicle performs the sensing operation (or sensing rate) is determined as a function of the speed v of the vehicle as follows:

$$Rs = \begin{cases} R_{low} & \text{if } v < v_{low} \\ \alpha v & \text{if } v_{low} \leqslant v < v_{high} \\ R_{high} & \text{if } v \geqslant v_{high} \end{cases}$$

The parameter R_{low} is set so that the time between two successive sensing operations is comparable to the estimated time of expiry of the data at the RSU, i.e., the time after which a decision stored at the RSU stops being considered fresh. The parameter R_{high} ensures that the overhead in the network stays minimal. We set the maximum rate of sensing to be one sensing operation per SCH slot (and no sensing operation during the CCH slot as usual). Each slot has a default duration of 50 ms, and thus we can set R_{high} to 10 samples/s. The parameter α ensures that vehicles with any speed between v_{low} and v_{high} collect approximately the same amount of samples per cell. Assuming a vehicle at speed v_1 collects N_s samples per cell, we require that at $v_2 \neq v_1$, it also collects N_s samples. The number of collected samples for all channels can be expressed as follows: $N_s = \frac{Rs\,L}{v}$ where L is the length of the cell side. Solving for α yields $\alpha = \frac{N_s}{L}$, where again, N_s is the target number of samples per cell to be achieved in the ideal case where the car is idle and does the sensing continuously. The value of v_{low} is set to 2 km/h (the car is approximately stationary), while v_{high} is determined when R_{high} and α are known, by ensuring the continuity of Rs at v_{high}.

3.2.3. Aggregation of samples

When leaving a cell, or when reaching a timeout, the vehicle aggregates the information collected within the cell, and sends it to the RSU. If the car cannot currently communicate with a RSU, it keeps the records in its buffer to send it at a later time when it enters in contact with another RSU. Individual samples are automatically deleted after the aggregation occurs. The aggregated spectrum information entry has the following format, taken from [12]:

$$\langle SAE, X, Y, Chan,\ Available\ NumSamples,\ Speed,\ Time\rangle$$

In the above line, X, Y, and $Chan$ are the same as before, and $NumSamples$ is the number of samples used for the aggregation. This number is needed to provide a measure of the reliability of the information sent to the RSU. Indeed, although our speed-dependent sensing rate minimizes the deviation in the number of samples per cell, this number may vary for very low or very high speeds. The parameter $Speed$ is the vehicle speed (km/h), and $Time$ is a timestamp that gives an indication on the freshness of the data. For this reason, we define $Time$ to be the time instant where the vehicle first enters the cell X, Y. This way if the sent information is not fresh enough for the decision at the RSU, the latter can simply discard it.

3.3. Fusion and decision at the RSUs

3.3.1. Spectrum availability information: fusion

Every T_d time, the RSU examines its collected data sent by the passing vehicles, and updates its decision for each $\langle channel, cell\rangle$ pair (for cells of interest, i.e., falling on roads only and assigned to the current RSU). This is done by assigning to it a "quality grade" G between 0 and 1. For a given cell $\Psi_{X,Y}$ and channel C_i, the grade $G^i_{X,Y}$ corresponding to the pair $\langle C_i, \Psi_{X,Y}\rangle$ is computed as follows:

$$G^i_{X,Y} = 1 - \frac{\sum_j SAE_j\{Available\} \times SAE_j\{NumSamples\}}{\sum_j SAE_j\{NumSamples\}}$$

In the above, we use the notation $SAE_j\{x\}$ to denote the x field of the jth Spectrum Availability Entry (i.e., SAE_j). The aggregated grade representing the current decision of the RSU for a given $\langle channel, cell\rangle$ pair is then updated as follows:

$$G^i_{X,Y}(t) = \gamma G^i_{X,Y} + (1-\gamma)G^i_{X,Y}(t-1)$$

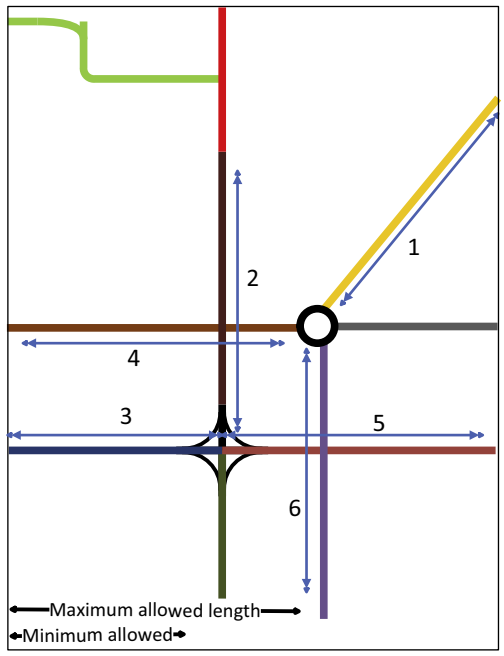

Fig. 4. Road segmentation for the channel assignment algorithm.

```
function GetNextCellIndex with input StrtCellIdx returns unassigned
   // looks for leftmost cell index to the right of StrtCellIdx
   unassigned = -1
   for each channel ch of the M channels
       starting at StrtCellIdx, scan cells in row of ch from left to right
         if channel ch in scanned cell sc is free
            if unassigned < index of sc
               unassigned = index of sc //leftmost cell has highest index
            end if
            break out of this scan loop //we're only interested in this cell
         end if
      end scan
   end for
end function
Sequence = {} // empty set of contiguous chains of channels
//get index of leftmost free cell across all channels
nextIndex = Nc
call GetNextCellIndex with input set to nextIndex and get unassigned
while unassigned > 0
   //find the next longest chain of contiguous cells for which the channel is free across all channels
   maxlength = 0
   for each channel ch of the M channels // consider all matrix rows
      length = 0
      starting with unassigned, scan cells in row of ch from left to right
         length = length + 1
         if ch in scanned cell sc is not free or sc is rightmost cell
            break out of scan loop
         end if
      end scan
      if length > maxlength
         maxlength = length
         nextIndex = nextIndex - maxlength
         maxchannel = ch
      end if
   end for
   add <maxlength, maxchannel> to Sequence
   //get the index of the next free channel (right to the chain we just identified above)
   call GetNextCellIndex with input set to nextIndex and get unassigned
end while
// Now, Sequence has a set of chains of free channels that maximally cover the cells (road regions)
```

