WIRELESS COMMUNICATIONS AND MOBILE COMPUTING
Wirel. Commun. Mob. Comput. **00**: 1–11 (0000)
Published online in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/wcm.0000

Simple Solutions May Still Be Best: On the Selection of Working Channels in a Channel-Hopping Cognitive Network

Vojislav B. Mišić[1], Mohammad Shahnoor Islam Khan[1], Md. Mizanur Rahman[1], Haleh Khojasteh[1], and Jelena Mišić[1]

[1]*Ryerson University, Toronto, ON, Canada*

Summary

Spectrum decision – i.e., the selection of a channel for the next hop – is one of the most important factors that affect the performance of a channel-hopping cognitive network. In this paper, we compare the performance of a number of channel selection algorithms through the probability of collisions with primary user transmissions. The results indicate that a simple histogram-based selection algorithm performs the best, except in the somewhat unrealistic scenario where primary users are homogeneous with respect to mean period and mean duty cycle of their channel activity, in which case selecting the next-hop channel among those that have most recently turned idle offers the best performance. Furthermore, histogram-based selection is shown to be quite resilient to errors inherent to channel sensing, and is thus a primary candidate for a wide range of applications of channel-hopping cognitive networks. Copyright © 0000 John Wiley & Sons, Ltd.

KEY WORDS: opportunistic spectrum access; channel-hopping cognitive networks; working channel selection; kernel-based estimation; performance evaluation

1. Introduction

Opportunistic or cognitive spectrum access often relies on channel hopping [2]. However, predefined hopping sequences, be they deterministic such as the one used in the so-called dynamic hopping communities [3] or pseudo-random such as the one used in Bluetooth [4, 5], are incapable of providing uninterrupted piconet operation under unpredictable activity of primary users [6]. Instead, the hopping sequence must be dynamically determined by choosing the channels with best transmission parameters and free from interference by primary users.

*This paper is a greatly expanded and revised version of the paper 'On the Selection of Working Channels in a Channel-Hopping Cognitive PAN' [1] presented at the IWCMC 2013 conference, held in Cagliari, Sardinia, Italy, in July 2013.

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls *[Version: 2007/01/09 v1.00]*

In this paper we present a comparative analysis of a number of techniques for working channel selection, using blind random selection as the convenient reference point. We use the transmission tax-based protocol from [7, 8] as the environment in which to implement these techniques, on account of its availability of superframe-based structure with integrated sensing protocol and adaptive channel hopping.

One of the techniques for working channel selection is based on selecting one among the channels that have most recently become free – preferably, but not necessarily, within the last superframe. The other techniques use statistical approaches – in one case a histogram, and two different kernel-based estimators in another two cases – to estimate the probability that individual channels will remain idle for the duration of the next superframe. In both cases, the required data structures are created and dynamically maintained by the piconet coordinator from sensing data regularly reported by individual nodes in the piconet. The channel with the highest probability is then selected as the next working channel (i.e., the working channel for the next hop). A simple random selection among channels that are currently idle is used as the benchmark against which other algorithms are measured. The most important performance indicator is the probability of collisions with primary user activity: namely, if the piconet hops on to a channel which is not idle, or if a primary user begins transmission on the current working channel. These two cases will be referred to as type 1 and type 2 collisions, respectively.

As will be seen, histogram-based estimation offers best results except in the somewhat impractical case when primary user activity is homogeneous with respect to mean activity period and mean duty cycle (i.e., the ratio of active period and the sum of active and inactive periods) in which case selecting the channel most recently turned idle gives best results. The ability to deal with heterogeneous primary user activity patterns and a remarkable resilience to sensing errors, as shown below, make histogram-based estimation the prime candidate for use in cognitive networks with a wide range of network and traffic parameters.

The rest of the paper is organized as follows. In Section 2 we present a brief overview of existing work on working channel selection. Section 3 outlines the operation of the transmission tax-based MAC protocol. Section 4 presents the working channel selection protocols and discusses their relative advantages. Section 5 presents the performance evaluation of the protocols, and Section 6 concludes the work.

2. Related work on spectrum decision

Selection of the working channel or, as it is often called, spectrum decision, has been identified as a crucial piece of functionality in the operation of cognitive networks [2]. While the spectrum decision problem has received some attention in the existing literature, its level of 'maturity' is well below that of the other processes such as spectrum sensing or spectrum access [9].

In cases where primary user activity patterns are known, spectrum decision process can be designed to make use of those patterns. In case of cognitive communications that use TV White Space [10, 11, 12], such information might be added to the extensive database of existing TV transmitters. Note that this addition is not defined in DARPA's documents – but it is not forbidden either.

Unfortunately, the cases where primary user activity is unpredictable are much more frequent in practice, and decisions have to be made on the basis of some statistical model of spectrum usage [6]. A prerequisite for statistically meaningful decisions is a certain degree of stationarity of primary user activity [13], which may or may not hold in a given scenario.

A formal analysis of spectrum availability in the context of ISM band where primary users are 802.11 transmitters has been proposed in [14]. This model is then used to develop an access strategy in which a channel is sensed by a secondary user and, if idle, utilized with a specified probability [15]. This approach, however, requires that secondary users are well synchronized, which is not a straightforward task. More importantly though, the approach holds for two nodes only and may not be easy to extend to a piconet with several such nodes.

A stochastic extension of the above approach that avoids the need for strict synchronization of secondary nodes has been described in [13].

Spectral estimation is the foundation of the approach described in [16], where distinction is made between white and gray zones in the scanned spectrum: the former contain noise only, while the latter contain signals with distinct idle periods. Separating the two, however, is noted to be a difficult task.

Some authors have also described game-theoretic approaches [17], but in the context of cooperation between primary and secondary users. Again, this cooperation is infeasible or, at least, impractical in most cases.

