JOINT UTILIZATION OF TEMPORAL AND SPATIAL DIVERSITY FOR VEHICULAR SPECTRUM SENSING

Haris Kremo (Toyota InfoTechnology Center, Tokyo, Japan; hkremo@jp.toyota-itc.com);
Onur Altintas (Toyota InfoTechnology Center, Tokyo, Japan; onur@jp.toyota-itc.com)

ABSTRACT

Diversity combining is a well known technique which improves signal detection performance through use of quasi–independently faded signal replicas. The conventional wireless propagation modeling decouples large scale shadow fading from the "rapidly changing" small scale fading and treats them as independent random processes. Using different spatiotemporal scales of fading correlation we decouple time periods of individual and collaborative sensing for the vehicular cognitive networks. We evaluate the proposed sensing scheme by means of computer simulations in rural and urban propagation environments using energy detection for simplicity. On the small scale, scheduling of large number of sensing intervals results in a significant gain from small scale fading, even if collaborating nodes already provide more than a few independent measurements. On the large scale, the ratio between the large scale decorrelation distance and the distance at which the nodes must re–evaluate spectrum availability determines whether collaboration can be substituted by temporal diversity on each sensor.

1. INTRODUCTION

In the prior work [1] we argued that, although it introduces significant challenges, dynamic spectrum access in the vehicular environment is necessary to satisfy growing demand for wireless communications. We also argued that, for highly mobile cognitive nodes, primary spectrum user protection based on geolocation database lookup has significant limitations. Therefore, enhancement of spectrum sensing accuracy remains important area of our research interest.

To that goal, we evaluate application of diversity combining to improve performance of spectrum sensing in the vehicular environment based on the conventional propagation modeling paradigm, which separates dynamics of the radio channel into two spatiotemporal scales. The first one is small scale fading, which describes power fluctuations and delay spread in areas comparable in diameter to the carrier wavelength λ_c. The second one is the large scale fading, which describes combination of the distance related path loss and the slow signal strength undulation. This local mean undulation is frequently, although somewhat arbitrarily, referred to as the shadow fading.

We introduce a two–tier scheduling scheme which exploits diversity gain from both the small and the large scale fading. The most important parameter for design of scheduling is the distance at which the nodes are required to reassess spectrum usage. It is imposed by a regulating authority such as The Federal Communications Commission (FCC), which currently sets it to 100 m [2]. We refer to this distance as the *decision distance*. First, while the vehicles traverse the decision distance, we apply temporal diversity to the small scale fading by repeating sensing intervals with the period larger than its coherence time T_s. Second, depending on the imposed decision distance, the diversity gain from large scale fading can be exploited either through temporal or spatial diversity. When the decision distance is much larger than the decorrelation distance of large scale fading D_l, a single sensor can achieve the same detection performance as multiple sensors spread over the decision distance. However, collaboration must be used to maximize diversity gain if the decision distance is comparable to, or smaller than D_l.

It is well known that the small scale fading gain does not grow linearly with each additional diversity branch [3]. Sufficient separation of sensors on the large scale guarantees sufficient separation on the small scale as well, and the small scale fading gain diminishes as more cars/sensors are added. We simply overcome this by exponentially increasing the number of sensing intervals. This is practically impossible to do in space using multiple antennas. However, it is straightforward to use temporal diversity with cars as mobile sensor. The additional delay to collect samples is limited by the decision distance, which is typically by orders of magnitude larger than the coherence distance of the small scale fading D_s.