Fig. 5. Algorithm for free channel assignment.

where γ is a parameter that represents the importance given to the current computed grade with respect to previous aggregated grades. It is determined by:

$$\gamma = \min\left\{\gamma_{high}, \frac{\sum_j SAE_j\{NumSamples\}}{N_{max}}\gamma_{high}\right\}$$

where γ_{high} is an upper limit for γ (say around 85–90%) and N_{max} is an estimate of the maximum possible number of samples. This reflects the fact that a higher number of samples used for the calculation of the current $G^i_{X,Y}$ would give a higher accuracy and hence a higher trust in $G^i_{X,Y}$.

3.3.2. Channel assignment: decision

At a given instant t, the RSU has a list of grades $G^i_{X,Y}(t)$ for each $\langle channel, cell\rangle$ pair. The RSU can use the speed information sent by the cars to infer road traffic conditions. A low overall speed is most likely caused by high traffic, and vice versa. It can hence relate the number of ISM channels to the average speed combined with the rate at which it is receiving information from cars, in every cell: $N_c = c\frac{R_{avg}}{V_{avg}}$, where $R_{avg} = \frac{m}{T}$, m being the number of *SAE*'s received from the cars during period T, and $V_{avg}(t) = V_{avg}(t-1) + SAE\{Speed\}$, every time an SAE is received.

The subject of adapting the rate of channel assignment to road conditions was addressed in our previous work using a Fuzzy Logic Controller [14]. Moreover, the RSU can adopt a regular ISM channel assignment update rate that is also inversely proportional to the average speed.

To simplify the analysis, we assume that it is sufficient to assign one free channel to use for each cell (knowing that in some applications more than one channel may be needed to extend the CCH). Since there may be several channels falling under a certain grade threshold, choosing in a cell the lowest occupancy channel may produce a non-homogeneous distribution of free channels across cells. For this, the channel assignment for cells has to be done with a spatial awareness that minimizes the deviation in channels assigned to spatially correlated cells, and therefore ultimately minimize channel switching at the level of the cognitive users (vehicles). To visualize the problem, we consider a configuration where all cells within a certain

	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6	Cell 7	Cell 8	Cell 9	Cell 10	Cell 11	Cell 12	Cell 13	Cell 14
Channel 1	0	0	1	1	1	0	0	0	1	1	0	1	1	1
Channel 2	1	1	1	0	1	1	0	1	1	1	1	1	0	0
Channel 3	0	0	1	1	1	1	0	0	0	1	1	1	0	0
Channel 4	0	1	0	0	0	1	1	1	0	0	1	1	1	0

Fig. 6. Example of free channel selection algorithm before edge adjustment.

region are assigned channel C_1 as a free channel that passing vehicles could use. Among these cells, only one (call it Ψ_0) is assigned a different free channel, say C_2. This situation would be very undesirable since a vehicle with Ψ_0 on its path would be forced to change the channel it uses twice in a short period of time, hence introducing unwanted delays. A better configuration would be to have uninterrupted paths of cells that are assigned the same channel, at the cost of shortening their average length. The motivation behind this is the following. A cognitive transceiver usually uses a tunable or reconfigurable RF frontend in order to operate in several frequency bands. Since the Cognitive Radio is an SDR (Software Defined Radio) based technology, its RF frontend could be controlled by the software to enable the switching from one frequency band to another. Accordingly, the delay to switch from one channel to another comes both from hardware and software. A typical upper limit for this delay is 120 μs [23]. Switching from one channel to another very frequently might affect the network performance if it is not controlled. For this reason, we want to reduce both the average number of switches per time unit and the time elapsed between two consecutive switches. Since the configuration of the cell map is two-dimensional, a reduction of the problem to a single dimension is useful. We propose to segment the road map as follows. First, the segment extremities are defined by road intersections, as illustrated in Fig. 4. If no intersection is found over a long road stretch, this stretch is segmented so as to keep the segments under a maximum allowable length, set to approximately the transmission range of the RSU. This is the case for instance of the segment numbered 2 in Fig. 4, whose total length would have exceeded the maximum length if it were not truncated at the upper side. Similarly, if an intersection is found before a minimum allowable length (5 contiguous cells for instance), then it is discarded, taking into account the next allowable intersection to do the segmentation. This is the case of the segment number 4 or 5 in the figure, where the intersection with Segment 2 and 6, respectively, is ignored.

Over each road segment or stretch, we propose to run a heuristic algorithm that reduces the number of channel switches between contiguous cells. Since most of the segments are defined by road intersections, it can be assumed that the vehicle slows down at segment extremities, hence having better signal quality (as far as fast fading and Doppler effects are concerned). This means that the effect of a car switching channels at an intersection on its communication performance is mitigated. Now within each road segment, given the number of achievable switches, we need to reduce the time between two consecutive switches, meaning that we require a good spatial extension over the individual segments. An additional advantage of such a result is that inter-vehicle communication on the same assigned channel is more likely to happen among spatially close-by cars.

