COOPERATIVE AND MULTI-CHANNEL ENERGY-BASED SENSING IN THE VEHICULAR ENVIRONMENT: ON THE MINIMUM TIME TO SENSE

BY DUŠAN BOROTA

A thesis submitted to the

Graduate School—New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Master of Science

Graduate Program in Electrical and Computer Engineering

Written under the direction of

Professor Predrag Spasojević

and approved by

____

____

____

New Brunswick, New Jersey

January, 2012

ABSTRACT OF THE THESIS

COOPERATIVE AND MULTI-CHANNEL ENERGY-BASED SENSING IN THE VEHICULAR ENVIRONMENT: ON THE MINIMUM TIME TO SENSE

by Dušan Borota

Thesis Director: Professor Predrag Spasojević

Vehicular networking has significant potential to enable diverse range of applications, including safety and convenience. As the number of vehicles and applications using wireless spectrum grow, one can expect to see a shortage of either spatially or temporally available spectrum. In this thesis, we advocate that dynamic spectrum access for vehicles be the first step towards solving the spectrum shortage. For this, vehicles must be able to sense the availability of spectrum before attempting to transmit. The existence of other transmitters should be detected in order not to cause or experience interference. However, spectrum sensing in vehicular environments is a challenging task due to mobility, shadowing and other factors that govern vehicular environments. Therefore, spectrum sensing by a single vehicle may not be able to provide accurate information about the spectrum vacancies. Cooperative spectrum sensing, on the other hand, uses spatial diversity and can be employed to overcome the limitations associated with a single sensor/vehicle. Moreover, spectrum sensing in vehicular environments is challenged by mobility of sensors and reflectors causing significant variations in received signal power. Signal power variations over time were not included in sensing system

models dealing with wide spectrum sensing.

In the first part of this thesis we investigate cooperative spectrum sensing performance in a vehicular environment for sensing signals transmitted from i) a roadside infrastructure and ii) radios located on other vehicles, by using energy-based detection of a transmitted pilot tone as an example. Our goal is to characterize the limits on detection speed and reliability of simple hard and soft cooperative energy-based schemes for this environment. We show how cooperation reduces sensing time by a factor of five in an AWGN channel. The cooperative sensing time reduction is far more significant in a vehicular environment with fading and shadowing. Finally, we illustrate how infrastructure-to-vehicle scenario favors soft equal gain combining while vehicle-to-vehicle scenario favors hard fusion OR rule.

In the second part of this thesis we propose a sensing system model for wide band spectrum sensing that encompasses signal power variations over time. Then we propose to use Maximum Likelihood (ML) channel occupancy detection to determine spectrum sub-band activity vector. We are using adjacent lane traffic channel model with set of parameters validated in Winlab experiments, and focus on determining sensing time needed to achieve certain sensing performance. We focus on NTSC TV spectrum and show how using energy-based ML channel occupancy detector of three adjacent NTSC channels, with transmit power of $1kW$, at $10km$ distance from transmitter, with power variance higher than 3dB, sensing time of $1msec$ is sufficient to obtain $P_{MISS} = 0.01$ for range of speeds from 20 to $140km/h$. Moreover, since we use ML which minimizes overall probability of error when all activity vectors are equally probable, this work provides not only a sensing approach but an assessment of how well any other technique may perform in a mobile environment.

Acknowledgements

Firstly, I would like to thank my family for their unreserved support and encouragement. Also, I would like to thank my advisor Prof.Predrag Spasojević for his invaluable guidance of my research. His advice as well as the numerous discussions we had, helped me understand mathematical and engineering concepts essential for this kind of research. I would like to thank Prof. Dipankar Raychaudhuri and Prof. Marco Gruteser for being members of my thesis committee.

I am grateful to all my friends here at WINLAB, for making this research experience unique. In particular I would like to thank Ivan Šeškar, Haris Kremo, and Goran Ivković for their support, participation in this research and encouragement both in academic and non-academic matters. I would also like to thank WINLAB staff for giving me opportunity to be part of their extraordinary research environment, for their assistance and the facilities provided.

I extend my gratitude to Rama Vuyyuru and Onur Altintas from TOYOTA InfoTechnology Center for funding projects that resulted in this research and for their valuable suggestions and guidance.

Table of Contents

List of Figures

Chapter 1

Introduction

1.1 Background Overview

Future Intelligent Transportation Systems are expected to support many new applications including safety, traffic information, comfort and convenience to drivers [1]. Based on the type of application, whether it is safety, information dissemination or comfort, communication requirements will be different. These technologies may not only utilize current wireless infrastructure technologies like Cellular and WiFi but also require proprietary wireless technologies (Ex. 5.9GHz DSRC in US) specific to vehicular applications.

Numerous projects are under progress in US, Europe and Asia for enhancing safety and comfort in transportation systems by using wireless communication technologies [2]. As a major development in this direction, FCC in US allocated 75MHz spectrum for Dedicated Short-Range Communications DSRC services [3]. Furthermore, FCC recently ruled that TV white-spaces (unused TV channels) may be utilized for un-licensed secondary communications [4]. Still, having a large number of vehicular wireless nodes communicating in a limited space may quickly exhaust available spectrum. Due to stringent QoS requirements on DSRC spectrum, it is not-possible for all applications to depend only on licensed DSRC spectrum. Non-safety and comfort applications may have to look for un-licensed spectrum bands like TV white space for their communication requirements [5]. Also, a significant number of radio transmitters/receivers used by large number of applications with limited number of available channels increases the possibility of network congestion and spectrum shortage. Coordination of channel usage and CSMA/CA may lead to congestion as both simulations [6] and experiments [7] indicate. Furthermore, data broadcast, which is a predominant scheme for safety message delivery, is the most vulnerable to failure since no handshake mechanism is involved. Quick and reliable detection of available channels in this band is necessary to make spectrum usage and congestion control more efficient.

1.2 Cooperative Sensing Approach

Here, we consider energy detector as an example since it requires no other knowledge of the primary signal and because of implementation simplicity. Detection performance of a single sensor using energy detection depends on the received signal level, the observation time, the observed bandwidth and ability to accurately determine the noise level [8]. However,such detector is sensitive to fading and/or shadowing in the environment. Cooperative spectrum sensing is considered here since it takes advantage of spatial diversity and may overcome single sensor limitations. Detection performance of cooperative spectrum sensing depends on both the selected fusion technique and the sensor topology. Previous work shows that cooperative spectrum sensing brings benefits even in the case of an AWGN channel [9]. Beneficial influence of spatial diversity on cooperative detection was extensively studied under different fading conditions [10–12]. In [10] and [12] the effect of log-normal shadowing and Ricean and Nakagami fading on hard decision combining is analyzed. Soft combining performance in Nakagami fading was studied in [11]. However, vehicular environment in the sense of sensor topologies and appropriate channels has not been considered. This research contributes to ongoing research by examining influence of these effects to the overall cooperative spectrum sensing system performance. In particular, this thesis focuses on the time to reliably detect channel availability as a measure critical for fast changing vehicular environments and their typical safety applications.

We examine the performance of a set of hard and soft fusion rules when applied to two canonical vehicular environment topologies. Whenever difficult to evaluate/derive analytical expressions, we use simulations of a pilot tone signal and the choice of appropriate vehicular environment channel to show benefits of cooperation on sensing. We study sensing reliability as a function of the sensing time interval. Studied test cases suggest that selecting hard decision combining as universal rule for cooperative spectrum sensing in vehicular environment would be a good option in terms of overhead, while not sacrificing too much on the performance in the I2V scenario.

1.3 Multi-channel Energy Based Sensing Approach

In this research we are dealing with wideband sensing by dividing wide band into sub-bands and analyzing if sub-bands are occupied or free of transmission. We propose system model with parameters that characterize vehicular environments, and use Maximum Likelihood (ML) to determine spectrum occupancy from measured data. We use ML Estimation since, when available, it minimizes the probability of error in finding spectrum occupancy and hence its performance provides an upper bound to the performance of any other sensing technique. The performance limits have been evaluated for realistic parameters, in terms of the primary's distance, transmit power, vehicular speeds, etc.. The channel model includes assessment of the signal power variation magnitude due to adjacent channel vehicular reflections following our experimental works [13].

1.4 Thesis Organization

Chapter 2 provides details of using cooperative sensing of to improve time needed to obtain certain sensing performance. Chapter 3 describes multi-channel sensing approach using ML estimation. Appendices A and B provide details of ML Estimation and Linear Gaussian Model used in Chapter 3.

Chapter 2

On the Delay to Reliably Detect Channel Availability in Cooperative Vehicular Environments

2.1 System model

In order to perform wide band sensing consisting of several channels (and sub-channels), we assume that sensors perform sensing algorithm one channel at a time sequentially. We assume that coordination channel for exchange of sensing information is available, such as the one we proposed in [14], and that any sensing node can perform fusion, so fusion decision is available to all sensors.

2.1.1 Single sensor sensing technique

The goal of detection is to decide between two hypotheses:

$$x(t) = \begin{cases} n(t), & H_0 \\ hs(t) + n(t), & H_1 \end{cases} \tag{2.1}$$

Where $x(t)$ is received signal, $s(t)$ is signal which presence has to be detected, $n(t)$ is additive Gaussian noise (AWGN) and h is channel gain. We assume that every sensor performs energy detection of received signal as shown in Fig. 2.1.