To the best of our knowledge, performance of multiple sensors under correlated composite (large and small scale) fading in the vehicular environment, and with regard to the regulatory domain requirements was not previously considered. The benefits of diversity combining in general are, for instance, evaluated in [4]. The tradeoff between temporal and spatial diversity on a large fading scale is

Table 1: Simulation settings and parameters

Environment	Rural	Urban
Shadow fading	mild	severe
standard dev. σ	3 dB	10 dB
decorrelation dist. D_l	100 m	10 m
local area size (m)	10 λ_c	5 λ_c
Small scale fading	LOS, GSM rural	NLOS, GSM urban
tap delays (μs)	0 0.2 0.4 0.6	0 0.2 0.6 1.6 2.4 5.0
relative powers (dB)	0 -2 -10 -20	-3 0 -2 -6 -8 -10
Rice K-factor	1	n/a
Doppler spectra	LOS: Jakes+δ(0.7f_{max}) all other taps: Jakes	all taps: Jakes
Sensor speed v	100 km/h	50 km/h
Carrier frequency f_c	700 MHz	
Sensing bandwidth	100 kHz	
Baseline sensing interval	0.1 ms (N = 10 samples)	1 ms (N = 100 samples)
Sensing period	40 ms	80 ms
Decision distance	100 m or 10 m	10 m or 107 m
SNR	-10 dB or -5 dB	
Sensor link budget	-5 dB	

analyzed in [5]. Performance of energy detection under small scale fading is modeled analytically in [6], and under correlated shadowing in [7]. Detection performance of a single energy detector under composite fading is evaluated in [8]. Our system model builds upon [9], which addresses performance of vehicular sensors under path loss and shadow fading.

In the following, we use the terms coherence distance D_s and coherence time T_s to quantify coherence of the small scale fading. The terms decorrelation distance D_l and the decorrelation time T_l are used to quantify correlation of the large scale fading.

In the next section we introduce the system model. In Section 3 we explain specific settings used in the simulations. Section 4 contains results of the performance evaluation. We formulate conclusions in Section 5.

2. SYSTEM MODEL

We consider two types of propagation environments to describe radio channel between the primary spectrum user and the sensors positioned on the vehicles. The *urban* and the *rural* environments have different large and small scale fading parameters, which are summarized in Table 1. The rationale behind selection of some of the parameters in Table 1 is explained in Section 3. With respect to propagation, we use the rural, open space model to describe fading of the primary signal on a freeway surrounded by flat terrain. The urban model describes fading in a downtown city area, which is characterized by much larger delay spread, absence of the line–of–sight (LOS), and shorter decorrelation distance of shadowing.

We focus on the TV white space and assume a channel centered at f_c = 700 MHz.

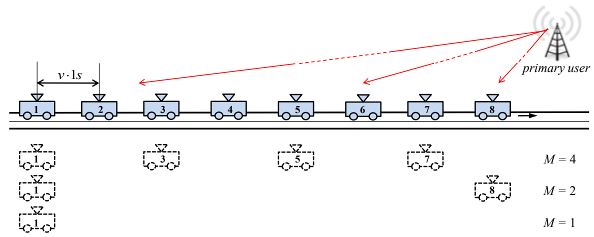

Fig. 1: Mobility model.

2.1. Mobility

We assume a model with either a single car, or a convoy of up to M = 8 vehicles (presented in Fig. 1) traveling straight in the same direction with constant speed v. The vehicles are separated by a fixed distance. This distance is the distance each vehicle passes in a second, and it corresponds to a dense traffic scenario. By expressing the distance in time units we take into account intuitive behavior of drivers to positively correlate the speed and the separation among vehicles. The reason for this is to maintain distance between the vehicles which is sufficient to accommodate the reaction time in case a decisive maneuver is needed.

It is important to emphasize that shortening the distance among vehicles has profound influence on sensing, since the diversity gain depends on the correlation between channel realizations.

2.2. Fading

2.2.1. Large Scale Fading

We assume that the distance between the sensors is much smaller than the distance between the primary user and the sensors. Therefore, we neglect change in primary power due to path loss and take into account only the lognormal shadowing.