3.3.3. Channel assignment: algorithm

In this section, we describe the algorithm which achieves the above-mentioned goals, i.e. reducing the number of switches in a segment, and reducing the variance in length for the sub-segments assigned to the same channel. A matrix *cell_view* is constructed based on the RSU information. *Cell_view* consists of M rows (corresponding to M potential channels to be used) and N columns corresponding to N successive cells (so N is the length, in number of cells, of the road stretch over which the algorithm is run). Channels with a grade less than a certain threshold κ (set to 0.5 or slightly higher) will be mapped to 0 within cell i, otherwise they are mapped to 1, meaning that they are respectively occupied or free. For instance, in the below *Cell_view* representation, Channel2 is free for Cell1, whereas Channels 1 and 3 are free for Cell 2, and so on. Therefore in this example, intuitively, one of the optimal channel assignment arrays is: 2 1 1 2 2 2 (second row of channels).

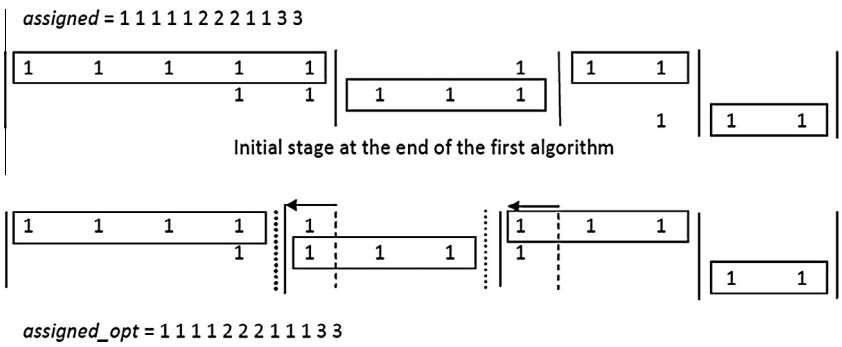

Fig. 7. Edge adjustment illustration: top is before edge adjustment, while bottom is afterwards.

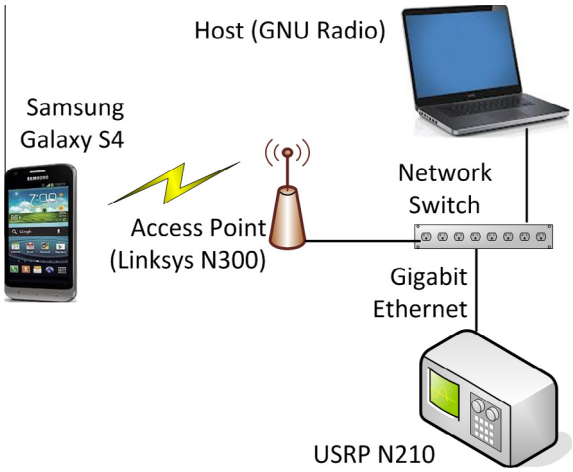

Fig. 8. Diagram of the experimental test-bed.

$$\begin{array}{c|cccccc} & \text{Cell 1} & \text{Cell 2} & \text{Cell 3} & \text{Cell 4} & \text{Cell 5} & \text{Cell 6} \\ \hline \text{Channel 1} & 0 & 1 & 1 & 0 & 0 & 1 \\ \text{Channel 2} & 1 & 0 & 0 & 1 & 1 & 1 \\ \text{Channel 3} & 0 & 1 & 1 & 0 & 0 & 0 \end{array}$$

The aim is to construct the sequence S of channel numbers assigned for each cell, such that the number of maximum-length subsequences having the same channel number is reduced. To do so, we span *cell_view* from left to right to greedily identify the longest chain of consecutive cells that can possibly share the same channel. Once it is identified, the process is repeated starting from the first unassigned cell. This heuristic procedure reduces channel switching for the car that will be traversing the road segment, but it does nothing concerning the reduced variance requirement. For this, in a second stage, S is readjusted at the edges of the subsequences mentioned above such that the variance in length between these subsequences is reduced. The algorithm is presented through the pseudo-code in Fig. 5 and an example in Fig. 6. Fig. 7 on the other hand illustrates an example showing the transformation of the schedule Sequence to an adjusted schedule, one that has a minimum length-variance.

4. Performance evaluation

In this section we study the performance of the blind detector by comparing it to the energy detector, then evaluate the performance of the system as a whole, and finally examine the overhead of the system by assessing the wireless traffic associated with spectrum measurements collection by the RSUs.

4.1. Vehicle sensing performance

Here, we describe the performance of the blind detector which we described in Section 3.2.1 and proposed for usage at the vehicle level. It represents an alternative to the energy detector that is typically employed for spectrum sensing in Cognitive Radio environments [4]. In this subsection, we compare the performance of this detector

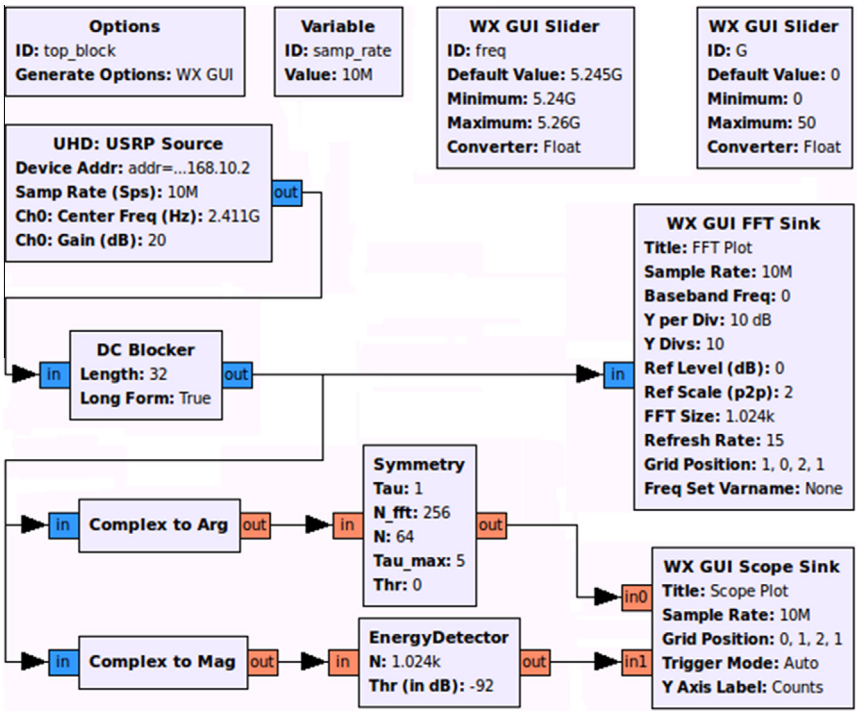

Fig. 9. GNU Radio setup.

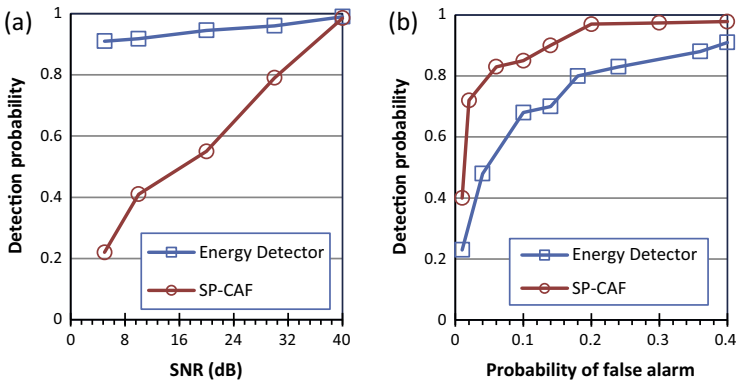

Fig. 10. Probability of detection for the ED and SP-CAF.

to that of the energy detector by running representative scenarios using a prototypical implementation that we describe below.

The performance measurements were acquired using the setup illustrated in Fig. 8. The prototype is built on top of the USRP N210 (Universal Software Radio Peripheral) motherboard, with the XCVR2450 daughterboard (2.4–2.5 GHz, 4.9–5.9 GHz) to implement the RF receiver, and a wideband antenna to perform spectrum sensing. The motherboard is a computer-hosted software radio that can be controlled to transmit and receive real signals. The RF and sampling processing are implemented in hardware modules that are associated with the daughterboard and the antenna, whereas the physical layer baseband operations, such as coding/decoding, interleaving, frequency hopping, equalization, and compression are implemented in software that is driven via a Xilinx Spartan 3A-DSP 3400 FPGA embedded within the USRP N210 [13].

To control the USRP transceiver and implement the proposed sensing technique, we use the GNU Radio [16], which is an open source software toolkit for software defined radios. The GNU Radio offers a simple and sophisticated graphical design environment, known as GNU Radio Companion (GRC), which allows users to create signal flow graphs with built-in communication blocks or out-of-tree modules. The SP-CAF algorithm was programmed using C++ and inserted in a GRC file along with a block connected to the USRP to receive real time data and perform spectrum sensing and detection. For comparison purposes, the energy detector was implemented in a similar manner and connected to the USRP. The setup of the system is shown in Fig. 9.

To imitate the real scenario where vehicular communications can access 802.11a outdoor channels centered around 5.8 GHz, we conducted the experiments on the 802.11a indoor channel number 48, centered around 5.24 GHz using a dual band wireless access point. The Linksys N300 [21] was used as the primary transmitter, a Galaxy S4 smartphone [24] supporting the 5 GHz 802.11a technology as the primary WiFi receiver, while the USRP was employed to act as an opportunistic secondary user. The aim of the experiment was to measure the probability of detection and that of false alarms for the classical ED and for the SP-CAF detector in order to compare the performance of the detectors. In order to do so, five different scenarios were studied:

Table 1
Simulations parameters and their values.

Parameter	Default value
802.11p bandwidth	6 Mbps
Packet payload size	350 bytes
802.11p Transmission range (cars and RSU)	250 m
ISM devices (primary users) transmission range	100 m
Communication method	Broadcast
Radio model	Nakagami
Simulation time	1200 s
Simulation area	1 km^2
Default% of primary users	40
Primary users transmission rate	1 Hz

- *Scenario 1:* The distance between the wireless access point (AP) and the USRP was less than 1 meter, which corresponded to 4 bars in the wireless meter of the smartphone (excellent signal). The estimated SNR value was 40 dB.
- *Scenario 2:* The distance between the AP and the USRP was 2 meters, resulting in 3 bars on the meter of the smartphone (good signal). The estimated SNR value was 30 dB.
- *Scenario 3:* The distance between the AP and the USRP was 2 meters, but a thick concrete wall separated the AP from the USRP. This corresponded to 2 bars in the wireless meter of the smartphone (low signal). The estimated SNR value was 20 dB.
- *Scenario 4:* The distance between the AP and the USRP was 3 meters, and a thick concrete wall separated the AP from the USRP. This gave 1 bar on the wireless meter of the smartphone (very low signal). The estimated SNR value in this scenario was 10 dB.
- *Scenario 5:* The distance between the AP and the USRP was 4 meters, and two thick walls separated the wireless access point from the USRP. This corresponded to 0 bars in the wireless meter of the smartphone (no signal). The estimated SNR value was 5 dB.