From this brief overview, some important observations can be made. First, spectrum decision – i.e., the selection of the best available channel – necessitates frequent and accurate spectrum sensing at all times [18]. Sensing may be performed in centralized or distributed fashion, but the decision about the channel to use for the next hop must be made in a centralized manner. Once made, the decision must be announced to all the nodes in the piconet in a timely manner, e.g., through a beacon frame that is periodically broadcast.

Second, if spectrum decision is to be guided by a statistical model of primary user spectrum usage, such model must be built through some kind of learning process based on accurate sensing of primary user activity in the working band. However, the learning

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

DOI: 10.1002/wcm

process must be capable of dynamically adapting to patterns of primary user activity. If these patterns exhibit nonstationarity (which is to be expected in practice), few, if any, of the aforementioned approaches are equipped to adapt to such changes in a satisfactory manner; instead, their respective algorithms need to be restarted, which would render them rather crude and, possibly, inapplicable in practice.

These two observations form the foundation for our approach to spectrum selection, which will be described in the context of the transmission tax-based MAC protocol explained in the following.

3. Transmission tax-based MAC protocol

A number of nodes with cognitive capabilities form a cognitive piconet through a so-called rendezvous procedure [19], the details of which are beyond the scope of this paper. All nodes are assumed to be capable of half-duplex operation, and any node with sufficient computational capability can act as a coordinator, similar to Bluetooth [5].

The time in each superframe is divided into the following components: beacon frame, data exchange sub-frame, reporting sub-frame in which sensing results are sent back to the coordinator, reservation sub-frame in which bandwidth requests and other administrative frames are sent, and trailing beacon frame. The leading beacon allows nodes to synchronize with the beginning of the superframe on a new channel. The trailing beacon contains bandwidth allocation decisions, information about nodes joining the piconet or leaving it, network allocation vector outlining the boundaries of sub-frames in the next superframe, and the announcements about the next-hop channel – i.e., the channel to be used for the next superframe.

The superframe lasts for a fixed or variable number of fixed-duration time slots, and each superframe may take place on a different channel according to the hopping sequence dynamically selected by the coordinator. Performance implications of adaptive superframe duration in the transmission tax-based MAC protocol were discussed in [20].

The structure of the superframe is schematically shown in Fig. 1. Successive superframes are separates by a guard interval of sufficient duration which allows all nodes to hop to the next channel.

The label 'transmission tax' stems from the fact that a node, once it request and receive bandwidth allocation to transmit a packet – and then successfully

Fig. 1. Structure of the piconet superframe.

transmits it – is obliged to perform the sensing duty for a specified number of superframes. It reports the results in each of the superframes during which it performs the sensing duty. Thus transmission is effectively paid for by sensing; by adjusting the amount of transmission tax (i.e., the number of superframes for sensing per transmitted packet or packet burst), the coordinator is able to maintain a steady influx of accurate sensing information in a timely fashion [21].

An important component of the sensing report is the information about the time of sensing. In the simplest case, the coordinator will just record the superframe in which it received the report; alternatively, the node may report (and the coordinator will record) the nearest time slot in which the sensing actually took place. The former approach suffices for all of the algorithms described below.

Finally, we note that nodes about to receive packets can temporarily suspend the sensing during that superframe, and resume it in the next one. In other words, sensing is preempted by packet reception. In this manner, reception is not actually taxed, unlike transmission. However, the coordinator must ensure that a node can request bandwidth for a new packet only upon completing the sensing duty imposed on account of its previous transmission.

4. Channel selection algorithms

Let us now describe spectrum decision algorithms in more detail. We assume that ordinary nodes perform sensing for a number of channels in each of the superframes which they spend doing sensing. We also assume that sensing reports are truthful; while reporting may be blocked by noise and interference, we can easily account for this through reducing the number of sensing reports per each superframe. More details on the impact of the number of sensing reports will be presented in Section 5.3 below. (Accuracy of cooperative sensing at the MAC level has been investigated in detail in [24].)

Sensing results are collected by the coordinator which maintains a map of busy and idle channels, as

Copyright © 0000 John Wiley & Sons, Ltd.

Wirel. Commun. Mob. Comput. 00: 1–11 (0000)
DOI: 10.1002/wcm

well as the last time at which the channel has turned idle or busy, and other relevant information necessary for the working channel selection algorithms outlined below.

Our main performance indicators are the probability of collisions with the transmission from a primary user. Fewer collisions mean more usable superframes and, consequently, higher throughput. (More details on improving throughput in the cognitive piconet with transmission tax-based MAC protocol can be found in [21, 20].) Two types of collisions are possible:

- Type 1 collision occurs when the coordinator selects a channel it thinks is idle, but is in fact busy. Collisions of this type may occur if (a) the channel selection algorithm erroneously select a busy channel, or (b) the selected channel becomes busy in the time interval between sensing and the beginning of the next superframe. The probability of this event depends, then, on the performance of the channel selection algorithm but also on the accuracy of the sensing process and the dynamics of primary user activity.
- Type 2 collision occurs when the channel is idle at the beginning of the next superframe but becomes busy during that superframe. The probability of this event depends on the dynamics of primary user activity.

In case of a collision, the piconet must undertake a recovery process, i.e., it must try to continue operation on another channel [22]; should that fail, the piconet has to undergo a full piconet formation process or rendezvous [23].

4.1. Random selection among idle channels

The yardstick against which we will measure the performance of both algorithms is the simple random selection algorithm. In this approach, the next working channel is selected through random choice from the set of channels that are currently assumed to be idle according to the information in the channel map. It is worth noting that the set of idle channels may be empty. This may be the actual state of the medium, or may be just the result of the inertia of the sensing process and the resulting errors [18]. In this case, the piconet may attempt recovery, or simply decide to repeat the piconet formation process; detailed analysis of both processes is beyond the scope of the present paper.