The standard deviation of shadowing is provided in Table 1. Selected values are representative for corresponding environments, that is, larger in the urban environment and smaller in the rural environment. The correlation of shadowing is described by the empirical exponential model [10]. Correlation is realized by multiplying M uncorrelated normally distributed vectors with a Cholesky decomposition of the desired correlation matrix. The decorrelation distance D_l corresponds to the distance d between the sensors at which the correlation coefficient is equal to 0.5:

$$\rho = \exp\left(-\ln 2 \cdot \frac{d}{D_l}\right). \quad (1)$$

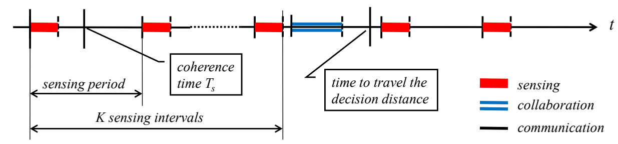

Fig. 2: Scheduling of sensing.

Once a realization of shadowing is created, the moving vehicles observe the same values at the corresponding positions.

2.2.2. Small Scale Fading

Small scale fading is modeled using the simplified GSM wideband propagation models, applicable for channels with bandwidth of up to 10 MHz [11]. Since small scale fading decorrelates rapidly, we generate independent initial tap coefficients at the start of every sensing interval. The model parameters are also given in Table 1.

2.2.3. Received Signal

Since the purpose of our work is to evaluate diversity combining on different spatiotemporal scales, we assume simple energy detection as the underlying local sensing algorithm. For simplicity, we assume that the signal to be detected is a pilot tone. This somewhat resembles detection of the pilot tone which is embedded into the Advanced Television Systems Committee (ATSC) digital TV signal by adding the constant 1.25 to the baseband signal [12].

The constant signal of amplitude A is passed through the time varying filter representing the small scale fading $h_s(t;\tau)$ and then scaled with the value which is zero mean normally distributed on the logarithmic scale

$$10\log_{10}(h_l) \sim \mathcal{N}(0,\sigma^2). \tag{2}$$

Since the value of shadowing represents local mean of the channel response, it is constant during a sensing interval. The complex baseband representation of the faded signal is then given as

$$y(t) = \left[A * h_s(t;\tau)\right] \cdot h_l \tag{3}$$

where * represents convolution.

After passing it through the random filter representing the channel between the primary transmitter and the sensors, we decimate the signal y to narrow the bandwidth to 100 kHz and insert additive white Gaussian noise (AWGN) $n(t)$ with power corresponding to that bandwidth

$$r(t) = y(t) + n(t). \tag{4}$$

We model the contribution of the receiver noise figure, cable losses, and antenna gain with a 5 dB increase in the noise floor.

2.3. Primary User Detection

To formulate the decision statistics we use a number of samples of the received signal r. Let us represent a vector of these complex values with $\boldsymbol{R}$. We collect these samples in two ways:

1. In the proposed scheduling scheme, presented in Fig. 2, vector $\boldsymbol{R}$ contains $N \cdot K$ samples. At each of K sensing intervals N samples are collected. The sampling intervals occur with the period much larger than the coherence time of the small scale fading T_s. On the other hand, the time to acquire N samples is shorter than T_s. In other words, N samples are collected while the channel is statistically time invariant. In this manner K uncorrelated sets of samples are acquired.
2. As the benchmark test, we repeat the same simulations with distinction that all $N \cdot K$ samples are collected consecutively. In this case, the total sensing time needed to acquire these samples is shorter or comparable to T_s.

For a given detection threshold η, we decide between the two hypotheses

$$\begin{cases} H_1 : \text{Primary user present} \\ H_0 : \text{Channel is free} \end{cases}. \tag{5}$$

2.3.1 Hard Decision Combining

Let index m denote one of M mobile sensors. The local hypothesis testing is

$$\boldsymbol{R}_m' \boldsymbol{R}_m \underset{H_0}{\overset{H_1}{\gtrless}} KN\eta \tag{6}$$

where $'$ represents conjugate transpose. These M local decisions can then be combined using different logical rules: AND, OR, or majority.

2.3.2. Soft Decision Combining

The local test statistics can be averaged across M vehicles

$$\sum_{m=1}^{M} \boldsymbol{R}_m' \boldsymbol{R}_m \underset{H_0}{\overset{H_1}{\gtrless}} MKN\eta \tag{7}$$

resembling the equal gain combining (EGC). Another approach is to put more weight to stronger signals, similar to the maximum ratio combining (MRC)

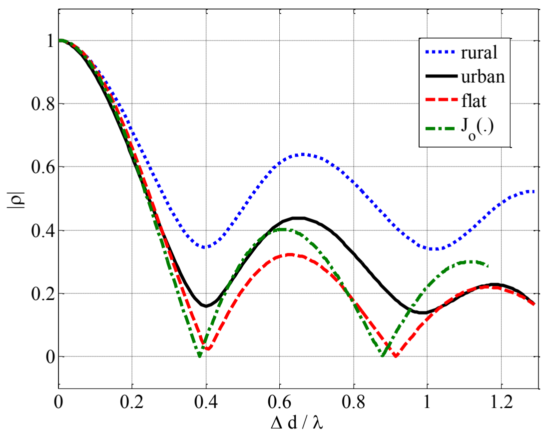

Fig. 3: Numerically generated normalized correlation coefficients of 100 kHz channels for different small scale fading models.

$$\sum_{m=1}^{M} a_m \boldsymbol{R}_m' \boldsymbol{R}_m \underset{H_0}{\overset{H_1}{\gtrless}} MKN\eta \tag{8}$$

with weights a_m provided from crude signal–to–noise ratio (SNR) estimates

$$a_m = \frac{\boldsymbol{R}_m' \boldsymbol{R}_m}{\sum_{m=1}^{M} \boldsymbol{R}_m' \boldsymbol{R}_m}. \tag{9}$$

3. NUMERICAL ANALYSIS IN DETAIL

In practice, a regulatory body imposes requirement that the decision about presence of a primary user is reached in regular intervals. For instance, the FCC [2] requires that spectrum sensing should be performed at least once every 60 s. This requirement is not intended for highly mobile white space devices. More adequate requirement is the one intended for devices which rely on geolocation database access to acquire spectrum occupancy. The database should be accessed each time a device moves by 100 m. It is reasonable to assume similar rule for vehicular networks. By relating primary user protection to traveled distance it can then be made independent of the speed, which varies widely with location and time of day.

We selected two values for the decision making distance. The first one—100 m—is following the current FCC rules. The second—10 m—is more stringent, with rationale that it should provide better protection of primary users. Both values are comparable to realistic values of the large scale fading decorrelation D_l.

We assume that the sensors move by 50 km/h in the urban environment and 100 km/h in the rural environment. The one–second separation between the cars then corresponds to 13.9 m and 27.8 m, respectively. The convoy of $M = 8$ vehicles is 97.2 m and 194.4 m long, respectively.

To decide on duration of the sensing interval we performed simple tests on used multipath models to determine the coherence distance D_c statistically from a number of realizations of $y(t)$

$$\rho(\Delta t) = \frac{\sum_i \left(y(t_i + \Delta t) - \mu_{i,\Delta t}\right)\left(\overline{y(t_i) - \mu_i}\right)}{\sqrt{\sum_i \left|y(t_i + \Delta t) - \mu_{i,\Delta t}\right|^2} \sqrt{\sum_i \left|y(t_i) - \mu_i\right|^2}} \tag{10}$$

where $\mu_{i,\Delta t}$ and μ_i represent the sample means calculated over samples $y(t_i+\Delta t)$ and $y(t_i)$, respectively. The bar denotes complex conjugate.

For a given constant speed v it is trivial to convert time lag into distance $\Delta d = v\Delta t$, and normalize the lag with respect to the carrier wavelength λ_c. In Fig. 3 we present these results for decimated (100 kHz) channels in a form independent of speed and carrier frequency. The Rice model selected to represent small scale fading in the rural environment decorrelates much slower than the Rayleigh urban model due to the deterministic portion of the LOS component. The Jake's Doppler spectra of the taps in the urban model result in correlation very similar to the flat (single tap) Rayleigh fading. As a sanity check we also provide theoretical flat fading correlation [3], given by the Bessel function of the first kind and zero order J_o.

When evaluating the sensing performance we vary the number of vehicles $M \in \{1,2,4,8\}$ (Fig. 1). For $M = 2$ we simply keep the first and the last car in the convoy $m \in \{1,8\}$. When $M = 4$, we consider only cars with odd indexes $m \in \{1,3,5,7\}$. To make fair comparison for different M we scale the sensing interval (number of samples N). For instance, when $M = 2$ we increase the number of samples four times. This way we keep the time–bandwidth product constant in all simulations.

When $M = 8$ in the urban environment we set the sensing interval to 1 ms ($N = 100$). Convenient setting of the period of sensing intervals to 40 ms for rural and 80 ms for urban environment results in $K = 100$ in the rural and $K = 10$ in the urban environment. To keep constant the product $MKN = 8000$ we set $N = 10$ in the rural environment. If, for instance, $M = 1$ the number of samples increases to $N = 80$ in the rural and $N = 800$ in the urban environment.

In each simulation run, as the vehicles traverse the decision making distance, we keep the shadow fading h_l constant in discrete steps representing the local areas. Following the channel modeling heuristics detailed in [13] and [10] we conveniently set the local area to be ten carrier

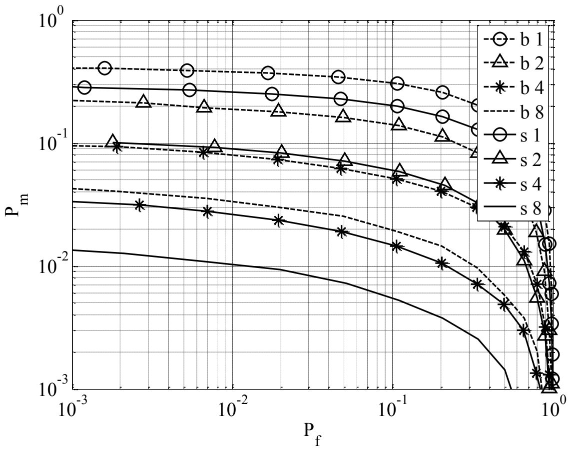

Fig. 4: Performance of EGC in urban environment for 1, 2, 4 and 8 collaborating cars, under -5 dB SNR (-22.8 dB SNR for 6 MHz channel), and with decision distance 10 m. Dashed line represents benchmark sensing in a single slot (denoted with 'b') and full line represents proposed slotted sensing (denoted with 's').

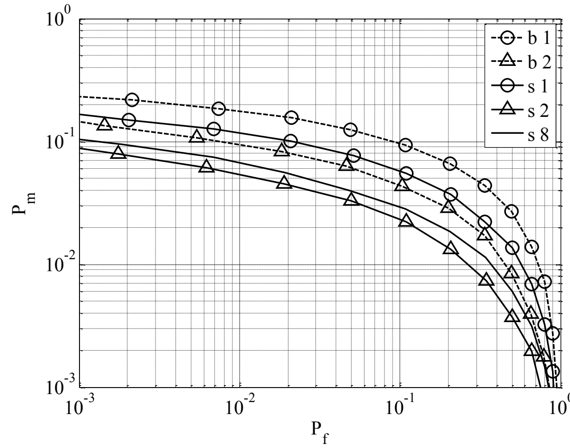

Fig. 5: Performance of EGC in rural environment for 1, 2 and 8 cars, under -5 dB SNR (-22.8 dB SNR for 6 MHz channel), for decision distance 100 m. Dashed line represents benchmark sensing in a single slot (denoted with 'b') and full line represents proposed slotted sensing (denoted with 's').

wavelengths λ_c in the rural environment and five carrier wavelengths in the urban environment.

The detection probability P_d—and its complement, the probability of missed detection P_m—are evaluated for different SNRs by creating a channel realization, adjusting the amplitude A, and calculating the test statistics. This procedure is repeated for a large number of channel realizations. The false alarm probability P_f is evaluated by setting $A = 0$. It is then possible to relate P_f and P_m through different values of threshold η and generate complementary Receiver Operating Curves (ROC).