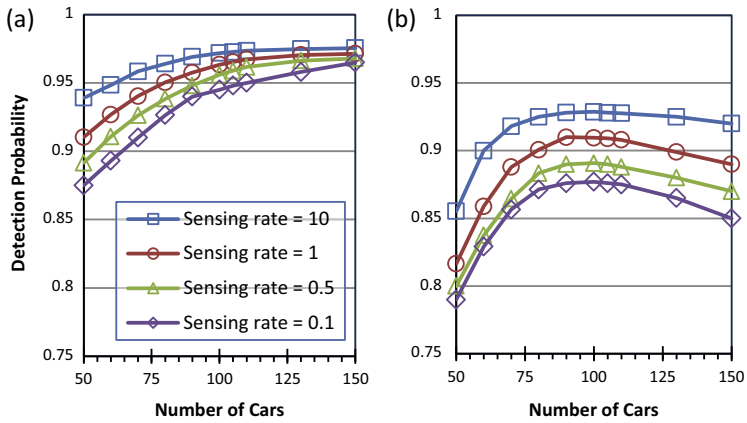

Fig. 11. Probability of detection vs. number of cars for our approach (a) and that for [25] (b).

In all the above scenarios, the smartphone was connected to the Internet via the dual band access point programmed to occupy channel 48 at 5.24 GHz. We started a long download using the smartphone to ensure a primary transmission, while the USRP was scanning the 10 MHz centered at 5.24 GHz. On the hosting computer, a GRC file was generated to process the data acquired by the USRP. As illustrated in Fig. 9, data streams were inserted into two blocks: the ED and the blind (SP-CAF) detector. The threshold for ED was set to −62 dBm, as defined in the 802.11a standard [3]. The SP-CAF detector did not require a threshold since it only studies the symmetry of the CAF. Based on the Boolean output of the detectors, the detection probability was measured for all scenarios and plotted in Fig. 10(a). As was mentioned earlier, the probability of false alarms, which is the probability of classifying particular 802.11a channels as free when actually they are not, was also tracked during the experiment. Using these measurements, the probability of detection versus the probability of false alarm, known as the receiver operating characteristic (ROC), is shown in Fig. 10(b). This plot highlights the performance of the sensing technique and reflects the efficacy of its outputs.

The results depicted in Fig. 10 prove the advantage of the blind detector. It is clear that this detector outperforms the classical ED, especially in low SNR scenarios. This makes it more suitable for vehicular communications which are subject to various dynamically changing scenarios.

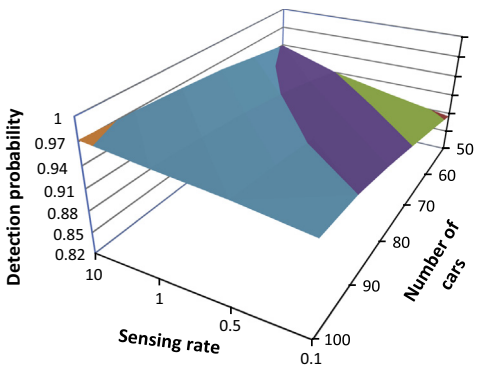

Fig. 12. Probability of detection versus sensing interval.

4.2. System performance

In this section we present additional experimental results that quantify the performance of our proposed system as a whole. We implemented our system using the ns2 Network Simulator software (ns2.34 with the 802.11p amendment), and used our simulation tool proposed in [15], where we have proposed a WAVE implementation within ns2. The resultant environment completely simulates the vehicular network stack. The SUMO tool [2] was employed to generate the node movement file that was inputted to ns2, and the map we used to generate the movement file had a size of 1×1 km^2 and closely resembles the layout shown in Fig. 2. The wireless bandwidth and the radio transmission range were set to 11 Mbps and 250 m respectively for both the cars and the RSUs. The three RSUs (as shown in Fig. 2) were wired via dedicated connections, and were placed in such a way that RSUs on the same lane have slightly overlapping coverage areas. The default number of vehicles was set to 100, and their minimum and maximum speeds (V_{min} and V_{max}) were set to 50 and 100 km/h respectively. Car communication was restricted to 1 hop, meaning that only cars within direct transmission range of each other communicated.

A percentage of the cars (default 40%) was given the role of primary users transmitting WiFi (802.11a) packets with known signatures on the 7 WiFi outdoor channels (randomly chosen) at given rates (default 1 s), independent of each other. The Cognitive Radio (CR) cars sense the 7 channels sequentially during the time of one of the 802.11p Service Channels (SCH), chosen independently and randomly, to simulate the fact that cars may be engaged in communications on particular SCH channels. The settings of the ns2 experiments are summarized in Table 1, showing for some of the parameters the defaults values.