4.2. Selecting the most recently idle channel

This algorithm consists of selecting an idle channel that has most recently turned idle. The underlying assumption is that the channel that has most recently turned idle has the highest probability of remaining idle during the next superframe. If there are several such channels (a scenario which is more likely if the coordinator just records the superframe, but still possible even at finer time granularity), the coordinator will choose one of the channels at random.

The other algorithms attempt to select the channel which is most likely to remain idle throughout the next superframe. Selection must rely on estimated probability that the idle channels remain idle for the specified time interval. As the exact beginning of channel activity is not known, and neither is the exact probability distribution of channel active and idle times, we must use non-parametric estimation [25].

4.3. Selecting the most likely idle channel using histogram-based estimation

The second algorithm attempts to estimate the probability that the channels which are currently idle will remain idle throughout the next superframe. Since the coordinator can't know the exact probability distribution of channel idle times, non-parametric estimation is a preferred approach [26]. The simplest solution is based on a histogram of the durations of idle periods for each channel. The width of each bin is set to the shortest possible duration of the superframe, $h = s_{fm}$, while the number of bins is calculated as the longest channel idle time divided by s_{fm}. For each recorded idle-to-busy transition on a channel, the coordinator calculates t_i, the duration of the idle time on the channel, and increments $N_i(j)$, i.e., the value in bin j of the histogram for channel i ($t_i/h - 1 \leq j < t_i/h$). In this manner, the values in the bins measure the probability that the channel will remain idle for the time interval that corresponds to the appropriate bin.

The next-hop channel is selected as follows. For each channel i that is currently idle, the coordinator calculates the index k of the bin that corresponds to the time interval from the last time when the channel has turned idle until the end of the next superframe as $k_i = (\tau_i + s_f)/h$. Note that different channels may have turned idle at different times and their respective bins will differ. The (estimated) probability for the given channel is then obtained as

$$\hat{f}_i = \frac{N_i(k_i)}{\sum_k N_i(k)} \tag{1}$$

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

DOI: 10.1002/wcm

since the histogram values are not real probabilities – their sum is not one – and must be normalized to obtain actual probabilities. The coordinator then finds the next-hop channel C as the one with the maximum estimated probability in the bin k_i:

$$C = \arg\max_i \{\hat{f}_i\} \tag{2}$$

As before, in (the much less likely) case there are several such channels, the decision is made by random choice. Note that the channel selection will actually depend on the calculated duration of the next superframe, unlike in algorithm 1.

The accuracy of histogram-based estimation depends on many factors, including in no small measure the bin width h. Moreover, bins are not necessarily centered on the required value of channel idle time [25] and some bins may even be empty as the histogram is not a continuous function of the duration of channel idle time.

Given that the coordinator can't know the longest duration of channel idle time, the number of bins must be determined on the basis of observations, preferably many of them. The coordinator is still obliged to make decisions about the next-hop channel while these observations are being collected.

Also, if channel activity exhibits non-stationary behavior, older observations become progressively less relevant but they are still kept in the histogram, even though greater weight should be given to the more recent ones. This problem may be alleviated by restricting the number of observations from which the histogram is constructed. The required number n may be found through a tradeoff between accuracy (which, ideally, increases with n) and storage and computational requirements on the coordinator node (as n values need to be stored for each channel, and updated with each status change on the channel).

4.4. Selecting the most likely idle channel using kernel-based density estimation

Another approach to non-parametric estimation is the so-called kernel density estimation [25, 26]. In this scheme, for a number of observations $t_j, i = 1 \,..\, n$ of a random variable, the estimated pdf f at the point t can be obtained as

$$\hat{f}(t) = \frac{1}{n}\sum_{j=1}^{n} K_h(t - t_j) \tag{3}$$

where $K()$ is a so-called kernel, a standardized nonnegative weighting function that satisfies the conditions $\int K(z)dz = 1$, $\int zK(z)dz = 0$, and $\int z^2K(z)dz = \kappa_2 < +\infty$ [25].

Similar to the case of histogram-based estimation, the coordinator first calculates the time interval from the last time when the channel has turned idle until the end of the next superframe as $t = \tau + s_f$, calculates the pdf estimate using (3) and chooses the next-hop channel C by as the one with the maximum estimated probability :

$$C = \arg\max_i \{\hat{f}_i\} \tag{4}$$

Kernel-based estimation can be tailored to the characteristics of the process being observed and the desired accuracy by adjusting the number of observations n and the so called bandwidth or smoothing parameter h which determines the amount of smoothing introduced by the kernel function

$$K_h(z) := \frac{1}{h}K\left(\frac{z}{h}\right). \tag{5}$$

A number of kernels exist which differ in the choice of the function K as well as in the parameter h. Bandwidth selection is an important topic of its own and many algorithms have been described in the literature [27]. In our model we have set the bandwidth to the shortest superframe duration, $h = s_{fm}$; besides simplicity, this choice has the added advantage of allowing direct comparisons with the histogram-based approach where bin width of equal size is used.

Estimation accuracy is measured by the mean integrated square error or efficiency, defined as *MISE* $(\hat{f}) = E\left[\int(\hat{f}(x) - f(x))^2dx\right]$. It was shown [28] that the most efficient kernel – the one which achieves the lowest MISE for a given number of observations n – is the Epanechnikov kernel [29] of the form

$$K_{epa}(t) = \begin{cases} \frac{3}{4}\left(1 - \frac{1}{5}t^2\right)/\sqrt{5}, & |t| \leq \sqrt{5} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

Another very popular kernel is the Gaussian kernel [28] of the form

$$K_{bw}(t) = \begin{cases} \frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}t^2}, & |t| \leq 1 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

which achieves about 95.1% efficiency compared to the Epanechnikov kernel. The two kernels are shown in Fig. 2 in the range of independent variable t from -3 to 3, inclusive.

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

DOI: 10.1002/wcm

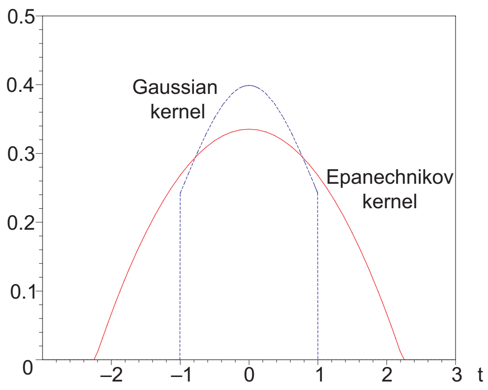


Fig. 2. Epanechnikov and Gaussian kernels.

5. Experimental evaluation

To evaluate the performance impact of different channel selection algorithms, we have built a simulator of the cognitive piconet using the object-oriented, Petri net-based simulation engine Artifex by RSoftDesign, Inc. [30]. The simulator implements the transmission tax-based MAC protocol with integrated sensing and the five channel selection algorithms: random selection, selection of the most recently idle channel, and selection of the channel most likely to remain idle using histogram- and two kernel-based estimation algorithms. The main performance indicators are the probability of type 1 and type 2 collisions, as defined above.

Unless otherwise note, the following parameter values were used:

- The piconet has 15 nodes and the coordinator.
- The working set of channels contains 15 channels.
- Superframe duration was fixed at 100 time units, 15 of which were set aside for administrative superframes.
- Each channel contains an independent primary source with random activity with Erlang-distributed ON (busy) and OFF (idle) intervals. The mean ratio of active period vs. total period (i.e., activity factor or duty cycle) is 0.5, while the mean period of primary user activity is 1000 time units.
- Each node has a traffic generator which generates Poisson-distributed single packet traffic at a rate of 0.002 packets per node per time unit, with each packet lasting 10 time units.

These values correspond to a loaded piconet operating at the offered load of about $15 \cdot 0.002 \cdot 10 \approx 0.3$, which is a non-negligible value, but still light enough to ensure that the network operates well below saturation.

Both histogram- and kernel-based algorithms use a list of $n = 100$ latest observations per channel each, with each new observation simply replacing the oldest one in the list. Both are, thus, well equipped to deal with nonstationarity in primary user activity. The former organizes the observations into a total of $n_b = 21$ bins of width $h_h = s_{fm} = 50$ time units, while the latter use Epanechnikov and Gaussian kernels with bandwidth $h_{kde} = s_{fm}$.

5.1. Homogeneous primary users

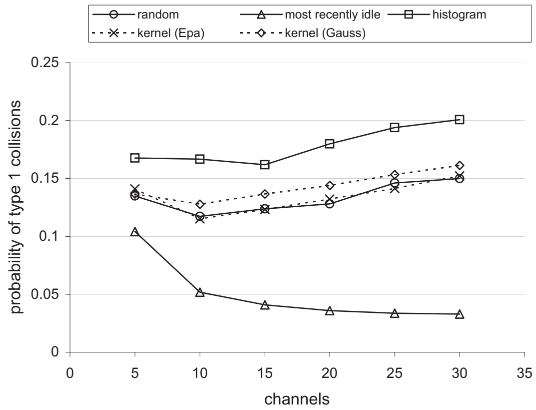
In our first experiment, we investigated the performance of the algorithms with Erlang-distributed busy and idle periods of primary sources. As all primary sources use the same probability distribution, we refer to this scenario as homogeneous. The results are shown in Fig. 3 for variable number of channels (top row) and primary user activity factor (bottom row); to facilitate comparison, both collision probabilities are shown using the same vertical scale.

As can be seen in Figs. 3(a) and 3(a), both collision probabilities are rather high, which may be attributed to high primary user activity factor of $\gamma = 0.5$ and Erlang-distributed idle and active intervals. As the number of channels increases, only the selection of most recently idle channel offers reduced probability of type 1 collisions on account of higher number of channels which increases the number of opportunities. All other algorithms exhibit either steady or slowly increasing probability of type 1 collisions, which can be explained as follows. Namely, more channels does mean more opportunities but it also means that sensing error will be higher because the number of nodes that perform sensing is constant. As the result, not all opportunities will be recognized as such by the coordinator, and the probability of type 1 collisions remains steady or slowly increases. However, once an idle channel is selected, the probability of type 2 collision depends only on the dynamics of primary user activity, which is why it is mostly independent of the number of channels.

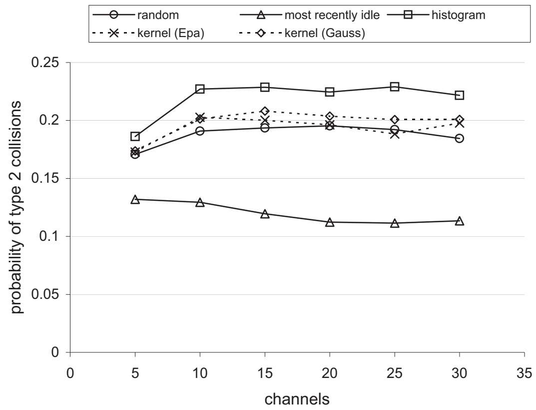
Similar observations may be made for the diagrams in Figs. 3(c) and 3(d) where the primary user activity factor, i.e., the ratio between the mean active period and the mean total period, is varied. Increasing activity factor translates into shorter idle periods, and working

Copyright © 0000 John Wiley & Sons, Ltd.