4. RESULTS

We assume the SNR to be the ratio between the power of signal that must be detected A^2 and the noise floor of 100 kHz sensing bandwidth (without mentioned 5 dB budget penalty). We consider two such SNRs, -10 dB and -5 dB. These correspond to -27.8 dB and -22.8 dB in comparison to the noise floor of a 6 MHz TV channel, respectively. Of course, the performance of a detection system suffers from many implementation issues, but it can be further improved in two ways: 1) by increasing the sensing interval; and 2) by applying feature detection. Since energy detection is used as the underlying sensing algorithm for simplicity, we assume perfect estimation of the noise floor.

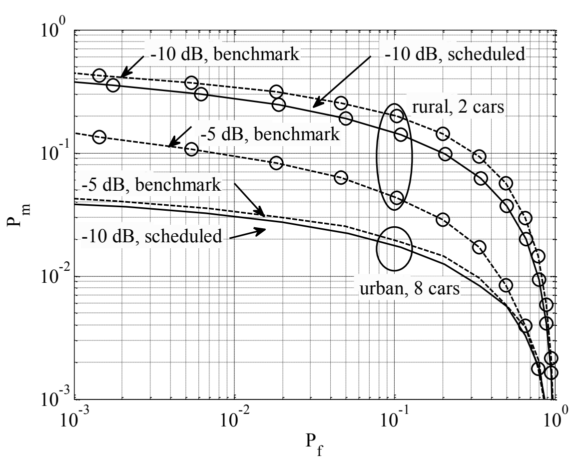

Fig. 6: Diversity gain achieved through the scheduling of sensing is between 1 and 2 dB in the rural environment, and around 5 dB in the urban environment.

4.1. Diversity Gain

In Figs. 4 and 5 we present detection performance of EGC in the urban and in the rural environment with -5 dB SNR, for different number of sensors M.

In the urban environment (Fig. 4), assuming 10 m decision distance, scheduling of sensing with $M = 2$ and 4 sensors shows practically the same performance as sensing in a single slot for the same time with $M = 4$ and 8 sensors, respectively.

In the rural environment (Fig. 5), the diversity gain is much smaller for two reasons. First, half of the power related to the small scale fading is deterministic. Second, the variance of shadowing is much smaller in comparison to the urban environment. With decorrelation distance of 100 m, even only $M = 2$ sensors, separated by almost 200 m, achieve maximum diversity. We attribute slightly worse performance of $M = 8$ sensors to their dense arrangement being exposed to the same shadowing as they move. For clarity, we omitted the results for benchmark sensing with eight cars, which is similar to benchmark sensing with two cars.

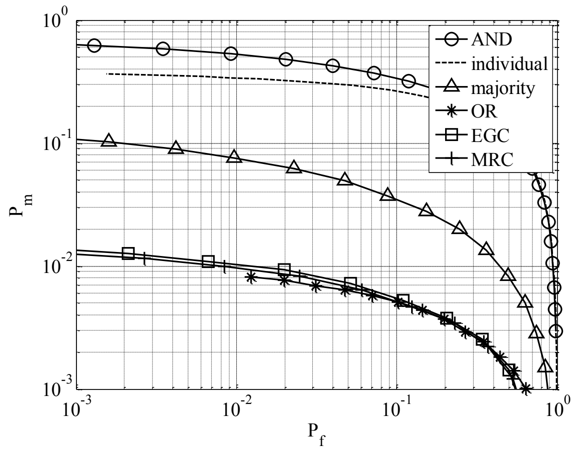

Fig. 7: Performance of different hard and soft fusion algorithms in urban environment for 10 m decision distance, and -5 dB SNR (-22.8 dB SNR for 6 MHz channel).

To illustrate the gain achieved by scheduling, we present in Fig. 6 results for the rural environment with two cars, together with results for the urban environment with eight cars. The gain in the rural environment is between 1 and 2 dB. The gain in the urban environment is approximately 5 dB.

4.2. Performance of Different Fusion Algorithms

Fig. 7 provides an overview of detection performance of our scheduling scheme across different fusion algorithms for SNR -5 dB in the urban environment. Here "individual" sensing represents the average of local decisions across all $M = 8$ vehicles and all realizations.

Among hard fusion algorithms, the OR rule shows the best performance. This is easy to justify having in mind that all sensors are considered equally reliable and, on the average, all experience the same fading statistics. Therefore,

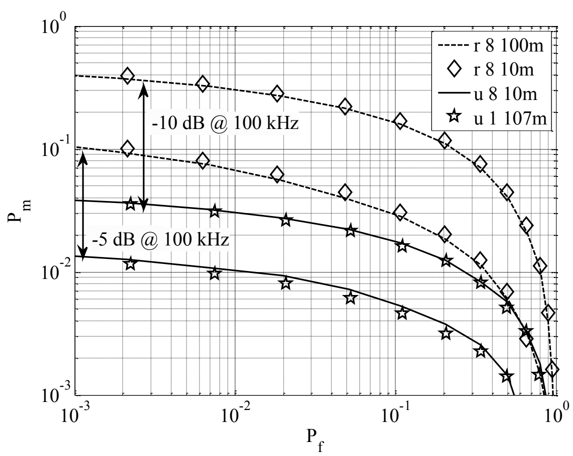

Fig. 9: Performance of EGC in rural and urban environments for different decision distances, and -10 dB and -5 dB SNR (-27.8 dB and -22.8 dB SNR for 6 MHz channel).

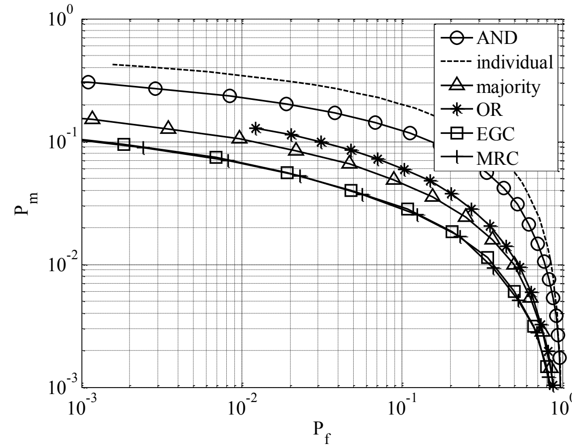

Fig. 8: Performance of different hard and soft fusion algorithms in rural environment for 100 m decision distance, and -5 dB SNR (-22.8 dB SNR for 6 MHz channel).

when a sensor correctly detects the primary user, it is most likely the sensor with the best propagation conditions.

The weighted sum performs only marginally better than the equal gain combining. It is well known that, when all diversity branches exercise the same average power, MRC performs only slightly better than EGC [3]. However, when path loss fading is not negligible across the sensors, the MRC should provide larger performance improvement.

To complement results in Fig. 7 we present in Fig. 8 the same results for the rural environment. In this case, with less variation in signal strength due to shadowing, soft methods perform better than all hard rules. These results qualitatively agree well with the results reported in [9] for a similar shadowing statistics.

4.3. Decision Distance versus Spatiotemporal Tradeoff

The same argument we used to describe performance of two and eight sensors in Fig. 5 can be used to explain some of the results in Fig. 9, represented with dashed line and diamond marker. Here we look into the rural environment with eight sensors which are distributed over a distance twice the shadowing decorrelation distance. In such a scenario any decision distance smaller or equal to the decorrelation distance (e.g. 10 m or 100 m) does not help to decorrelate the shadow fading.

Complementary to that, if a single sensor can "wait enough" to experience the same diversity gain experienced by many collaborating nodes, it can achieve the same performance as they do. For instance, M = 8 nodes cover 107 m while each travelling for 10 m. If a single node travels the same distance before making decision, it achieves the same performance as eight nodes, indicated with star markers in Fig. 9.

The tradeoff between space and time has both pros and cons. Collaboration involves communication overhead to exchange local sensing information and distribute the fusion outcome by means of unreliable wireless communication. In comparison to that, a single sensor utilizing temporal diversity suffers from additional delay needed to traverse the same distance.