To compare our system with another sensing approach, we also simulated the system in [25] (described in Section 2) in which CR cars wishing to communicate contact the RSU (coordinating node) requesting the set of channels to

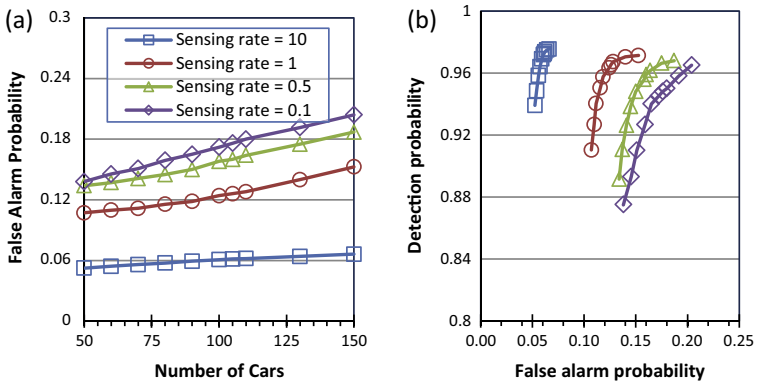

Fig. 13. Probability of false alarm (left) of the proposed system.

sense. We note that the work in [25] senses the VHF/UHF TV bands, but for the sake of comparison, we simulate this approach to sense the 802.11a channels as we do in our own approach. We also note that our simulation setup is favorable to the approach in [25] since the transmission ranges of the RSUs cover the cars on the roads of the employed map and similarly, each car can reach one of the RSUs in the map.

The metrics used for comparison are (1) the detection probability, and (2) the number of times of switching between free channels. The first one is computed versus several parameters, and it can be defined as the ratio between the number of successfully identified channels and the number of channels that are actually free. The second metric is an indication of the efficiency and robustness of the sensing approach. That is, less switching between free channels is more efficient since there will be fewer interruptions of any ongoing communications. It is also more reliable because if a transmitter switches to a different free channel, there is no guarantee that the receiver will find that same channel free. Finally, before presenting the results, we should note that unlike other approaches, like the one in [25], there is virtually no delay overhead since cars entering (or leaving a road segment) will be transmitting their accumulated spectrum sensing data to the nearest RSU. This RSU will in turn be aggregating received data, making channel assignments, and transmitting them to cars in its transmission range on an ongoing basis. In contrast, and as was described in Section 2, the approach in [25] requires that a car that wishes to communicate, must request a so-called coordination instructions from the RSU, and afterwards conduct its own sensing based on which it identifies a free channel.

Starting with the first set of results, we analyze the detection probability for both our approach and the one in [25]. Fig. 11(a) illustrates the detection probability of our proposed system versus the number of cars moving in the simulated area and for different car sensing rates. In our proposed approach, the presence of additional cars improves the detection performance of the approach even though the number of primary users increases (since the percentage was held constant at 40%). This can be attributed to two properties of our approach: (1) the centralized channel assignment mechanism employed by the RSU based on aggregated readings from cars in the area, and (2) the channels switching frequency minimization algorithm, also employed by the RSU. On the other hand, the approach in [25] suffers if the number of cars is increased beyond a certain density in the presence of primary users, as illustrated in Fig. 11(b). We attribute the shown decline in the detection probability of the approach in [25] around 90 cars to the fact that a car (C_1) must determine a free channel autonomously after receiving suggestions from the RSU, and then communicate with the intended receiver (C_2). C_2 should in turn check if the same channel is free on its end, which may not necessarily be the case. As the number of cars increases, the above situation will occur more often, as it will be more likely for cars near C_2 or for C_2 itself to be using the channel.

In Fig. 12, in addition to varying the number of cars, we also vary the rate of sensing performed by the cars. Increasing the rate leads to an increased number of sensing samples sent by the cars to the RSU, which serves to decrease the probability of missing free channels, as can be clearly seen in the figure. However, with a larger number of cars, the results show that the performance of the system is slightly affected by the sensing interval. This is due to the fact that the decision algorithm of the proposed scheme utilizes only a subset of the available samples in presence of high spatial correlation in the data. As a result, when the car density is sufficiently large we can still improve the spectrum exploitation by reducing the sensing frequency performed by vehicles without increasing the interference with active (primary) users. These results confirm the analysis made in [12].

Next we examine the false alarm probability which we define as the probability of identifying a WiFi channel as being free when, at the time the vehicle needs to switch to it, the channel is being utilized by a "primary" WiFi user. In our proposed scheme, the feature of the system that could contribute to increasing false alarms is the gap between the times when cars take sensing samples and the time when the decision of the RSU reaches the cognitive cars. That is, there is a non-zero probability that during this time gap, the utilization conditions of the WiFi channels could change. On the other hand, the feature that contributes negatively (i.e., decreasing the probability of false alarms) is the aggregation of sensing samples by the RSU from cars that could cover the majority of the surrounding roads area. As can be seen through the results in the graphs

of Fig. 13, the false alarm probability increases, although mildly, with increasing number of cars and decreasing sensing rate, naturally because there are more opportunities for users to initiate WiFi traffic during the time gap we mentioned above. Fig. 13(b) shows that the detection probability increases with the increase in the false alarm probability, thus indicating that false alarm events can be regarded as a cost for improving channel utilization detection. The system in [25] offers somewhat worse false alarm performance, especially for high sensing rates (Fig. 14(b)). This can be attributed to the way free ISM channels are detected and used. That is, and as was described in Section 2, an RSU decides on a free channel, e.g., CH_i, autonomously before suggesting it to an inquiring car, e.g., C1, that wishes to send packets to another car C2 cognitively. After receiving the suggestion from the RSU, C1 senses the spectrum to ensure that CH_i is indeed free. However, and as was also described in Section 2, the use of CH_i is still subject to C2 finding it free on its end. In other words, the lack of coordination between C1 and C2 in the initial selection of CH_i could result in scenarios where CH_i may not be free in C2's area. We believe that this aspect of the system in [25] is the main contributor to the false alarms. In contrast, in our scheme, even though there is a time period between channel occupancy determination and channel utilization, the issue is mitigated by the aggregation of sensing measurements from cars that could potentially cover the entire area. This can be observed in Fig. 13(a), where false alarm levels are better in our scheme relative to that in [25] particularly when the sensing rate is high (Fig. 14(a)).