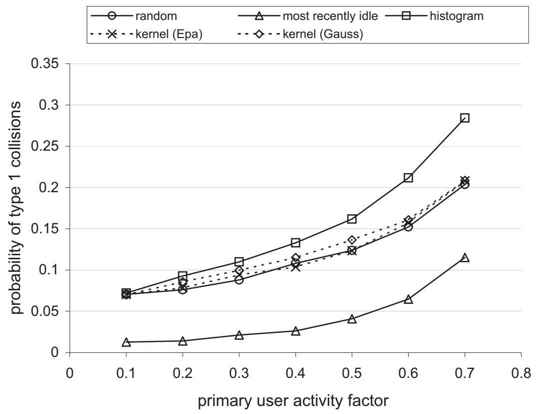
DOI: 10.1002/wcm



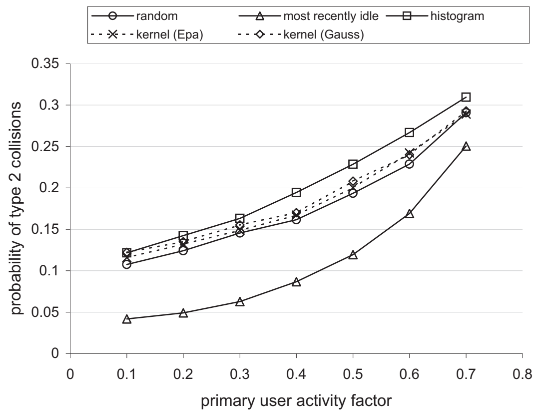
(a) Probability of type 1 collisions under variable number of primary channels.



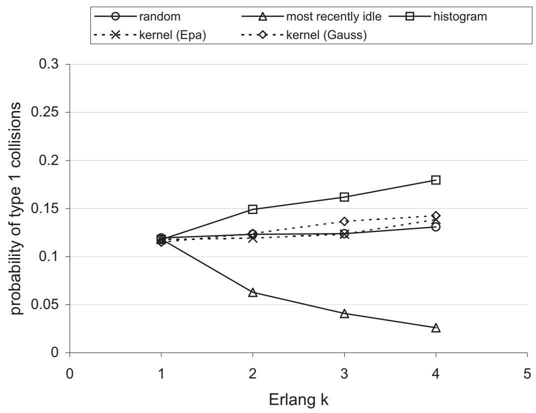
(b) Probability of type 2 collisions under variable number of primary channels.



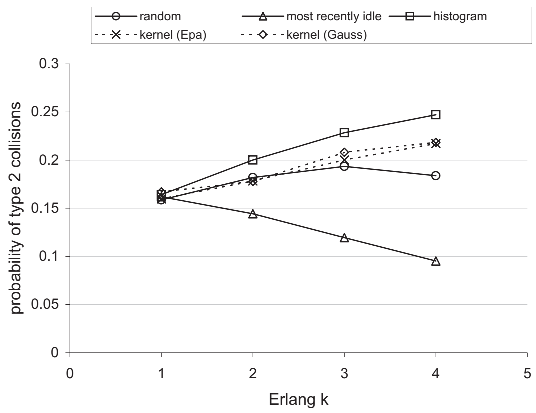
(c) Probability of type 1 collisions under variable primary user activity factor.



(d) Probability of type 2 collisions under variable primary user activity factor.



(e) Probability of type 1 collisions, variable Erlang k.

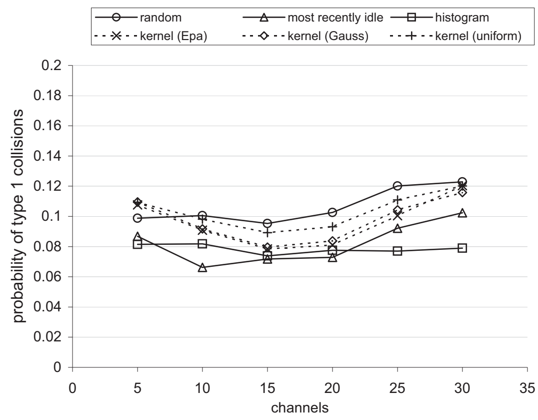


(f) Probability of type 2 collisions, variable Erlang k.

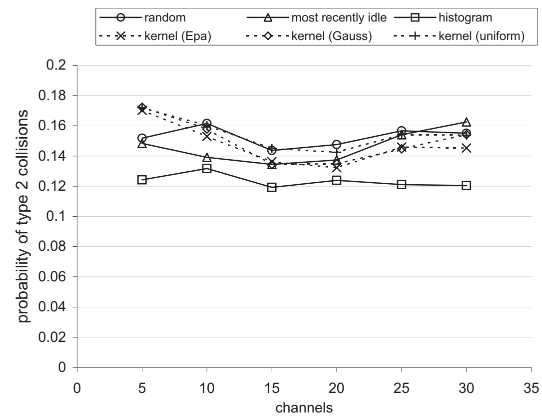
Fig. 3. Performance of working channel selection algorithms under homogeneous primary user activity. Mean period of primary user activity is 1000, primary user activity factor is 0.5, active and idle periods are Erlang-distributed with $k = 3$, and the number of channels is 15, unless explicitly designated as variable.

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

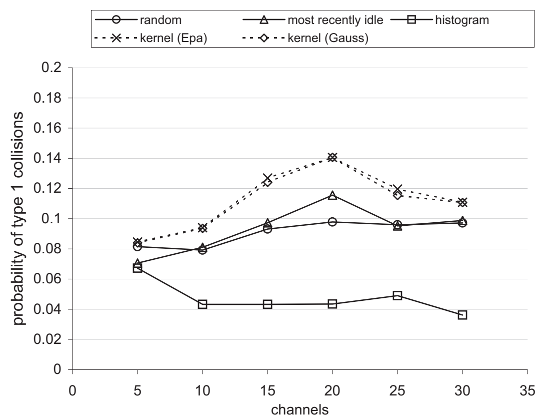
DOI: 10.1002/wcm



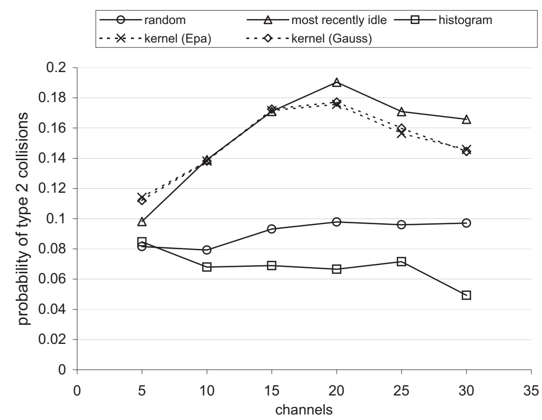
(a) Probability of type 1 collisions under randomly chosen primary user activity factor.