Received signal $x(t)$ is prefiltered by bandpass filter of width W. Filtered signal is squared and integrated over observation time T. Integrator output y creates a decision statistic for two hypothesis H_0 when signal is absent and H_1 when signal is present. In [8] it has been shown that distribution of y can be approximated as Gaussian for large time-bandwidth product TW (i.e. number of samples observed). Then, for a given threshold λ, probability of false alarm of a single i-th sensor can be determined

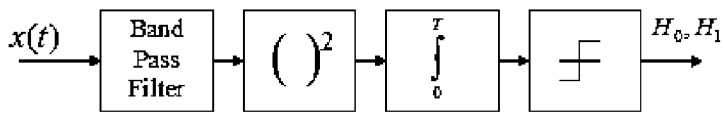

Figure 2.1: Energy detector block diagram

as

$$P_{fa,i} = \frac{1}{2} erfc\left(\frac{\lambda - 2TW}{2\sqrt{2}\sqrt{TW}}\right) \tag{2.2}$$

Probability of detection can be determined as:

$$P_{d,i} = \frac{1}{2} erfc\left(\frac{\lambda - 2TW - SNR_i}{2\sqrt{2}\sqrt{TW + SNR_i}}\right) \tag{2.3}$$

where, for given two-sided noise power spectrum density $N_0/2$, signal-to-noise ratio SNR_i is defined as:

$$SNR_i = \frac{1}{N_0}\int_0^T s^2(t)dt = \frac{E_s}{N_0} \tag{2.4}$$

This "energy based" definition of SNR is related to more widely used "power based" definition as : $SNR_{energy} = SNR_{power}/TW$. We also assume that all sensors have the same TW.

We first study how sensing performance depends on observation time for different bandwidths. In Fig. 2.2 are given the analytical results for the following single sensor setting: transmit power $200mW$,free space propagation with propagation exponent $\alpha = 2$ receiver at $500m$ distance, $N_0/2 = -120dBW/Hz$ and observed $100kHz$, $1MHz$, and $10MHz$ bands. We can observe how with increasing observation bandwidth, sensing performance deteriorates since more noise is introduced. On the other hand, increasing observation time improves sensing performance. Clearly, there is a need to balance these three parameters as we want to have good sensing performance when observing band as wide as possible, in as short as possible time. Curves of this type provide data needed for such balancing. At the same time overall sensing time has to be as short as possible in order to ensure usage of communication opportunity. In next sections

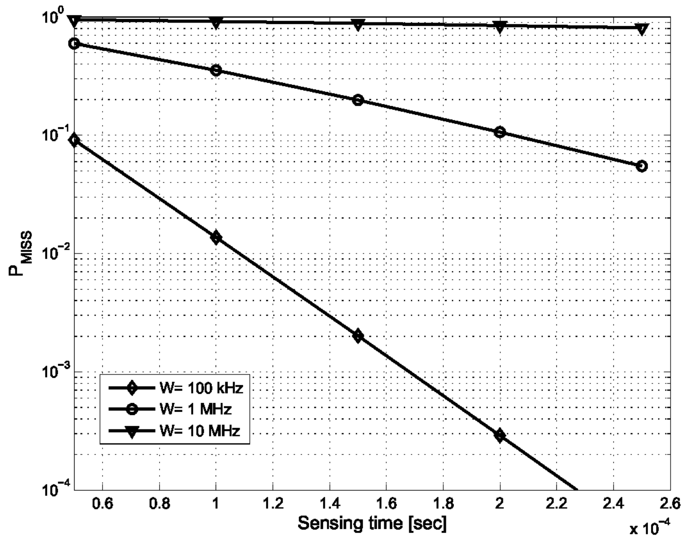

Figure 2.2: Single sensor performance: P_{MISS} vs sensing time for different bandwidth observed. Transmitter power $200mW$, propagation exponent $\alpha = 2$, distance from transmitter $500m$, $N_0/2 = -120dBW/Hz$ and $P_{fa} = 0.01$

we investigate limits of detection time while improving energy detection performance through cooperation.

2.1.2 Channel Modeling and Vehicular Sensing Scenarios

Wireless channel modeling for vehicular environment has been intensively studied with several different approaches as summarized in [15] and [16]. Wireless channel characteristics strongly depend on the environment and setting (frequency band used, antenna positioning [17], reflections from other cars [18] etc.).

Vehicle to Vehicle (V2V) Scenario

We examine the topology that consists of 1 transmitter and 5 sensors as presented in Fig. 2.3. Distances between vehicles (D_1) follow 1 second rule at 40mph i.e. $D_1 = 11m$, $D_2 = 1.6m$, and we assume zero relative speeds of transmitter and sensors. This assumption would be equal to claiming that observation time is much smaller than the time it takes vehicle topology to change. Observation time has to be as small as possible in order to ensure usage of communication opportunity. Examples of this

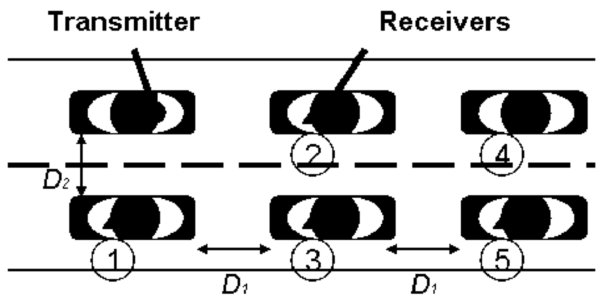

Figure 2.3: Vehicle-to-vehicle scenario

topology would be approaching emergency vehicle warning, vehicle-based road condition warning, etc.

Infrastructure to Vehicle (I2V) Scenario

We examine the topology that consists of 1 roadside transmitter and 5 sensors as presented in Figure 2.4. Examples of this topology would be work zone warning, curve speed warning, intersection collision warning, low bridge warning, etc. We assume that distances D_1 between vehicles again follow 1 second rule at 40mph, and we assume zero relative speed between sensors.

Channel Model

We focus on channel model for $5.9GHz$ band presented in [19]. The model was derived using sets of measurements in suburban environment to describe path loss, shadowing and fading conditions. Using continuously present signal at transmitter with antennas mounted on the roofs of the driven cars, dual slope path loss model with lognormal shadowing was derived as shown in 2.5.

$$P_d = \begin{cases} P(d_0) - 10\gamma_1 log_{10}(\frac{d}{d_0}) + X_{\sigma_1} & if\, d_0 \leq d \leq d_c \\ \\ P(d_0) - 10\gamma_1 log_{10}(\frac{d_c}{d_0}) - & if\, d \geq d_c \\ -10\gamma_2 log_{10}(\frac{d}{d_c}) + X_{\sigma_2} & \end{cases} \tag{2.5}$$

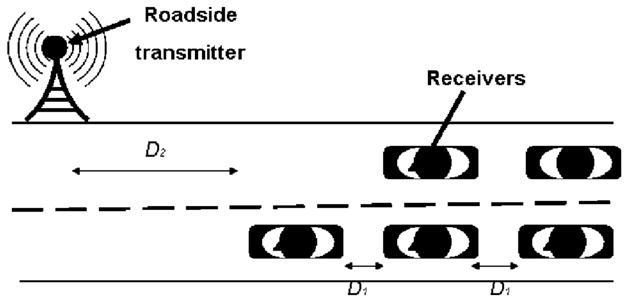

Figure 2.4: Infrastructure-to-vehicle scenario

We use set of parameters where $\gamma_1 = 2.1$, $\sigma_1 = 2.6dB$ $\gamma_2 = 3.8$, and $\sigma_2 = 4.4dB$ with break point at $d_c = 100m$. Fading analysis has shown alignment with Nakagami model with μ parameters depending on the distance between transmitter and sensor.

2.2 Cooperative Spectrum Sensing

2.2.1 Hard decision fusion

Hard decision combining assumes that each sensor performs sensing algorithm and detection decision by comparing sensing data to local threshold. The input of fusion center is the binary value where zero indicates spectrum hole one indicates occupied spectrum bin. Universal logical hard decision combining rule for M sensors would be "decide 1 if K out of M sensors says 1" also known as $K - out - of - M$ [9]. Cooperative sensing increases overall probability of false alarm Q_{fa}, but also increases overall probability of detection Q_d. Assuming all sensors have the same performance i.e. $P_{d,i} = P_d$ and uncorrelated decisions, overall probability of detection depending on threshold K is:

$$Q_d = \sum_{n=K}^{M} \binom{M}{n} P_d^n (1 - P_d)^{M-n} \tag{2.6}$$

At the same time Q_{fa} change has a similar form.

2.2.2 Soft decision fusion - weighted summation

Soft decision combining assumes that single sensor observations y_i are delivered from all sensors. At the fusion center these observations are linearly combined:

$$y_f = \sum_{i=1}^{M} w_i y_i \tag{2.7}$$

Equal gain combining (EGC) would assume all $w_i = 1$. Optimization problem of maximizing Q_d by choosing appropriate values of w_i has been approximately solved in [20] and in [11] SNR weighted summation was found to be optimal. In [21] instantaneous SNR based cooperative scheme was given. Since these techniques require SNR to be estimated, which is also time consuming, we examine only simpler, faster techniques.

