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Exploiting Historical Spectrum Occupancy Information for Adaptive Spectrum Sensing

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***Abstract*—At present wireless devices are able to select their working frequency only to a limited extend although several measurements have shown that the current spectrum regulations are inefficient. Dynamic spectrum access is seen as a promising approach that might solve this inefficiency. Spectrum sensing is one of the main tasks involved. We compare in this paper four methods to efficiently sense the current spectrum based on the spectrum occupancy information statistics. The parameters of all methods are extracted from spectrum occupancy data gathered during an extensive measurement campaign. We show that the usage of historical information considerably improves the spectrum sensing process. We also show that the modelling of the periodic behaviour of the licensed signals leads to negligible performance enhancements because only very few periods shorter than several minutes can be found within 20 MHz-6 GHz.**

I. Introduction

The flexibility and adaptiveness of wireless devices has been significantly improved during the recent years. Meanwhile the involved system complexity increased considerably. In the Cognitive Radio paradigm [1], [2], devices are aware of their surroundings and capable of learning in order to manage this system complexity. The working frequency and the used bandwidth are two of the main working parameters that cognitive radios could dynamically optimize in order to adapt to the environment variations [3]. These proposals are motivated by several measurement results (e.g., [4]–[7]) that showed the inefficiency of the current mostly static spectrum regulations. All these measurement campaigns have found significant amount of unused spectrum (e.g., 80 % in GSM bands in the case of normal usage [7]). