Distributed Channel Allocation Using Kernel Density Estimation in Cognitive Radio Networks

M. Ejaz Ahmed, Joo Seuk Kim, Runkun Mao, Ju Bin Song, and Husheng Li

Typical channel allocation algorithms for secondary users do not include processes to reduce the frequency of switching from one channel to another caused by random interruptions by primary users, which results in high packet drops and delays. In this letter, with the purpose of decreasing the number of switches made between channels, we propose a nonparametric channel allocation algorithm that uses robust kernel density estimation to effectively schedule idle channel resources. Experiment and simulation results demonstrate that the proposed algorithm outperforms both random and parametric channel allocation algorithms in terms of throughput and packet drops.

Keywords: Cognitive radio, distributed channel allocation, robust kernel density estimation, primary user occupancy, idle-channel duration.

I. Introduction

One problem in cognitive radio networks is that secondary users often suffer from the stochastic arrival of primary users, resulting in packet collisions and delays [1]-[6]. These interruptions force the secondary user to switch to another available channel [7]. Recent studies have shown that the time a channel is inactive, which we will henceforth refer to as "idle-channel duration," is an important factor in decreasing switching and that a channel with a high probability of being idle may not always have long durations of being idle [3], [7].

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Using parametric methods, preexisting channel allocation algorithms apply the probability of inactivity in a channel allocated to a primary user to the functioning of a secondary user [6], [7]. Effective throughput for a secondary user is proportional to the durations of inactivity in its channels [3], [7] and can be maximized by allocating the channels with long remaining periods of inactivity to the secondary user. Parametric channel allocation schemes [3], [6], [7] have operated on the assumption that the secondary user knows the primary user's idle-channel durations based on a cumulative function or a probability density function (PDF). Such schemes produce serious discrepancies [5]-[7] because the predicted distribution of the durations that channels are idle is almost never correct for real world data. To the best of our knowledge, a distributed channel allocation scheme using a nonparametric estimation of a primary user's idle-channel durations has not been proposed to date.

In this letter, we propose a novel nonparametric channel allocation approach for distributed secondary users using robust kernel density estimation (RKDE), which uses practical knowledge regarding the durations channels will remain idle. Via network simulations and experiment measurements for WLAN primary users, we demonstrate that the proposed algorithm converges quickly and significantly outperforms random allocation and probability-based allocation algorithms in terms of packet drops, throughput, and the number of switches made between channels.

II. System Model

Estimation of idle-channel durations is fundamentally important for maximizing throughput in secondary user networks. We assume that the secondary user can perfectly sense primary user channels in a sensing period and is able to

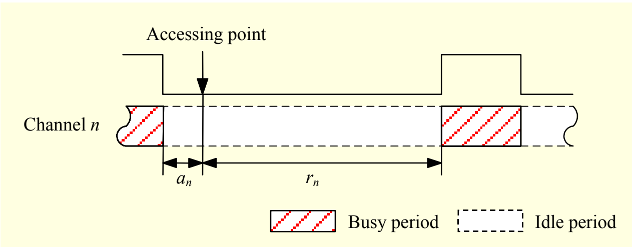

Fig. 1. Duration channel will remain inactive (r_n).

record idle states for N channels. For simplicity, we assume that the number of channels is identical to the number of primary users. Since the sensing results are used to model the distribution of the idle-channel durations, the secondary user can immediately generate a channel schedule. A data transmission point a_n is then located at any idle point of an available channel n following the access control period [5]-[7]. The packet data can only be transmitted during the remaining idle period from a_n. The time that a channel will remain inactive is represented by r_n, as shown in Fig. 1. Let t_n be the observed duration of a channel's inactivity, and $t_n=a_n+r_n$.

III. Proposed Nonparametric Channel Allocation

The proposed algorithm uses RKDE to reduce channel switching and to achieve lower packet drops and higher throughput than can be achieved by typical random channel allocation schemes. The secondary user must estimate the density of the idle-channel duration according to the measurements for a given sensing period, and those measurements may contain many outliers for such a short period. Thus, among the various nonparametric methods for learning densities, we have chosen the method proposed in [8] that estimates the underlying density robustly.