2.3 Analytical and Simulation Results

2.3.1 Timing Analysis of Cooperation in AWGN Channel

In order to show how cooperation influences sensing time and sensing performance we firstly analyze the following scenario: pilot tone transmitter of power $200mW$, free space propagation with propagation exponent $\alpha = 2$, all sensors are at the same distance of $500m$ from transmitter , $W = 1MHz$, $N_0/2 = -120dBW/Hz$ and $Q_{fa} = 0.01$. Analytical results in Fig. 2.5 indicate that even in only AWGN environment using 2-out-of-5 hard fusion rule in order to achieve $Q_{MISS} = 10^{-2}$ would reduce sensing time 3.5 times. Similarly, as simulation results show in Fig. 2.6, in order to achieve $Q_{MISS} = 10^{-2}$ when 5 nodes cooperate using EGC sensing time is reduced 5 times.

2.3.2 Timing Analysis of Cooperation in Vehicular Environment

I2V Scenario

We simulated I2V topology described above. For the channel we applied appropriate parameters of attenuation, shadowing and fading. Transmitter is at $D_2 = 300m$ distance from the closest receiver, transmit power is $2W$, $N_0/2 = -120dBW/Hz$, and $Q_{fa} = 0.01$. Simulation results are shown in Figure 2.7. The fact that vehicles are much

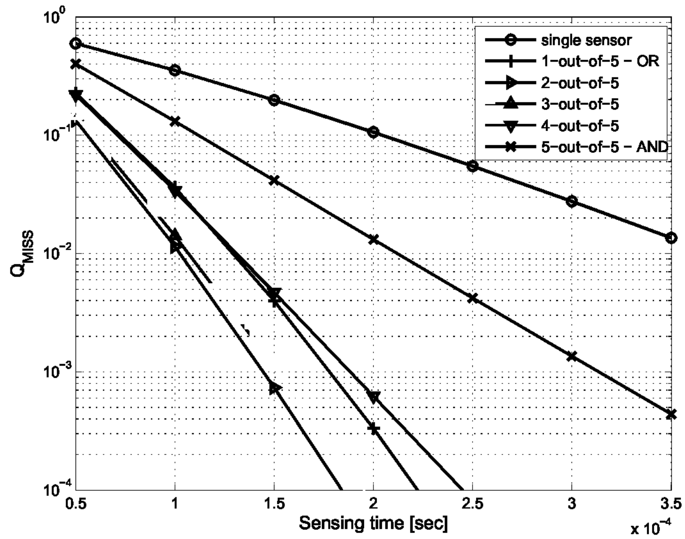

Figure 2.5: Hard fusion performance in AWGN channel: Q_{MISS} vs sensing time for 5 nodes cooperating using different hard fusion rules. Transmitter power $200mW$, propagation exponent $\alpha = 2$, distance from transmitter $500m$, $W = 1MHz$, $N_0/2 = -120dBW/Hz$ and $Q_{fa} = 0.01$

closer to each other than to transmitter results in similar average SNR of all sensors. We can observe that of all hard decision fusion techniques OR yields the biggest improvement for this scenario, while using AND rule yields no improvements when compared to a single user. Also, it is shown that EGC soft combining results in the biggest gains for this scenario. On the other hand, soft combining creates communication overhead since measurements have to be transmitted to fusion center, not single bit decisions. Overall, cooperative sensing in this scenario results in significantly shorter sensing time needed to achieve certain Q_{MISS}.

V2V Scenario

We simulated V2V topology and channel model described above, with the following parameters: transmit power is $10mW$, $N_0/2 = -100dBW/Hz$, and $Q_{fa} = 0.01$. Simulation results are shown in Figure 2.8. This topology has two extreme single nodes - one the closest (node 1) and the other the furthest (node 5) from the transmitter, so we compare fusion results to performance of these nodes. Influence of node 1 as the closest to transmitter is dominant, and thus cooperation using OR rule results in the

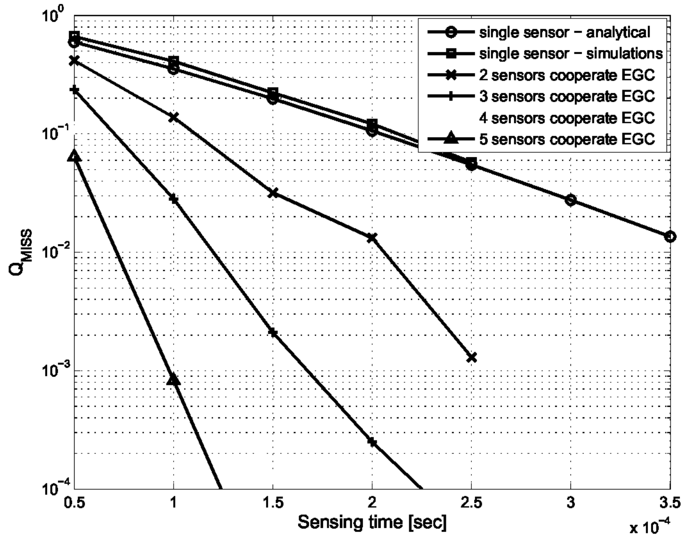

Figure 2.6: EGC fusion performance in AWGN channel: Q_{MISS} vs sensing time for different number of nodes cooperating. Transmitter power is $200mW$, propagation exponent $\alpha = 2$, distance from transmitter $500m$, $W = 1MHz$, $N_0/2 = -120dBW/Hz$ and $Q_{fa} = 0.01$

most improved performance. Using soft EGC does not outperform OR rule because of influence of nodes further from the transmitter on EGC fusion.

2.3.3 Simulation Results Conclusions

Simulation results illustrate the delay of various fusion rules for canonical vehicular scenarios. We observe that cooperation gain, in the AWGN channel, with the OR fusion rule is 2.5 (to achieve $Q_{MISS} = 0.01$), while in channel with fading and shadowing increases to over 20 times relative to the delay of a single sensor detector. Similarly, EGC cooperation gain increases from 5 for the AWGN channel to 50 with fading and shadowing. As is intuitive, fading/shadowing in the channel improve cooperation gains. Moreover, while I2V scenario favors soft decision combining, V2V scenario gains the most when the OR hard fusion rule is employed. This is an important observation, since previous work suggests that EGC soft combining outperforms hard combining.

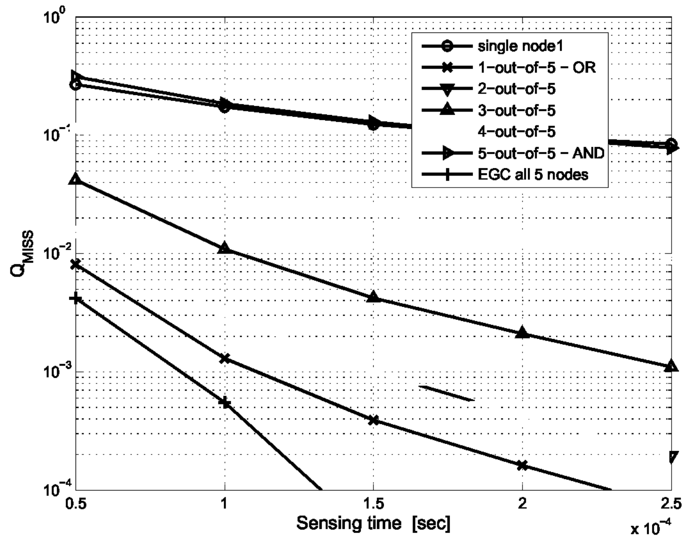

Figure 2.7: I2V topology: Q_{MISS} vs sensing time for hard and soft fusion and a single node. Transmit power is $2W$, $D_1 = 11m$, $D_2 = 300m$, lognormal shadowing with $\sigma = 4.4dB$, Nakagami fading $\mu = 0.84$, $N_0/2 = -120dBW/Hz$, and $Q_{fa} = 0.01$.

2.4 Conclusion

The goal of this work is to examine how to balance the need for fast and reliable wide band sensing in vehicular environments. Through analytical results we first show how a choice of sensing bandwidth affects the overall sensing delay. Next, we consider cooperative spectrum sensing for two canonical vehicular scenarios - I2V and V2V. Simulation results indicate how fusion rules decrease overall sensing time for these scenarios. Studied test cases suggest selecting hard decision combining as universal rule for cooperative spectrum sensing in vehicular environment would be a good option in terms of overhead, while not sacrificing too much on the performance in the I2V scenario.

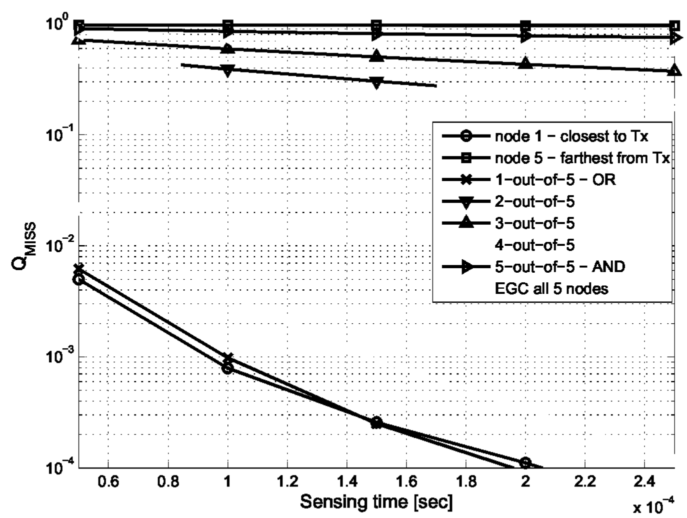

Figure 2.8: V2V topology: Q_{MISS} vs sensing time for hard and soft fusion and typical single nodes. Transmit power is $10mW$, $D_1 = 11m$, $D2 = 1.6m$, lognormal shadowing with $\sigma = 2.6dB$, Nakagami fading $\mu = 3.08$, $N_0/2 = -100dBW/Hz$, and $Q_{fa} = 0.01$.

Chapter 3

Multi-Channel Energy-Based Sensing in the Vehicular Environment: On the Minimum Time to Sense

3.1 Problem statement and our approach

Spectrum sensing has been subject of in depth analysis in recent years, as appearance of idea of cognitive radios [22] brought into light need for fast and reliable sensing of weak radio signals. Several sensing techniques are wide accepted as having most potential in to be used in cognitive radios [23]. Among them energy detector is the most general as it does not need any prior knowledge about signal it is sensing. In Chapter 2 we explored how speed and reliability of spectrum sensing in vehicular environments can be improved by cooperative sensing. However, single sensor sensing algorithms investigated earlier model static scenarios which do not include into model changes of signal over time. Therefore, our goal is to construct primary sensing algorithm for an environment with varying signal power (due to mobility).

We use power spectrum estimator to obtain power in frequency bins within wide band of interest. Then, we use Maximum Likelihood estimation derived for system model that includes modeling of power changes over time. Output of this algorithm is spectrum activity vector describing sub-bands occupancy (0 vacant and 1 occupied sub-bands). Again, by using ML estimation, results presented provide not only a sensing approach but also an assessment on how well any other technique may perform in a mobile environment.

3.1.1 Why ML estimation?

We use Maximum Likelihood Estimation (MLE) since it is mathematically efficient and optimal even for finite sample size in that it minimizes the overall error rate [24]. Here, it minimizes overall probability of error when channel occupancy is detected. MLE converts into Generalized Likelihood problem when some parameters are unknown (noise, changing signal power) [24]. Also, MLE has numerous applications for different statistical models: linear, general linear, factor analysis, hypothesis testing, confidence interval formation..) MLE is widely used in different areas of application: electromagnetic and acoustics detection, path-choice in transport networks, magnetic resonance imaging..). Drawback to using MLE are the limitations it has in non-normal complex problems as it may be too complex to determine.

In Appendix A we give theory background and definitions associated with MLE. In Appendix B we give one example of well-defined MLE: Linear Gaussian Model.

3.2 Previous work on similar systems

In our previous work we showed the need to balance energy detector observation bandwidth and sensing time to achieve certain sensing performance. Here, we examine wideband sensing by dividing wide band into sub-bands. Out of plethora of sensing approaches [23], we present details of two approaches similar to ours as they use power spectrum density and ML for sensing of wide spectrum band. While [25] explores correlation between frequency sub-bands to determine spectrum occupancy, in [26] second order statistics are used to determine activity of OFDM sub-band channels. Details are given in the following sections.

3.2.1 Energy based spectrum sensing: sub-band correlation approach

In [25] ML based sensing algorithm of multiple sub-band signal was derived. Also, power spectrum density is used to create data observation. Then auto-regressive modeling of sub-band correlation is performed. Method is mathematically complex, so dynamic programming (DL) is employed to deal with complexity of finding MLE of noise and occupied sub-bands. Method has general approach since it does not make any assumptions about the signal being sensed.

Model proposed does not consider change in power of received signal over time, but assumes that for next time instance whole algorithm has to be repeated. Challenge to apply this model in vehicular environment would be the fact that it is computationally complex. Also when applying it in fast changing environment, to obtain valuable results observation time would have to be short and whole algorithm repeated often.

3.2.2 Sensing of OFDM signal: exploiting cyclic prefix signal structure

In [26] ML based spectrum sensing algorithm of multiple sub-band OFDM signal was derived using second order statistics. System model models non-stationary correlation structure of observed OFDM signal and then Generalized Likelihood is employed to determine unknown parameters (noise variance, variance of complex signal samples and synchronization mis-match). It was proposed that complexity of approach can be reduced if some of the parameters are empirically known.

Also, important conclusion is given in this work that energy detector is near-optimal when noise is known, so there is no need to employ more complex approaches. Again, this model does not model signal level change over time.

3.3 Our approach motivation

Measurements of radio channel in vehicular environment [27], [13], [28] have shown that there are significant and fast received power variations due to numerous reflectors and fast changes in vehicular environment. Here, we are motivated by adjacent lane channel model [13], which experimentally confirmed parameter values for vehicular environment channel modeling. We are using Maximum Likelihood detection of spectrum sub-bands activity since it minimizes the probability of error in finding spectrum occupancy and hence its performance provides an upper bound to the performance of any other sensing technique.

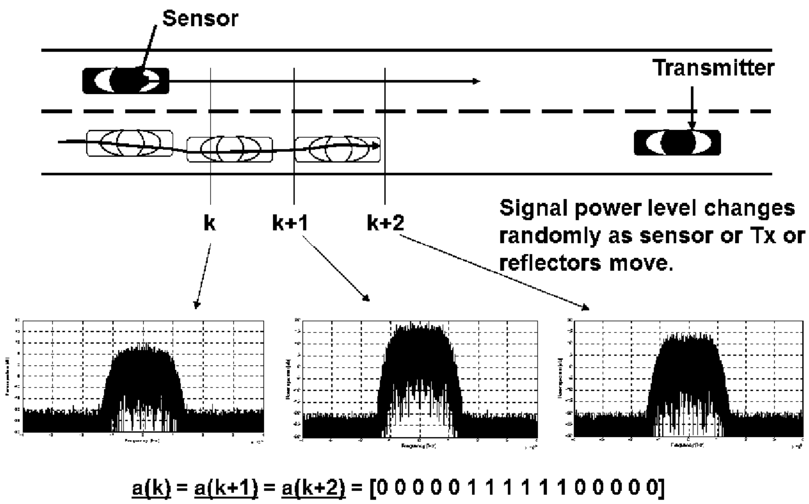

Figure 3.1: V2V topology example with PSD example at different time instances k

Therefore, we propose sensing algorithm that:

- Has low complexity (i.e. is implementation ready) - attempting complexity linear with number of sub-bands
- Does not exploit specific signal structure - we use energy detection based approach
- Can use either Generalized Likelihood to estimate spectrum activity vector with unknown parameters (noise and power level) or simpler techniques
- Is able to take into account power level variability (due to mobility)
- Incorporates specifics of vehicular environment - modeling power changes for I2V and V2V scenarios

In Fig. 3.1 and 3.2 we give examples of measured Power Spectral Density for I2V and V2V scenarios.

3.4 System model and problem formulation

Firstly, we define system parameters that we use to model conditions in different vehicular environments. Then we give details on how received signal samples are processed to finally obtain matrix of measured values. These are the "observations" at which

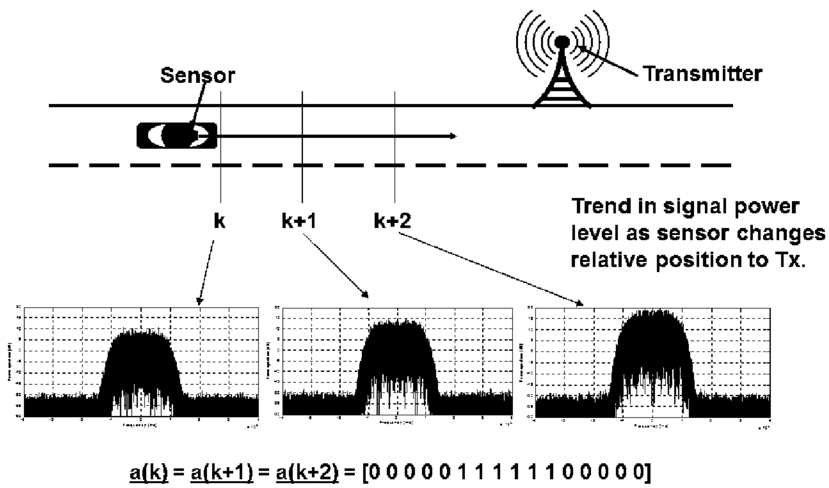

Figure 3.2: I2V topology example with PSD example at different time instances k

our ML algorithm is applied. Then we give details of derivations of ML detector of spectrum activity for this model.