(b) Probability of type 2 collisions under randomly chosen primary user activity factor.



(c) Probability of type 1 collisions under randomly chosen primary user activity period and activity factor.



(d) Probability of type 2 collisions under randomly chosen primary user activity period and activity factor.

Fig. 4. Performance of working channel selection algorithms under heterogeneous primary user activity. Mean period of primary user activity is 1000, active and idle periods are Erlang-distributed with $k = 3$, and the number of channels is 15, unless explicitly designated as variable.

channel selection is inevitably degraded. Again, best results are obtained by the selection of most recently idle channel.

These observations are corroborated by the diagrams in Figs. 3(e) and 3(f). For Erlang $k = 1$ which corresponds to exponential and, consequently, memoryless distribution of primary user active and idle periods, all algorithms perform about the same. However, when k increases, the performance curves for different algorithms begin to differ; again, the only one which shows actual reduction in collision probability is the selection of most recently idle channels.

The deterioration of performance for histogram- and kernel-based algorithms under increasing Erlang k may be explained by the non-monotonic shape of the probability density function for Erlang distribution with $k > 1$. Namely, the presence of the peak may 'trick' those algorithms to give preference to a channel which is already idle for a time longer than the distribution peak. As the result, while the algorithms essentially perform correctly, the probability of type 1 collision – i.e., of hopping to a busy channel – still increases. On the other hand, selection of most recently idle channel does not suffer from this effect as it does not consider the shape of the probability density function.

Copyright © 0000 John Wiley & Sons, Ltd.

DOI: 10.1002/wcm

5.2. Heterogeneous primary users

In our second experiment, we have introduced heterogeneity through randomly varying the primary user activity factor in the range of 0.1 to 0.9; the actual value was changed periodically throughout the simulation runs. The resulting diagram for the probability of type 1 collisions is shown in Figs. 4(a) and 4(c), while those for the probability of type 2 collisions are shown in Figs. 4(b) and 4(d). The relative performance of algorithms is now rather different. In the first case, the differences between them are much smaller, although histogram-based estimation appears to be the best, esp. when the number of channels is high, closely followed by the selection of most recently idle channel.

We have also ran the simulations with both primary user activity period and primary user activity factor randomly chosen; the corresponding range of values was 500 to 3000 unit slots and 0.1. to 0.9, respectively. The results are shown in Figs. 4(c) and 4(d). As can be seen, histogram-based evaluation is clearly superior to other algorithms. This can be explained as follows. As the coordinator maintains a separate histogram for each channel, random perturbations are efficiently accommodated and selection of the channel most likely to be idle remains accurate. Limiting the number of observations used to construct the histogram helps maintain accuracy when the parameters of primary user activity change. Selection of most recently idle channel, on the other hand, does not account for the differences in the duration of idle periods and may easily choose a channel with very short idle time.

5.3. The impact of sensing error

In all previous experiments, the transmission tax was set to 4 which means that, for each packet or group of packets transmitted, the transmitting node must perform the sensing duty for four consecutive superframes. As the result, the coordinator receives a substantial number of sensing reports and the sensing error was kept low [18]. To investigate the sensitivity of channel selection algorithms to the magnitude of sensing error, we have repeated the experiments described above but in a piconet which consisted of five nodes with packet arrival rate of 0.001 packets per node per time unit, which results in a rather low load of about $\rho = 0.05$; moreover, the transmission tax was set to one. As the result, the number of sensing reports that arrive to the coordinator is considerably reduced in comparison with the previous experiments, due to the much lower traffic intensity and lower transmission tax.

The diagrams in Fig. 5 present the probability of type 1 and type 2 collisions obtained in this setup under variable number of primary channels and variable primary user activity factor, respectively. As can be seen, the sensing error will be much higher and overall performance is worse than in the case with low sensing error, Figs. 3 and 4, since the performance of working channel selection algorithms critically depends on the accuracy and timeliness of sensing information.

However, the deterioration is mostly confined to the higher values of probability of type 1 collisions, shown in the diagrams in the left-hand column of Fig. 5. As explained in Section 4, these collisions depend on both accuracy of sensing information and the dynamics of primary user activity. Lower accuracy of sensing information leads to erroneous decisions of the channel selection process, regardless of the algorithm used, and the probability that a busy channel is selected increases. Still, the increase is not too high: the probability of type 1 collisions is below 0.15 under histogram-based estimation in both diagrams.

At the same time, the probability of type 2 collisions, diagrams in the right-hand column of Fig. 5, is only marginally higher than in the case where sensing error is low, Fig. 3. This is not unexpected: namely, once the piconet selects an idle channel, any error in sensing information becomes irrelevant and a collision may occur only if the channel becomes busy with primary user activity.