Within a given observation window m, the secondary user senses the idle channels of the primary users and records the durations those channels are idle. Let $T_n=\{t_{1n}, t_{2n}, \ldots, t_{mn}\}$ denote the set of observed idle-channel durations for channel n and $f_n(t_n)$ denote the distribution of idle-channel durations for the primary user's channel n within the observation window m. The kernel density estimation (KDE) of $f_n(t_n)$ is given by

$$f_{\mathrm{KDE}}\left(t_n\right)=\frac{1}{m}\sum_{i=1}^{m} k(t_n,t_{in}), \tag{1}$$

where $k(\cdot,\cdot)$ is the kernel function and t_{in} is the i-th observed idle-channel duration for channel n. A well-known example of a kernel is a Gaussian kernel [9]:

$$k\left(t_n,t_{in}\right)=\frac{1}{\left(2\pi h^2\right)^{1/2}}\exp\left(-\frac{\left(t_n-t_{in}\right)^2}{2h^2}\right), \tag{2}$$

where $h > 0$ is a smoothing parameter called "the bandwidth."

Algorithm 1. Proposed channel allocation.

1: **while** the secondary user has data to transmit **do**
2: initialize, calculate $t_{11},\ldots, t_{mn}$, and define N by sensing procedure;
3: **while** observation in running for N **do**
4: initialize $w_i^{(0)}$ for $i=1,\ldots, m$
5: **while** converges **do**
6: $f_n^{(j)} \leftarrow \sum_{i=1}^{m} w_i^{(j-1)}\Phi(t_{in})$;
7: $w_i^{(j-1)} \leftarrow \dfrac{\left(\left\|\Phi(t_{in})-f_n^{(j)}\right\|\right)/\left\|\Phi(t_{in})-f_n^{(j)}\right\|}{\sum_{l=1}^{m}\psi\left(\left\|\Phi(t_{\mathrm{ln}})-f_n^{(j)}\right\|\right)/\left\|\Phi(t_{\mathrm{ln}})-f_n^{(j)}\right\|}$;
8: $j\leftarrow j+1$;
9: **end while**
10: $f_{\mathrm{RKDE},\,n}(t_n)\leftarrow f_n^{(j)}(t_n)$;
11: $n\leftarrow n+1$;
12: **end while**
13: **if** there exist idle channels N **then**
14: $P(r_n\geq 0)$ using (5), $n\in N$;
15: select n satisfy max $P(r_n\geq 0)$;
16: start access control procedure using LCM MAC;
17: **if** the secondary user finish off transmission of packets **then**
18: break and go to step 22;
19: **else**
20: continue;
21: **end if**
22: **end while**

Let Φ be a feature map corresponding to the Gaussian kernel Hilbert space. The KDE can be considered as the sample mean of $\Phi(t_{in})$, or equivalently, a solution of

$$f_{\mathrm{KDE}}=\arg\min_{g}\sum_{i=1}^{m}\left\|g-\Phi\left(t_{in}\right)\right\|^2. \tag{3}$$

Due to the quadratic loss in (3), f_{KDE} is significantly affected by outliers. In [10], a robust loss ρ, such as Huber or Hampel's loss, is adopted instead of quadratic loss to yield a more robust density estimate. The RKDE is defined as

$$f_{\mathrm{RKDE}}=\arg\min_{g}\sum_{i=1}^{m}\rho\left(\left\|g-\Phi\left(t_{in}\right)\right\|\right) \tag{4}$$

and can be found using the kernelized iteratively reweighted least squares (IRWLS) algorithm (see lines 3 through 9 in Algorithm 1, where $\psi=\rho'$ and ρ' is the derivative function of ρ). It has been shown that the RKDE exhibits greater robustness than the standard KDE, in the presence of outliers. Under reasonable assumptions, the kernelized IRWLS algorithm converges [10].

When the secondary user has packet data to transmit, it will first estimate the set of instantaneously available channels N in the sensing period and determine the distribution of inactivity and the correlating durations using the previous observation results. In practice, the various available channels for the secondary user have different idle-channel durations. The best strategy for channel allocation is for the secondary user to choose the idle channel that will remain idle the longest, r_n, to reduce the frequency of the channel switching. The nonparametric density estimator generates the distribution of idle-channel durations, that is, $f_n(t_n)$, for channel n using RKDE within the observation window m. Given an, the probability of $r_n \geq 0$ is given by

$$P(r_n \geq 0) = P(t_n \geq a_n) = \int_{a_n}^{\infty} f_n(t_n)\, dt_n. \tag{5}$$

The secondary user then chooses an idle channel that has the largest $P(r_n \geq 0)$ on which to continue the access control procedure, as shown in Algorithm 1. After completing the proposed algorithm in a given sensing period, the secondary user starts the access control period. For network simulation, we apply the local coordination-based multichannel (LCM) MAC protocol [11].

IV. Experiment Results

For simplicity, we assume that all channels have the same frequency bandwidth B. Figure 2 shows the secondary user nodes, which are illustrated as small circles in the network. We measure idle/busy states of WLAN channels using a GNU Radio and Universal Software Radio Peripheral at Ferris Hall, University of Tennessee.

Figure 3 shows the estimated PDFs of the idle-channel durations for the measured WLAN channel, Channel 2 at 2,422 MHz, by comparing the standard KDE to the RKDE with Hampel's loss. We can see that RKDE eliminates the small bumps around 62 s and 78 s that seem to be caused by outlying measurements. In experiments, there are N=6 primary user channels and the observation window is m=3,125 samples, each 500 s long with a 160 ms sensing period. The convergence time results of RKDE are calculated using the idle states of each measured channel for 500 s. For example, Channel 1 is infrequently used out of six channels, that is, the expectation of t_1, $E[t_1]$, is 12.5867 s, and it quickly converges within 0.041267 s, while $E[t_5]$ is 1.4125 s for Channel 5 and results in a higher convergence time with 0.466029 s due to the higher kernel matrix size of idle-channel durations.

Regarding cumulative channel switching, the proposed algorithm outperforms random allocation and probability-based allocation algorithms, as shown in Fig. 4.

An NS-2 network simulator is used to construct a network topology with a 1 km^2 area for secondary users, as shown in Fig. 2. We consider flow 1 to be from node 1 to node 15 and flow 2 to be from node 5 to node 11 in the network. We suppose that the secondary users have the same maximum transmission distance and interference range of 250 m. There

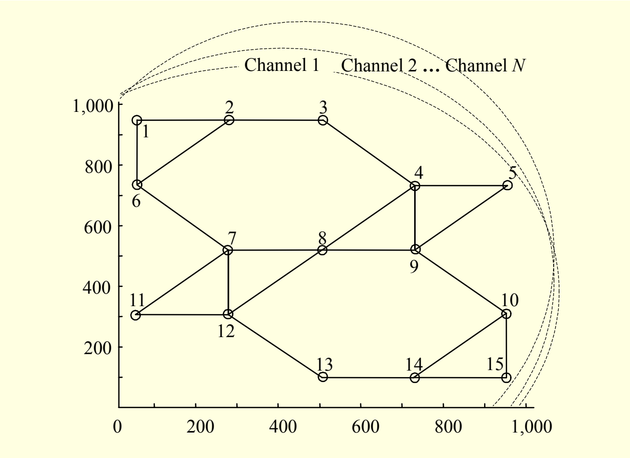

Fig. 2. Distributed cognitive radio network over 1 km^2 area.

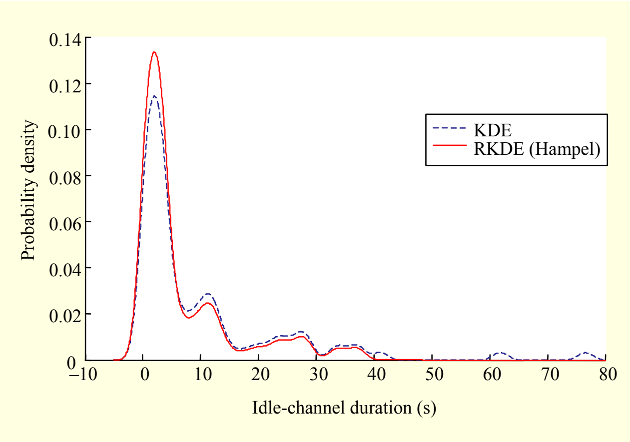

Fig. 3. PDFs of measured idle durations for Channel 2 ($E[t_2]$=9.8796 s).

are 22 active links, with the restriction of the transmission distance in the network. Each link has the same frequency bandwidth, which is 11 MHz. In the NS-2 simulation, we apply the LCM MAC protocol [11], which supports multiple channel scenarios with one radio interface and uses an ad hoc on-demand distance vector as the routing protocol for the distributed network setup. The packet length transmitted between secondary users is typically 1 kB/s, and the simulation period is 500 s.