To describe conditions in different vehicular environments we use the following two parameters:

1. Fading conditions in bandwidth of interest:
   - Frequency non-selective fading - Flat fading (measured power over different frequency bins is correlated)
   - Frequency selective fading (no correlation in measured power over different frequency bins)
2. Measured power change over time due to mobility:
   - Rapid changes (small "coherence time")
   - Slow changes (large "coherence time")

Where coherence time is defined as time period within which received power values are strongly correlated and can be calculated as [29] :

$$\Delta t \approx \frac{1}{2f_{dm}} = \frac{c}{2vf_c} \tag{3.1}$$

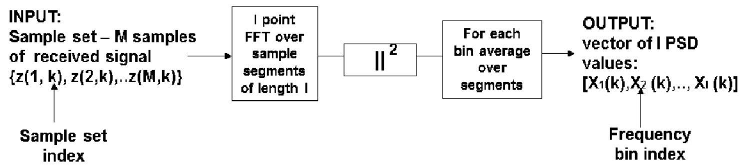

Figure 3.3: Functional diagram of periodogram calculation at one time instance

where $f_{dm} = \frac{v}{c} f_c$ is maximal Doppler shift c is speed of light, v relative velocity between transmitter and receiver and f_c is carrier frequency).

NOTE: Here, we examine "small-scale fading" a condition, assuming that sensor moves over very short distance during observation time. Having in mind goal that sensing time has to be as short as possible, this assumptions is very realistic.

3.4.1 System model data set creation

We assume that for a single time snapshot, sensor creates one sample set, by computing a periodogram estimate of the Power Spectral Density (PSD).

Functional diagram of this procedure is given in Fig. 3.3 where M is number of samples observed in each sample set, and I is number of output frequency bins (size of FFT).

For a fixed, known sampling frequency $f_{sample} = 1/T_{sample}$, M is related to coherence time as

$$M = \frac{\Delta t}{T_{sample}} \tag{3.2}$$

This relation reflect the fact that during coherence time assumption about power level not changing significantly holds. I is determined by desired frequency resolution or by structure of signal being sensed.

Mathematically, we model received signal samples of i-th channel as:

$$z_i(m) = a_i \sqrt{P_i} + n_i(m) \tag{3.3}$$

Where both power and noise have Gaussian distribution: $P_i \sim \mathcal{N}(P_0, \sigma_p^2)$ and $n_i(m) \sim$

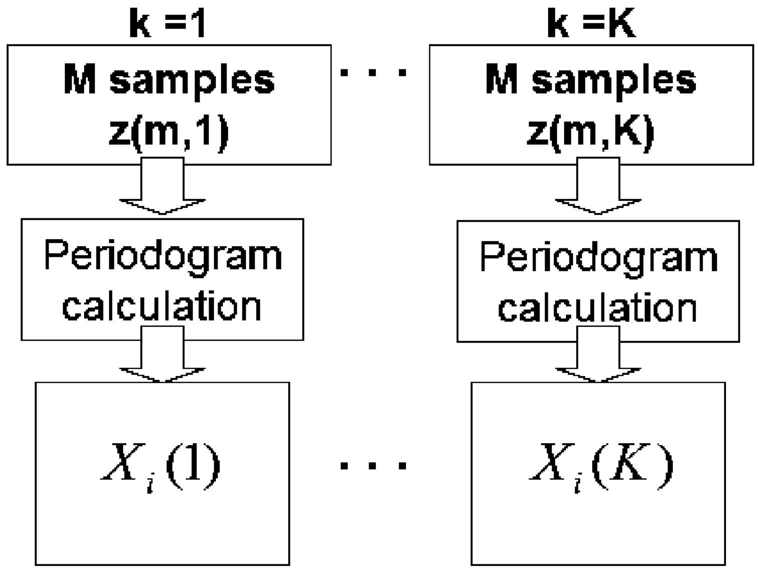

Figure 3.4: Block diagram of data set creation for a set of time instances

$\mathcal{N}(0, \sigma_n^2)$.Variance σ_p is used here as a parameter to describe variations of power due to mobility.

Now, power in each frequency bin can be determined as:

$$X_i = \frac{1}{M} \sum_{m=1}^{M} z_i^2(m) \approx a_i^2 P_i + w_i \tag{3.4}$$

where $E[w_i] = \sigma_n^2$ and $Var[w_i] = \frac{2}{M}\sigma_n^4$.

We assume that this periodogram calculation is repeated K times in subsequent time instances. Block diagram of this procedure is shown in Fig.3.4 . For each k-th time instance , one vector of measurements $X(i)$ of size I is calculated.

For a certain observation time T_s, K is related to M and T_s as

$$K = \frac{T_s}{MT_{sample}} \tag{3.5}$$

By applying this procedure, we assume that during taking M samples for each sample set, power does not change (i.e. choice of M depends on how fast signal power changes). As mentioned earlier, to make this assumption realistic, M has to be related to coherence time as stated above.

Data set creation described above results in the following matrix of measured values:

$$\begin{array}{cccccc}
X_1(1) & X_1(2) & \dots & X_1(k) & \dots & X_1(K) \\
X_2(1) & X_2(2) & \dots & X_2(k) & \dots & X_2(K) \\
 & & \vdots & & \vdots & \\
X_i(1) & X_i(2) & \dots & X_i(k) & \dots & X_i(K) \\
 & & \vdots & & \vdots & \\
X_I(1) & X_I(2) & \dots & X_I(k) & \dots & X_I(K)
\end{array}$$

Matrix of measured values has dimensions $I \times K$ where I is number of frequency bins and K number of time instances.

3.4.2 Proposed system model

3.5 Model derivations

In order to derive MLE for proposed model, let's first revisit assumptions we will use during derivation:

- We are observing I channels over K sample sets
- Each sample set is of size M samples
- We assume received signal samples are in AWGN
- Spectrum occupancy vector does not change over K time instances i.e. we assume that during observation time primary signal activity did not change i.e. $a_i(1) = a_i(2) = .. = a_i(K)$ for each $i = 1, .., I$.

We assume that each value in matrix of measured values from above is modeled as sum of received power level and noise (which we approximated above to be Gaussian with non-zero mean). This modeling approximation is similar to measurements results for vehicular channel in [27]. Mathematically this can be presented as:

$$X_i(k) = a_i P(k) + n_i(k) \tag{3.6}$$

where a_i is transmitter spectrum activity (on/off), $P(k)$ received power level, and $n_i(k)$ is Gaussian noise $n_i(k) \sim \mathcal{N}(\mu_n, \sigma_n^2)$. On-off activity of primary user in the band of interest is modeled using parameter:

$$a_i = \begin{cases} 0, off \\ 1, on \end{cases} \tag{3.7}$$

We describe variations of received power values using σ_p i.e. we assume power realizations for different index k are independent and Gaussian. Finally we use averaging over received power vectors within T_s. Therefore, power in each frequency bin is

$$X_{iK} = \frac{1}{K}\sum_{k=1}^{K} X_i(k) \approx a^2 \frac{1}{K}\sum_{k=1}^{K} P_i(k) + \frac{1}{K}\sum_{k=1}^{K} w_i(k) \tag{3.8}$$

where $E[w_i(k)] = \sigma_n^2$ and $Var[w_i(k)] = \frac{2}{M}\sigma_n^4$

Finally, for i-th frequency bin we obtain the following model:

$$X_{iK} = a_{i,k} q_K + N_{iK} \tag{3.9}$$

where $q_K \sim \mathcal{N}(P_0, \frac{1}{K}\sigma_p^2)$ and $N_{iK} \sim \mathcal{N}(\sigma_n^2, \frac{2}{KM}\sigma_n^4)$.

Let's introduce the following vector notation to accommodate multiple frequency bins:

$$\boldsymbol{X} = \begin{bmatrix} X_1 \\ \vdots \\ X_I \end{bmatrix} \qquad \boldsymbol{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_I \end{bmatrix} \qquad \boldsymbol{D_a} = \begin{bmatrix} a_1 & \dots & 0 \\ 0 & \ddots & 0 \\ 0 & \dots & a_I \end{bmatrix} \qquad \boldsymbol{q} = \begin{bmatrix} q_1 \\ \vdots \\ q_I \end{bmatrix} \tag{3.10}$$

Taking into account these vector notations, system model becomes:

$$\boldsymbol{X} = \boldsymbol{D_a q} + \boldsymbol{N} \tag{3.11}$$

Where $\boldsymbol{q} \sim \mathcal{N}(P_0\mathbf{1}, \frac{1}{K}\sigma_p^2\boldsymbol{I})$ and $N \sim \mathcal{N}(\sigma_n^2\mathbf{1}, \frac{2}{KM}\sigma_n^4\boldsymbol{I})$.

In order to derive maximum likelihood function, i.e. distribution of $\boldsymbol{X}$ conditioned on vector $\boldsymbol{a}$ we examine two cases:

1. Assuming that band of interest experiences frequency selective fading (i.e. values of vector $\boldsymbol{q}$ are uncorrelated and independent for each time instance) yields:

$$E[\boldsymbol{X}|\boldsymbol{a}] = P_0\boldsymbol{a} + \sigma_n^2\mathbf{1} \tag{3.12}$$

$$\boldsymbol{C}_{\boldsymbol{XX}|\boldsymbol{a}} = \frac{1}{K}\sigma_P^2\boldsymbol{D}_{\boldsymbol{a}} + \frac{2}{KM}\sigma_n^4\boldsymbol{I} \tag{3.13}$$

2. Assuming all bands of interest experiences flat fading (i.e. power change at one time instance over all frequency bins) yields:

$$E[\boldsymbol{X}|\boldsymbol{a}] = P_0\boldsymbol{a} + \sigma_n^2\mathbf{1} \tag{3.14}$$

$$\boldsymbol{C}_{\boldsymbol{XX}|\boldsymbol{a}} = \frac{1}{K}\sigma_P^2\boldsymbol{a}\boldsymbol{a}^H + \frac{2}{KM}\sigma_n^4\boldsymbol{I} \tag{3.15}$$

These two cases would be two extreme cases of usual circumstances of wireless propagation in vehicular environment. By examining performances of these two cases, we obtain boundary results.

Maximization of likelihood function derived above, would be equal to the following maximization problem:

$$\max_{\boldsymbol{a}}(lnP[\boldsymbol{X}|\boldsymbol{a}]) = max_{\boldsymbol{a}}\left\{-\frac{1}{2}ln\|\boldsymbol{C}_{\boldsymbol{XX}|\boldsymbol{a}}\| - \frac{1}{2}(\boldsymbol{X} - E[\boldsymbol{X}|\boldsymbol{a}])^T\boldsymbol{C}^{-1}_{\boldsymbol{XX}|\boldsymbol{a}}(\boldsymbol{X} - E[\boldsymbol{X}|\boldsymbol{a}])\right\} \tag{3.16}$$

Result of the above maximization problem is spectrum occupancy vector, for which overall detection error is minimized if all values of occupancy vector are equally likely.

3.6 Simulation Results

In our simulations we use example of sensing NTSC TV signal, focusing on three TV channels (each of 6MHz width) from 590MHz to 608MHz.

3.6.1 Detector performance in static environment

Firstly, we want to show how our sensing algorithm performs as detector i.e. what probability od miss it can achieve for different values of SNR. Firstly we assume completely static case (i.e. $\sigma_p = 0$) , where neither receiver nor reflectors move, uncorrelated fading and the following setting: transmitter power $P_t = 1kW$; bandwidth $W = 18MHz$, $N_0/2 = -120dBW/Hz$, sensing time $T_s = 10\mu sec$, propagation exponent $\alpha = 3.5$, sensor at distance $d = 10km$ from transmitter. We want to observe how probability of miss P_{MISS} (i.e. how often we did not get true value of activity vector) depends on the distance from transmitter d . Simulation results are shown in Fig. 3.5.

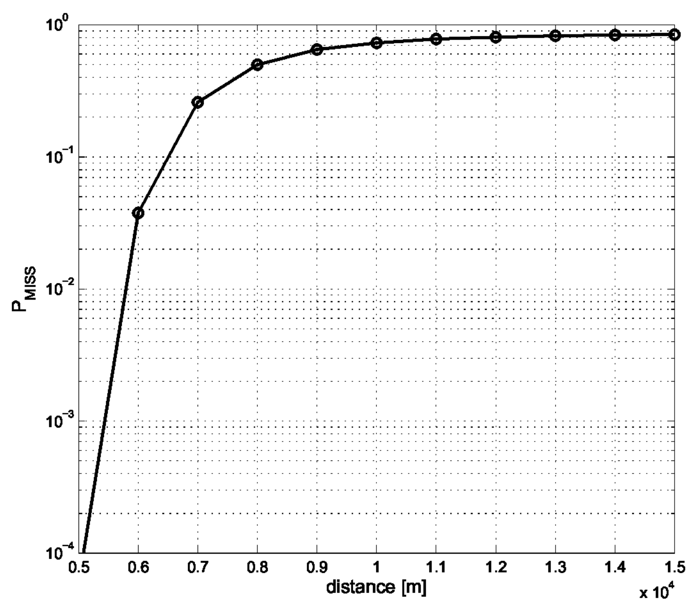

Figure 3.5: P_{MISS} vs distance from transmitter for detection of three channels of NTSC signal in static environment. $\sigma_p = 0$, uncorrelated fading, $P_t = 1kW$; $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $T_s = 10\mu sec$, $d = 10km$, $\alpha = 3.5$

Results indicate how ML algorithm performs as sensor for static environment. It also shows that sensor performance in static case does not depend on the value of activity vector, so in the following simulations choice of activity vector does not affect results.

Now we want to investigate for a static case how sensor performance depends on

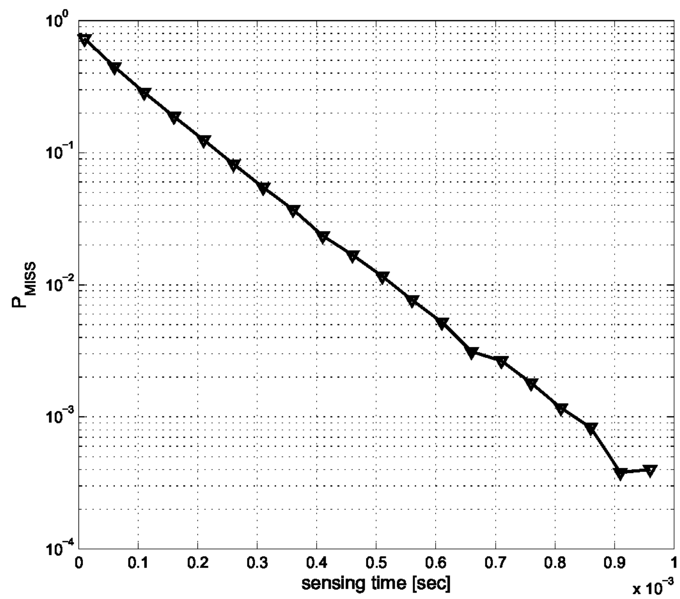

Figure 3.6: P_{MISS} for different sensing time ($\sigma_p = 0$, uncorrelated fading, $P_t = 1kW$, $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $d = 10km$, $\alpha = 3.5$)

sensing time. We assume the same transmitter setting from above, with sensor at distance $d = 10km$ from transmitter, and propagation exponent $\alpha = 3.5$. For a range of sensing time values from $T_s = 1\mu sec$ to $T_s = 1msec$ simulation results are shown in Fig.3.6. Again, value of activity vector does not affect sensor performance.

3.6.2 Detector performance in environment with mobility

Now we want to understand how changes in environment affect overall performance of the sensor. Firstly, we assume that only reflectors move, and sensor is static. Effects of reflectors to static receivers was experimentally examined in [18], where it was determined that variations in power can be approximated Gaussian with σ_p up to $5dB$ in reference to received power level. Here we examine sensor performance for static sensor and range of values for σ_p . We assume transmitter settings are the same as above, sensor at $d = 10km$ distance from transmitter and again we want to observe how fast certain sensing performance can be achieved. Also, here we assume "case 1" from above, when fading is frequency selective and values in vector of received power

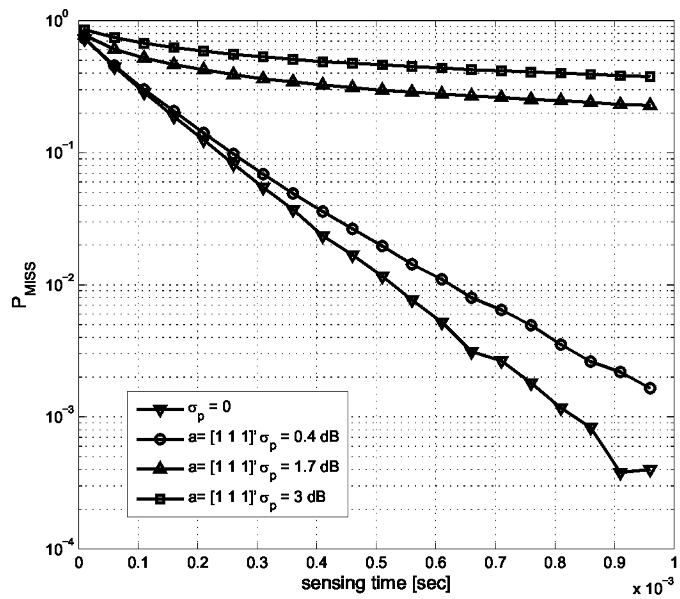

Figure 3.7: P_{MISS} vs sensing time for a range of values for σ_p (uncorrelated fading, $P_t = 1kW$, $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $d = 10km$, $\alpha = 3.5$)

are uncorrelated.

Simulation results are given in Fig. 3.7 . Results indicate how much increase of sensing time improves sensing performance, and how sensing performance decreases with increase in σ_p i.e. scattering from reflectors.

Performance dependence on the value of spectrum occupancy vector

Also, in order to understand how sensing performance depends on the value of occupancy vector, we simulated above result for all possible values of activity vector of length 3 and $\sigma_p = 1.7dB$. Results for two extreme cases when $\boldsymbol{a} = [000]^T$ and $\boldsymbol{a} = [111]^T$ are shown in Fig.3.8. Again, we assume frequency selective fading.

Results show that the worst performance is obtained for $\boldsymbol{a} = [111]$, so we will use that value of activity vector in the following simulations.