Continuing with detection probability, we now study the effect of car speed on our metrics. Obviously increased car speeds have an adverse effect on detection probability, simply because it becomes more probable to miss free channels. This phenomenon is illustrated in Fig. 15. The effect of speed however is less severe on our proposed scheme (shown in Fig. 15(a)), as measurement aggregation mitigates the events of missing free ISM channels by certain cars since others will "catch" these channels. This is not the case in [25], as seen in Fig. 15(b), since free channels are primarily decided on by individual cars, after receiving requested coordination instructions from the RSU.

Next, we look into the effects of varying the percentage of primary users on detection probability (Fig. 16) and on the frequency of switching between free channels (Fig. 17).

Increasing the percentage of primary users negatively affects probability of detection since the number of conflicts with primary users increases, making it more likely to miss unused ISM channels. The effect on efficiency is illustrated in Fig. 17 through showing the number of switching events between free channels, as the number of free channels becoming occupied by primary users increases. Fig. 17(a) experimentally proves the effective-

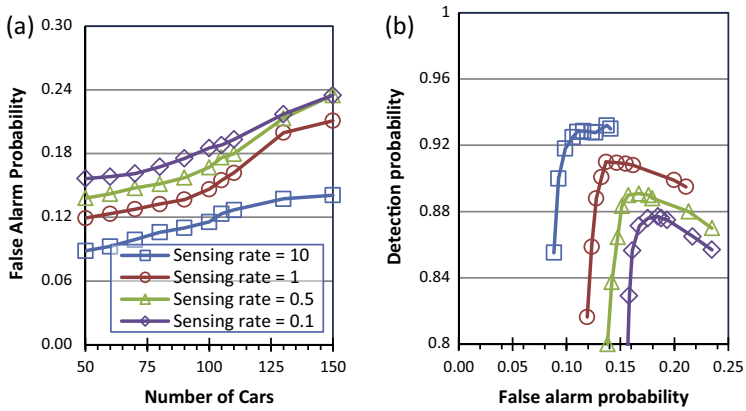

Fig. 14. Probability of false alarm (left) of the system in [25].

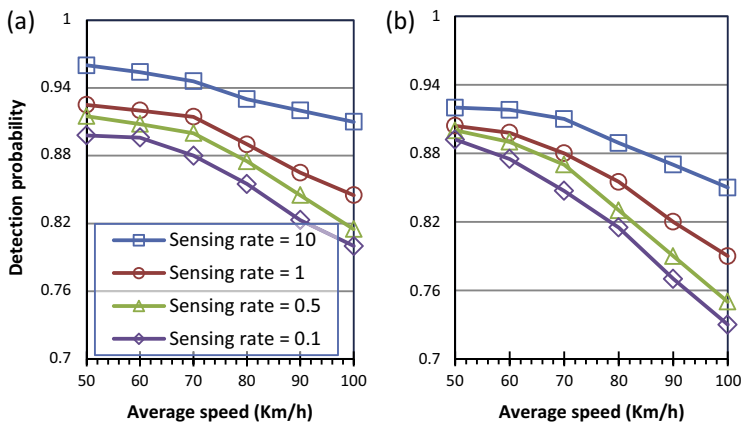

Fig. 15. Probability of detection versus car speed.

ness of the scheme we have developed to minimize the switching events between unoccupied ISM channels, in contrast to the approach in [25] which does not implement such an algorithm (Fig. 17(b)).

4.3. System overhead

The overhead of the proposed system results mainly from the transmissions made by cars performing sensing of spectrum availability to nearby RSUs. To get an insight about the overhead introduced by the proposed scheme, we consider a scenario by which cars are sensing the spectrum at an average rate *Rs*. Once a car leaves its current cell, as discussed earlier, the collected samples within the cell are aggregated and piggybacked with the upcoming HELLO beacon message and transmitted to the RSU, given that the car does not have to wait too long for the next Hello message (more than some period *T*). Hence, there may be situations where spectrum information will need to be sent in dedicated packets. The spectrum information entry, called Spectrum Availability Entry (SAE), has the following format:

$$\langle X, Y, Chan, Available, NumSamples, Speed, Time \rangle$$

In an SAE, the *X*, *Y*, and Time fields need four bytes each, while the remaining fields can be accommodated with 1 byte each, thus yielding a total of 16 bytes per channel. Since the car is supposed to sense 7 WiFi channels, then the total information has an overhead size of 112 bytes (896 bits). To compute the overall traffic overhead, we need to know the sampling frequency and how often a car crosses the boundary of a cell. Considering a cell side length of L meters (e.g., 100 m) and an average car speed of v meter/s (e.g., 15 m/s, as used in [12]), a car will therefore travel through the cell in L/v seconds (about 6.67 s). Considering N cars in the transmission range of an RSU, a ratio (r) of which are WiFi users, then the overall traffic flowing through the wireless network is $N(1-r) \times 896$ bps, which is linear in N. As an example, considering 100 total cars in the vicinity (transmission range) of an RSU, out of which 40 are WiFi users, the maximum traffic overhead in the area will be about 72 Kbps, which represents 1.2% of the 6 Mbps minimal bandwidth available in 802.11p vehicular environments [17]. This is not surprising since the overhead emerges from the aggregated data sent over the air interface, and not from the sampled data, knowing that the collected measurements are aggregated by the car and transmitted as one record.