Figure 5 shows the performance results for instantaneous packet drops and throughputs that are measured for two simultaneous flows in the network shown in Fig. 2. We compare the performance of our proposed algorithm with that of the parametric channel allocation method based on the probability that a channel is idle, which involves [5]-[7] and random channel allocation. When the number of flows is small, the proposed channel allocation algorithm provides somewhat better performance than both the idle-probability-based algorithm and the random channel allocation algorithm. As the

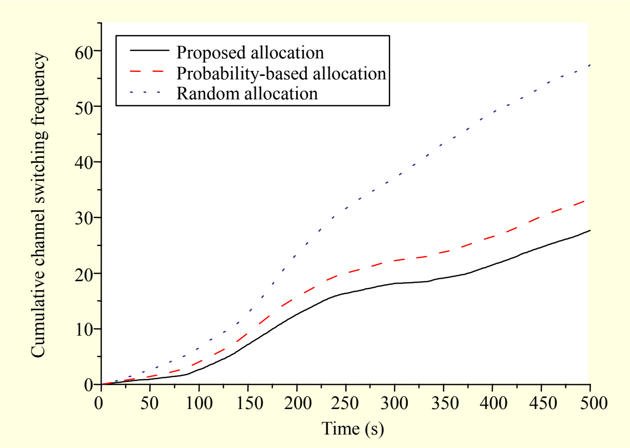

Fig. 4. Cumulative channel switching (switches per second).

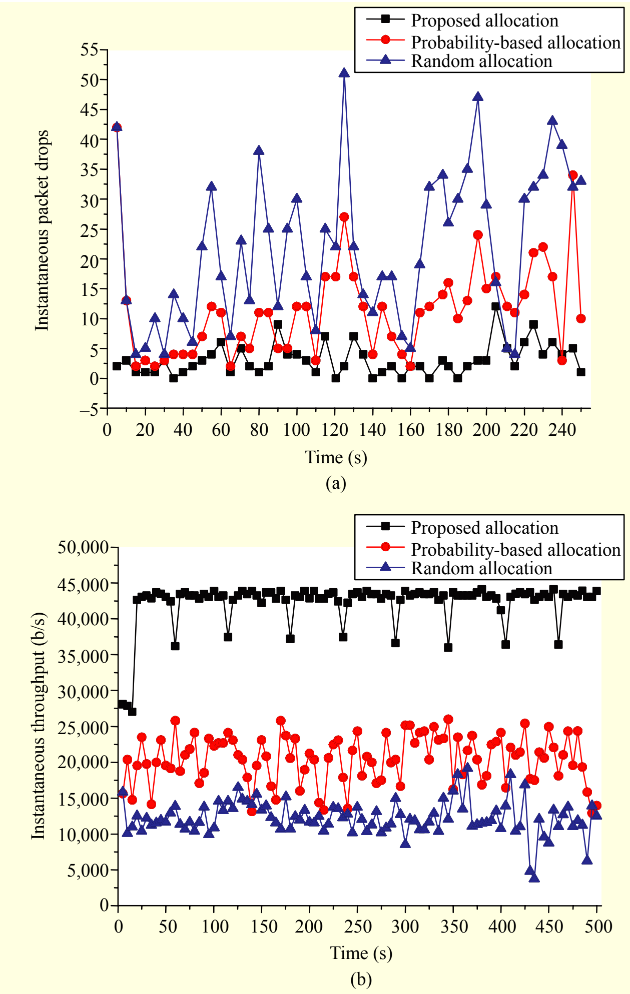

Fig. 5. Instantaneous (a) packet drops and (b) throughput.

number of flows increases, our proposed algorithm outperforms the others. Compared to the idle-probability-based algorithm, on average, our proposed algorithm increases throughput and decreases packet drops.

V. Conclusion

We proposed a nonparametric channel allocation algorithm and verified that it outperforms both random and parametric channel allocation algorithms in terms of system throughput and packet drops by reducing channel switching in distributed cognitive radio networks. The proposed algorithm can serve delay sensitive applications, which are the ultimate data to be transmitted in distributed cognitive radio networks. The proposed algorithm is also able to provide high throughput and low packet drops when primary user channels are densely utilized. An access protocol could be a future research topic.

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