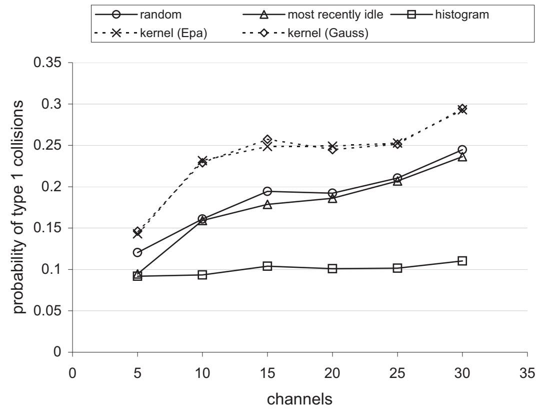
As before, histogram-based selection provides the best performance under both variable number of primary channels and variable parameter k of the Erlang-distributed active and idle periods of primary user activity. The advantage is more pronounced under heterogeneous primary user activity, shown in the diagrams in the bottom row of Fig. 5, but it is nevertheless noticeable under homogeneous primary user activity as well, as can be seen in the diagrams in the top row.

5.4. On estimation-based approaches to channel selection

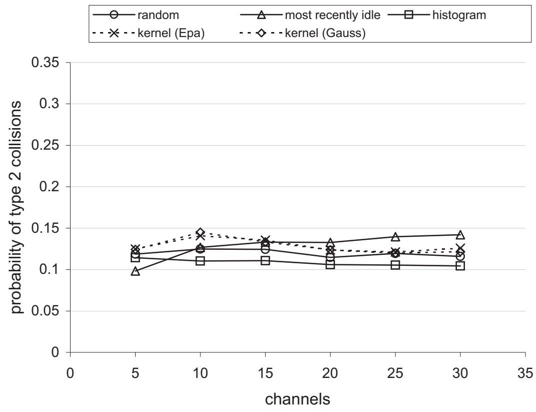
In particular, both kernel-based estimators are consistently inferior to histogram-based estimation. Experiments with the number of observations ranging from 20 to 200 and bandwidths ranging from $0.5s_{fm}$ to $2s_{fm}$ did not produce much improvement in this respect. The explanation seems to lie in the difference between the two estimation techniques.

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

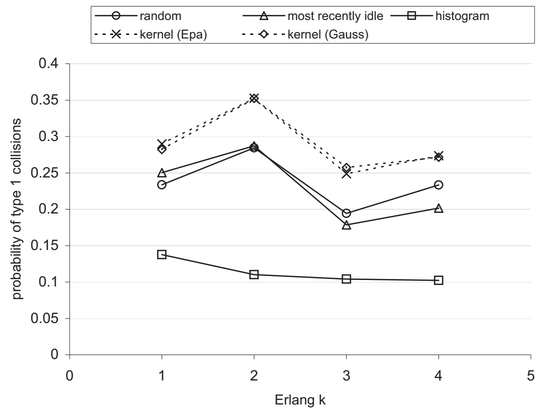
DOI: 10.1002/wcm



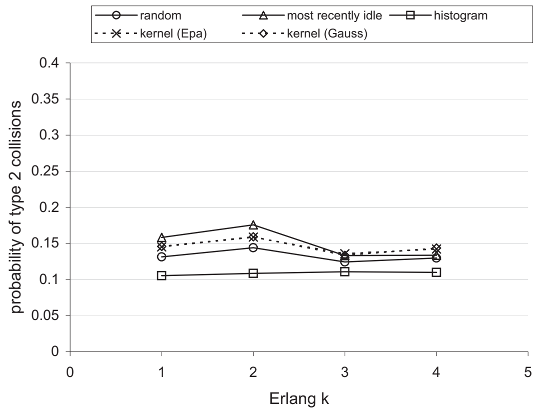
(a) Probability of type 1 collisions under homogeneous primary user activity, variable Erlang k factor of primary user activity distribution.



(b) Probability of type 2 collisions under homogeneous primary user activity, variable Erlang k factor of primary user activity distribution.



(c) Probability of type 1 collisions, under heterogeneous primary user activity, random primary user activity period and activity factor.



(d) Probability of type 2 collisions, under heterogeneous primary user activity, random primary user activity period and activity factor.

Fig. 5. Performance of working channel selection algorithms under high sensing error.

Namely, histogram-based estimation performs pooling of observations in appropriate bins, and the number of observations involved in the process is essentially unlimited.

On the other hand, kernel-based estimation attempts to achieve a similar effect through the use of the kernel function which tends to 'spread' the impact of each observation. The accuracy of this estimation is limited in practice by the need to keep track of individual observations, which is why the resulting error is higher than in the case of histogram-base estimation.

Furthermore, the actual times of channel status change (from active to idle and vice versa) are not really known due to sensing errors and the delay in conveying the results of sensing to the coordinator. The pooling which is 'naturally' provided by the histogram tends to absorb and suppress these errors which, in most cases, allows it to achieve superior accuracy. The diagrams in Fig. 5 confirm this hypothesis, as histogram-based channel selection provides good results despite the higher level of sensing errors.

6. Conclusions and future work

Our results confirm that knowledge of primary user activity patterns can reduce the probability that a cognitive piconet will experience collisions with primary user activity. We have compared the performance of different algorithms for working

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

DOI: 10.1002/wcm

channel selection. In case of homogeneous primary users, best results are obtained when the next working channel is selected among the channels that have most recently turned idle. In case of heterogeneous primary users, where mean activity periods and/or activity factors are different from one channel to the next, best results are obtained by a simple histogram-based estimation of the probability distribution of channel idle times. Histogram-based estimation is also least impacted by the accuracy of sensing information and it can easily be modified to adapt to nonstationarity of primary user activity patterns.

Our future work will focus on the design and performance evaluation of an adaptive channel selection approach whereby the coordinator would maintain historical information about the probability distributions of channel idle times, and make the decision to use one or the other selection algorithm on the basis of the shape of those probability distributions. Other possible improvements might involve taking into account channel active times as well, and also extending the algorithm to allow the selection of backup channels that are to be used in case of a collision.