To ascertain the above analysis, in the ns2 simulations we inspected the packets sent from the vehicles to the RSUs to account for those beacon (HELLO) messages that carry spectrum sensing information, the packets that solely contain sensing information, and the packets sent from the RSUs to the cars informing them about the spectrum maps

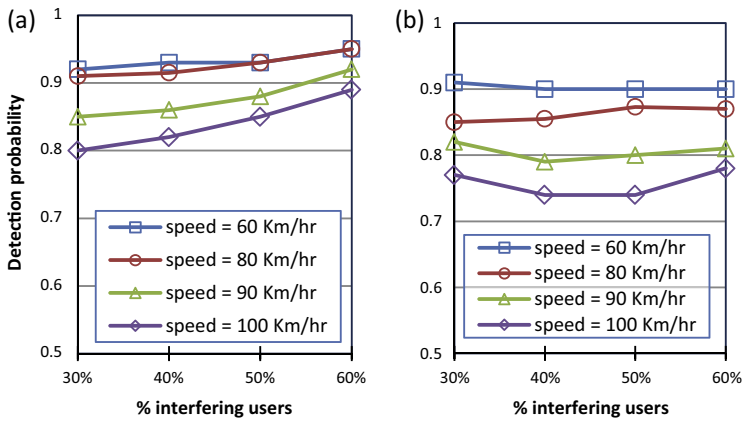

Fig. 16. Probability of detection versus percentage of WiFi users.

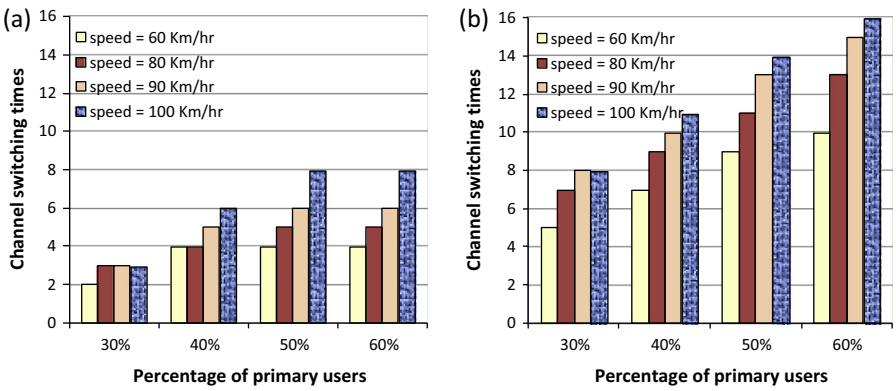

Fig. 17. Number of channel switching times versus number of WiFi users.

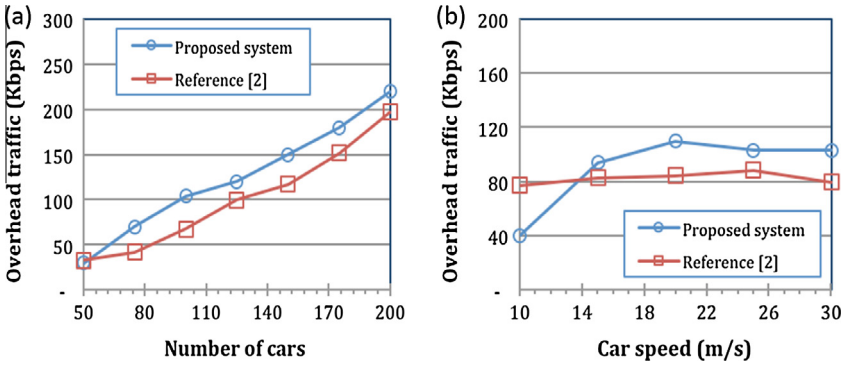

Fig. 18. Overhead traffic versus number of cars and versus car speed.

and which ISM channels to use cognitively. In our implementation of the system in [25], overhead traffic is due to requests sent from the cars to the RSU, coordination instructions from the latter, pilot signals from cars for sensing the spectrum, and management signals and feedback between transmitting and recipient cars. Such overhead obviously should increase when the rate of communications between cars increases, which in turn is dependent on the number of cars. In the simulations we set the communication rate to one per minute, meaning that a car needs to communicate with another car once per minute.

The results in Fig. 18(a) illustrate that our proposed scheme generates about 25 Kbps more traffic than the scheme in [25] (Fig. 18(b)), obviously because of the regular sensing information that needs to be sent by cars to the RSU in the area. We should emphasize though that this information is sent on one of the service channel of the 802.11p, and thus will not affect the state of the Control Channel, which we are trying to extend cognitively with available spectrum in the ISM band. On the other hand, and when comparing results from the analytical derivation to the experimental results, we observe about 15–20 Kbps difference, where the simulation results reported higher numbers. This can be explained by the fact that the ns2 simulator accounts for retransmissions and other causes of overhead traffic.

5. Conclusion

In this paper, we presented a sensing scheme for vehicular ad hoc networks that provides an accurate sensing method of the unlicensed spectrum, to be used for sharing with the surrounding vehicles. The proposed sensing procedure is based on a sophisticated blind detector and takes advantage of the vehicles mobility to span a large area of the roads. A hardware testbed based on GNU Radio was built to test the performance of the sensing itself, and then the whole system was simulated using ns2 to experimentally show the performance under various scenarios. For a sufficiently large number of cars and average highway speeds, our proposed system achieves over 90% detection of available channels and assigns them to cars that are using the WAVE protocol and may be suffering from congestion in the Control Channel of the lower-MAC 802.11p protocol. For future research, we intend to further study the effects of different mobility models on the system performance and the impact of Doppler-shift on the sensing performance.

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