5. CONCLUSION

We proposed and evaluated a method to improve performance of spectrum sensing in the vehicular environment by carefully scheduling sensing intervals to accommodate for different time scales of the primary user signal fading. Assuming energy detection, splitting of the sensing interval into many shorter intervals (with a period much larger than the coherence time of small scale fading) results in approximately 1 to 2 dB gain in the rural environment, and around 5 dB gain in the urban environment.

The soft combining techniques provide consistently good performance irrespective of the environment. This is not the case for hard combining. Under strong fading and equal average powers at the sensors, the OR rule is comparable to the soft methods. Under less severe fading simple majority outperforms all hard rules, but fails short of the accuracy achieved with the soft methods.

We also discussed influence of regulatory domain requirements, namely, the distance at which mobile sensors should re–evaluate spectrum occupancy, on the accuracy of detection. In severe fading, with detection distance much larger than the fading decorrelation distance, diversity gain can be utilized with a single sensor by trading spatial diversity for temporal diversity. This approach has the advantage of avoiding communication overhead (including failures) associated with cooperative sensing. Under mild fading conditions, for very short detection distance, the diversity must be exploited through collaboration of sensors.

6. REFERENCES

[1] H. Kremo, R. Vuyyuru and O. Altintas, "Spectrum Sensing in the Vehicular Environment: An Overview of the Requirements," in *Wireless Innovation Forum European Conference on Communications Technologies and Software Defined Radio*, Brussels, 2012.

[2] *Second Memorandum Opinion and Order In the Matter of Unlicensed Operation in the TV Broadcast Bands, Additional Spectrum for Unlicensed Devices Below 900 MHz and in the 3 GHz Band,* Federal Communication Commission, 2010.

[3] A. Goldsmith, Wireless Communications, New York: Cambridge University Press, 2009.

[4] S. M. Mishra, A. Sahai and R. W. Brodersen, "Cooperative Sensing Among Cognitive Radios," in *IEEE International Conference on Communications - ICC*, Istanbul, 2006.

[5] A. W. Min and K. G. Shin, "Impact of mobility on spectrum sensing in cognitive radio networks," in *ACM workshop on Cognitive radio networks (CoRoNet '09)*, 2009.

[6] S. P. Herath, N. Rajatheva and C. Tellambura, "Energy Detection of Unknown Signals in Fading and Diversity Reception," *IEEE Transactions on Communications,* vol. 59, no. 9, pp. 2443-2453, 2011.

[7] A. Ghasemi and E. S. Sousa, "Asymptotic Performance of Collaborative Spectrum Sensing under Correlated Log-Normal Shadowing," *IEEE Communication Letters,* vol. 11, no. 1, pp. 34-36, 2007.

[8] H. Rasheed and N. Rajatheva, "Spectrum Sensing for Cognitive Vehicular Networks over Composite Fading," *International Journal on Vehicular Technology,* vol. 2011, 2011.

[9] D. Borota, G. Ivkovic, R. Vuyyury, O. Altintas, I. Seskar and P. Spasojevic, "On the Delay to Reliably Detect Channel Availability in Cooperative Vehicular Environments," in *IEEE Vehicular Technology Conference*, Budapest, 2011.

[10] M. Gudmundson, "Correlation model for shadow fading in mobile radio systems," *IET Electronic Letters,* vol. 27, no. 23, pp. 2145-2146, November 1991.

[11] European Telecommunications Standards Institute, "Global System for Mobile Commuincations 05.05: Radio Transmission and Reception," Sophia Antipolis, 1996.

[12] Advanced Television Systems Committee, "ATSC Digital Television Standard Part 1 – Digital Television System (A/53, Part 1:2007)," 2007. [Online]. Available: http://www.atsc.org/cms/standards/a53/a_53-Part-1-6-2007.pdf. [Accessed 12 4 2013].

[13] T. S. Rappaport, Wireless Communications: Principles and Practice, 2 ed., Prentice Hall, 2002.