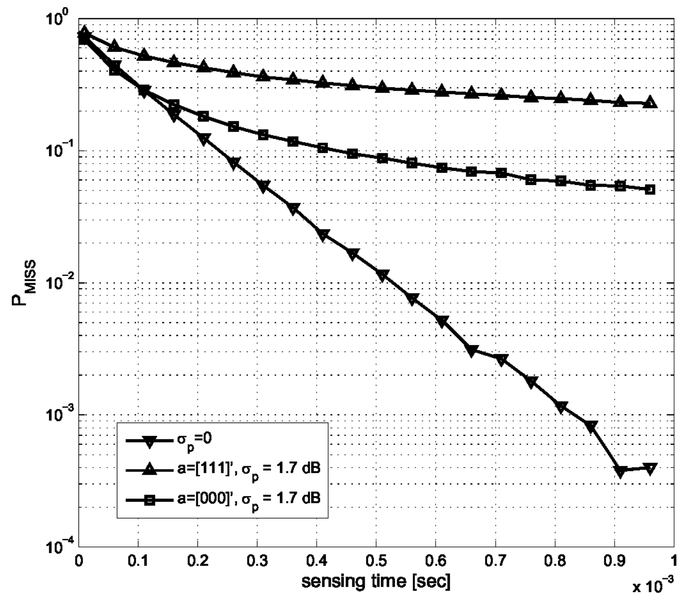

Figure 3.8: Sensor performance for two extreme values of activity vector, $\sigma_p = 1.7dB$, uncorrelated fading, $P_t = 1kW$; $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $d = 10km$, $\alpha = 3.5$

Performance dependence on the fading nature

In order to understand how fading influences performance, we simulated extreme cases considered - one when band of interest experiences frequency selective fading, and the other when band of interest experiences flat fading. Results of this simulation are shown in Fig. 3.9.

Results indicate that in frequency selective fading sensor performs the worst. Therefore, we will use frequency selective fading in the following simulations. In reality, sensors in vehicular environment experience somewhat frequency selective fading, so performance is somewhere between these two border cases.

Sensing time needed to obtain certain performance

Now we want to emphasize context of vehicular environments and timing of changes caused by mobility of sensor.

We showed earlier that period for which signal power can be considered unchanged

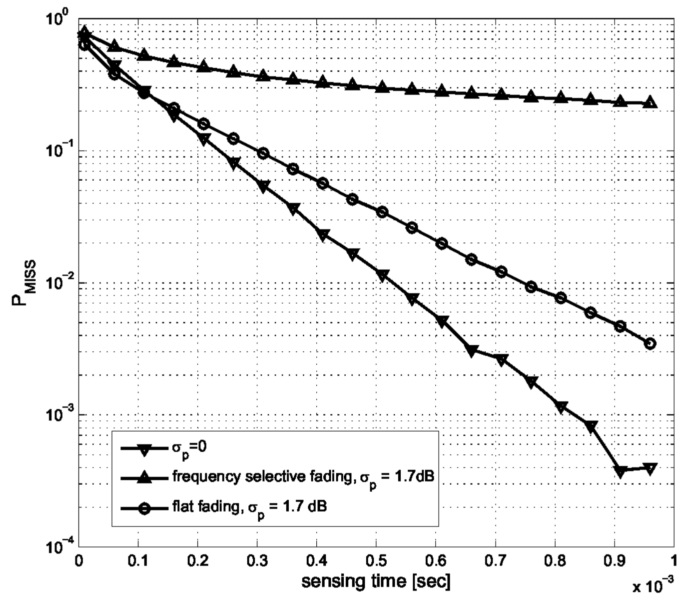

Figure 3.9: Sensor performance for flat and frequency selective fading ($\sigma_p = 1.7dB$, $P_t = 1kW$, $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $d = 10km$, $\alpha = 3.5$)

by channel is related to the speed of sensor as:

$$\Delta t \approx \frac{1}{2f_{dm}} = \frac{c}{2vf_c} \tag{3.17}$$

For example, taking that $f_c = 600MHz$ then $\Delta t = 0,000251\frac{1}{v}[sec]$ if velocity is given in km/hour. This shows that each car speed has its own coherence time. Here we assume we know sensor (car) speed. Therefore from expression above, we can determine coherence time that corresponds to each speed.

We want to show how, using this relation between speed and coherence time, we can determine sensor performance for each speed. To do so, we use values of $K = 50, 75, 100, 125, and 150$ as multiples of coherence time. Sensing time at each speed is determined as

$$T_s = K\Delta t \approx \frac{K}{v}\frac{c}{2f_c} \tag{3.18}$$

Since coherence time decreases as vehicle velocity increases, overall sensing time

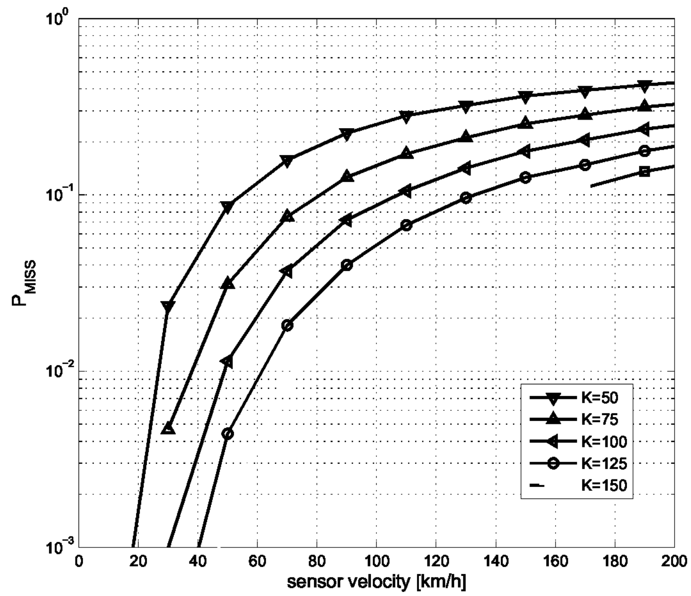

Figure 3.10: P_{MISS} vs sensor velocity for a set of values of coherence times ($\sigma_p = 0.4dB$, $P_t = 1kW$, $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $d = 10km$, $\alpha = 3.5$, $f_c = 600MHz$)

decreases which, for fixed K, results in increase of P_{MISS}.

Simulation settings are as follows: Transmitter settings are the same as above and sensor at $d = 10km$ distance from transmitter. Again, we assume 3 channels, total of $18MHz$ bandwidth, carrier frequency $f_c = 600MHz$, $\sigma_p = 0.4dB$, $N_0/2 = -120dBW/Hz$. Results of the simulation are shown in Fig. 3.10.

Now, our final goal is to determine how long sensing time has to be to meet certain P_{MISS} requirement for a mobile sensor.

Assuming that $P_{MISS} = 0.01$ is a design requirement, using the result from Fig.3.10 , we can obtain values of K and speeds for which that requirement is met. Then using the relationship 3.18 , knowing K and v , assuming $f_c = 600MHz$, T_s can be calculated. Results are shown in Fig. 3.11. dB values are obtained in reference to received signal power.

Firstly, results indicate that keeping sensing time below $1msec$ is sufficient to obtain $P_{MISS} = 0.01$ when sensing three channels of NTSC TV signals at relative speeds between transmitter and receiver ranging from 10 to $140km/h$. Also, results indicate

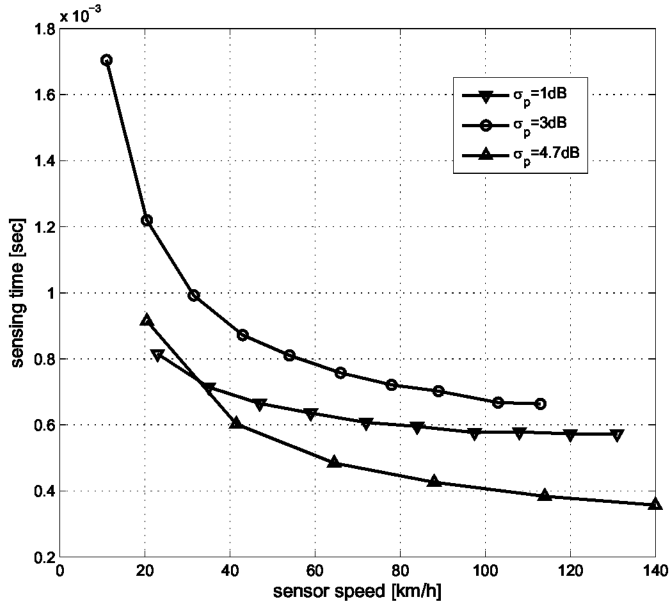

Figure 3.11: Sensing time needed for different sensor velocities to obtain $P_{MISS} = 0.01$ ($P_t = 1kW$, $W = 18MHz$, $N_0/2 = -120dBW/Hz$, $d = 10km$, $\alpha = 3.5$, $f_c = 600MHz$)

how adapting sensor parameters according to relative sensor speed can decrease sensing time required to meet $P_{MISS} = 0.01$. For example, having $\sigma_p > 3dB$, to achieve $P_{MISS} = 0.01$ for the same set of sensor speeds takes less than $1msec$. In other words, information of sensor speed can be used to adapt sensing time while still preserving the desired performance.

3.7 Conclusion

In this work we developed multi-band sensing algorithm motivated by the specifics of vehicular environment: fast changing environment resulting in fast changes of received signal power. Motivated by earlier experimental results of channel measurements for vehicular environment, we proposed a system model which includes received signal power change due to mobility. Then we apply Maximum Likelihood detection of spectrum occupancy for our approach to provide upper bound for any energy-based spectrum occupancy detector.