References

1. Mišić J, Mišić VB, Khan MSI. On the selection of working channels in a channel-hopping cognitive PAN. *9th Int. Wireless Communications and Mobile Computing Conf. (IWCMC 2013)*, Cagliari, Sardinia, Italy, 2013.
2. Akyildiz IF, Lee WY, Vuran MC, Mohanty S. NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey. *Computer Networks* 2006; **50**:2127–2159.
3. Hu W, Willkomm D, Abusubaih M, Gross J, Vlantis G, Gerla M, Wolisz A. Dynamic frequency hopping communities for efficient IEEE 802.22 operation. *IEEE Communications Magazine* May 2007; **45**(5):80–87.
4. Mišić J, Mišić VB. On Bluetooth piconet traffic performance. *Proc. 13th IEEE Int. Symp. on Personal, Indoor and Mobile Radio Communications*, vol. 1, Lisbon, Portugal, 2002; 501–505.
5. Mišić J, Mišić VB. *Performance Modeling and Analysis of Bluetooth Networks: Network Formation, Polling, Scheduling, and Traffic Control*. CRC Press: Boca Raton, FL, 2005.
6. Geirhofer S, Tong L, Sadler BM. Dynamic spectrum access in WLAN channels: empirical model and its stochastic analysis. *Proc. first int. workshop on Technology and policy for accessing spectrum (TAPAS '06)*, 2006.
7. Mišić J, Mišić VB. Simple and efficient MAC for cognitive wireless personal area networks. *Proc. Global Telecommunications Conference GLOBECOM'09*, Honolulu, HI, 2009.
8. Mišić VB, Mišić J. Performance of a cognitive MAC protocol with transmission tax. *Proc. IEEE INFOCOM Workshop on Cognitive Wireless Communications and Networking*, San Diego, CA, 2010.
9. Marinho J, Monteiro E. Cognitive radio: survey on communication protocols, spectrum decision issues, and future research directions. *Wireless Networks Journal (WINET)* Feb 2012; **18**(2):147–164.
10. DARPA. The XG architectural framework. *Request for comments* Jul 2003.
11. DARPA. The XG vision. *Request for comments* Jan 2004.
12. Geirhofer S, Tong L, Sadler BM. Dynamic spectrum access in the time domain: Modeling and exploiting white space. *IEEE Communications Magazine* May 2007; **45**(5):66–72.
13. Plummer Jr A, Taghizadeh M, Biswas S. Bandwidth scavenging for device coexistence in pervasive computing systems. *Pervasive and Mobile Computing* 2012; .
14. Geirhofer S, Tong L, Sadler B. A measurement-based model for dynamic spectrum access in WLAN channels. *IEEE Military Communications Conference (MILCOM 2006)*, 2006.
15. Geirhofer S, Tong L, Sadler B. Cognitive medium access: Constraining interference based on experimental models. *IEEE J. on Selected Areas in Communications – Wireless Series* Jan 2008; **26**(1):95–105.
16. Harris FJ. On detecting white space spectra for spectral scavenging in cognitive radios. *Wireless Personal Communications* May 2008; **45**(3):325–342.
17. Ercan AO, Lee J, Pollin S, Rabaey J. A revenue enhancing Stackelberg game for owners in opportunistic spectrum access. *3rd IEEE Int'l Symp. on New Frontiers in Dynamic Spectrum Access Networks DySPAN 2008*, Chicago, IL, 2008.
18. Mišić J, Mišić VB. Performance of cooperative sensing at the MAC level: Error minimization through differential sensing. *IEEE Transactions on Vehicular Technology* Jun 2009; **58**(5):2457–2470.
19. Mišić J, Khojasteh H, Khan N, Mišić VB. Towards an efficient rendezvous protocol for a cognitive PAN. *IEEE International Conference on Communications (ICC'2012)*, Ottawa, ON, 2012.
20. Mišić J, Mišić VB. Dynamic parameter adjustment in a cognitive MAC protocol with transmission tax. *Int. J. Autonomous and Adaptive Communications Systems* 2011; **4**(4):398–411.
21. Mišić VB, Mišić J. Cognitive MAC protocol with transmission tax: Dynamically adjusting sensing and data performance. *Proc. Global Telecommunications Conference GLOBECOM'10*, Miami, FL, 2010.
22. Mišić J, Mišić VB. Recovery in channel-hopping cognitive networks under random primary user activity. *IEEE Transactions on Vehicular Technology* 2014 (to appear); .
23. Mišić J, Mišić VB. Probabilistic vs. sequence-based rendezvous in channel-hopping cognitive networks. *IEEE Transactions on Parallel and Distributed Systems* 2014 (to appear); .
24. Mišić J. Cooperative sensing at the MAC level in simple cognitive personal area networks. *IEEE J. on Selected Areas in Communications – Wireless Series* 2012; **30**(9):1711–1718.
25. Racine JS. Nonparametric econometrics: A primer. *Foundations and Trends in Econometrics* 2008; **3**(1):1–88.
26. Zucchini W. Applied smoothing techniques, part 1: Kernel density estimation Oct 2003.
27. Köhler M, Schindler A, Sperlich S. A review and comparison of bandwidth selection methods for kernel regression. *discussion paper 95*, Courant Research Centre, Georg-August-Universität, Göttingen, Germany Sep 2011.
28. Wand MP, Jones MC. *Kernel smoothing*. CRC Press, 1995.
29. Epanechnikov VA. Non-parametric estimation of a multivariate probability density. *Theory of Probability & Its Applications* 1969; **14**(1):153–158.
30. RSoft Design. *Artifex v.4.4.2*. RSoft Design Group, Inc.: Ossining, NY, 2003.

Copyright © 0000 John Wiley & Sons, Ltd.
Prepared using wcmauth.cls

DOI: 10.1002/wcm