Using example of sensing 3 adjacent channels of TV NTSC spectrum, we showed how this approach performs using realistic set of values for parameters of algorithm and speed of vehicle. Our simulation results indicate that when sensing 3 adjacent NTSC channels at $10km$ distance from $1kW$ transmitter at transmitter-sensor relative speeds from 10 to $140km/h$, having power variation $\sigma_p > 3dB$, sensing time of $1msec$ is sufficient to meet $P_{MISS} = 0.01$. Also, results indicate how adapting sensor parameters according to relative sensor speed can decrease sensing time required to meet the same design requirement. In other words, approach shows how information about sensor speed can be used to adapt sensing time while still preserving the desired performance.

Chapter 4

APPENDIX A: Background on ML estimation

Firstly let's revisit definitions of some terms associated with ML estimation:

1. Model is mathematical description of data from natural process. Realistic simplifications are usually added to make model mathematically tractable.

2. Likelihood function is mathematical representation of dependence of signal characteristic on different parameters

3. Maximum Likelihood (ML) estimation is mathematically efficient method for determining unknown parameters when a priori distributions are not known

Definition of maximum likelihood estimate (MLE) of Θ:

$$\hat{\Theta}_M L(X) = argmaxp(X; \Theta) \tag{4.1}$$

where X is received/observed and Θ is parameter to be observed. In other words, for a fixed data (X) and probability model MLE selects model parameters that produce most likely distribution for observed data. For example, Θ can be spectrum activity vector, noise level.. and X can be sample output of A/D converter, FFT block, PSD estimator..

Chapter 5

APPENDIX B: Linear Gaussian Model

ML estimation example - Linear Gaussian model [24] is example of well-defined MLE for Gaussian distribution. Linear Gaussian model is given by:

$$x = H\Theta + w \tag{5.1}$$

where H is known $N \times p$ matrix, and w is $N \times 1$ noise vector, $w \sim \mathcal{N}(0, C)$, where C is $N \times N$ noise covariance matrix. Maximization of likelihood function would give:

$$\frac{\partial ln(x; \Theta)}{\partial \Theta_k} = \frac{\partial (H\Theta)^T}{\partial \Theta} C^{-1}(x - H\Theta) = 0 \tag{5.2}$$

And finally, parameter value for which upper derivative is zero i.e. value that maximizes likelihood function - ML estimate is given by:

$$\Theta = (H^T C^{-1} H)^{-1} H^T C^{-1} x \tag{5.3}$$

References

[1] K. Dar, M. Bakhouya, J. Gaber, M. Wack, and P. Lorenz, "Wireless communication technologies for its applications," *Communications Magazine, IEEE*, vol. 48, no. 5, pp. 156 –162, may. 2010.

[2] P. Papadimitratos, A. La Fortelle, K. Evenssen, R. Brignolo, and S. Cosenza, "Vehicular communication systems: Enabling technologies, applications, and future outlook on intelligent transportation," *Communications Magazine, IEEE*, vol. 47, no. 11, pp. 84 –95, nov. 2009.

[3] "Draft amendment to standard for information technology- telecommunications and information exchange between systems-local and metropolitan area networks-specific requirements part 11: Wireless lan medium access control (mac) and physical layer (phy) specifications: Amendment 7: Interworking with external networks," 2008.

[4] [Online]. Available: $http : //www.fcc.gov/Daily_Releases/Daily\_Business/2010/db0923/FCC-10-174A1.pdf$

[5] S. Pagadarai, A. Wyglinski, and R. Vuyyuru, "Characterization of vacant uhf tv channels for vehicular dynamic spectrum access," in *Vehicular Networking Conference (VNC), 2009 IEEE*, oct. 2009, pp. 1 –8.

[6] M. Torrent-Moreno, S. Corroy, F. Schmidt-Eisenlohr, and H. Hartenstein, "Ieee 802.11-based one-hop broadcast communications:understanding transmission success and failure under different radio propagation environments," *Proceedings of the 9th ACM international symposium on Modeling analysis and simulation of wireless and mobile systems*, pp. 68–77, 2006.

[7] K. Ramachandran, M. Gruteser, R. Onishi, and T. Hikita, "Experimental analysis of broadcast reliability in dense vehicular networks," *Vehicular Technology Magazine, IEEE*, vol. 2, no. 4, pp. 26 –32, dec. 2007.

[8] H. Urkowitz, "Energy detection of unknown deterministic signals," *Proceedings of the IEEE*, vol. 55, no. 4, pp. 523 – 531, apr. 1967.

[9] K. Varshney, *Distributed Detection and Data Fusion.* Springer-Verlang New York, Inc., 1996.

[10] A. Ghasemi and E. Sousa, "Collaborative spectrum sensing for opportunistic access in fading environments," in *New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on*, nov. 2005, pp. 131 –136.

[11] J. Ma, G. Zhao, and Y. Li, "Soft combination and detection for cooperative spectrum sensing in cognitive radio networks," *Wireless Communications, IEEE Transactions on*, vol. 7, no. 11, pp. 4502 –4507, nov. 2008.

[12] J. Duan and Y. Li, "Performance analysis of cooperative spectrum sensing in different fading channels," in *Computer Engineering and Technology (ICCET), 2010 2nd International Conference on*, vol. 3, apr. 2010, pp. V3–64 –V3–68.

[13] H. Kremo, I. Seskar, and P. Spasojevic, "Experimental modeling of the effect of adjacent lane traffic on the vehicular channel," in *Vehicular Networking Conference (VNC), 2009 IEEE*, oct. 2009, pp. 1 –8.

[14] O. Altintas, "Implementation and evaluation of distributed control and data channel coordination algorithms for v2v dynamic spectrum access," *SDR Forum Technical Conference*, dec. 2010.

[15] A. Molisch, F. Tufvesson, J. Karedal, and C. Mecklenbrauker, "A survey on vehicle-to-vehicle propagation channels," *Wireless Communications, IEEE*, vol. 16, no. 6, pp. 12 –22, dec. 2009.

[16] C. xiang Wang, X. Cheng, and D. Laurenson, "Vehicle-to-vehicle channel modeling and measurements: recent advances and future challenges," *Communications Magazine, IEEE*, vol. 47, no. 11, pp. 96 –103, nov. 2009.

[17] S. Kaul, K. Ramachandran, P. Shankar, S. Oh, M. Gruteser, I. Seskar, and T. Nadeem, "Effect of antenna placement and diversity on vehicular network communications," in *Sensor, Mesh and Ad Hoc Communications and Networks, 2007. SECON '07. 4th Annual IEEE Communications Society Conference on*, jun. 2007, pp. 112 –121.

[18] H. Kremo, I. Seskar, and P. Spasojevic, "Concurrent measurements of the vehicular channel transfer function and the 802.11 received signal strength index," in *6th IEEE Consumer Communications and Networking Conference*, January 2009, pp. 1–5.

[19] L. Cheng, B. Henty, D. Stancil, F. Bai, and P. Mudalige, "Mobile vehicle-to-vehicle narrow-band channel measurement and characterization of the 5.9 ghz dedicated short range communication (dsrc) frequency band," *Selected Areas in Communications, IEEE Journal on*, vol. 25, no. 8, pp. 1501 –1516, oct. 2007.

[20] Z. Quan, S. Cui, and A. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio networks," *Selected Topics in Signal Processing, IEEE Journal of*, vol. 2, no. 1, pp. 28 –40, feb. 2008.

[21] Y. Yan, A. Li, and H. Kayama, "Study on soft decision based cooperative sensing in cognitive radio network," in *Vehicular Technology Conference Fall (VTC 2009-Fall), 2009 IEEE 70th*, sep. 2009, pp. 1 –5.

[22] S. Haykin, "Cognitive radio: brain-empowered wireless communications," *Selected Areas in Communications, IEEE Journal on*, vol. 23, no. 2, pp. 201 – 220, Feb 2005.

[23] E. L. Axell and E. G. Larsson, "Overview of spectrum sensing for cognitive radio," *Cognitive Information Processing (CIP), 2010 2nd International Workshop on*, vol. 23, no. 2, pp. 322 – 327, June 2010.

[24] S. M. Kay, *Fundamentals of statistical signal processing: estimation theory.* PTR Prentice-Hall, 1993.

[25] C. Hwang, G. Lai, and S. Chen, "Spectrum sensing in wideband ofdm cognitive radios," *Signal Processing, IEEE Transactions on*, vol. 58, no. 2, pp. 709 – 719, Feb 2010.

[26] E. Axell, E.; Larsson, "Optimal and sub-optimal spectrum sensing of ofdm signals in known and unknown noise variance," *Selected Areas in Communications, IEEE Journal on*, vol. 29, no. 2, pp. 290 – 304, Feb 2011.

[27] L. Cheng, B. Henty, D. Stancil, F. Bai, and P. Mudalige, "Mobile vehicle-to-vehicle narrow-band channel measurement and characterization of the 5.9 ghz dedicated short range communication (dsrc) frequency band," *Selected Areas in Communications, IEEE Journal on*, vol. 25, no. 8, pp. 1501 – 1516, Oct 2007.

[28] M. Acosta-Marum, G.; Ingram, "Six time- and frequency-selective empirical channel models for vehicular wireless lans," *Vehicular Technology Conference, 2007. VTC-2007 Fall. 2007 IEEE 66th*, pp. 2134 – 2138, 2007.

[29] J. Proakis, *Digital Communications.* McGraw-Hill, 1995.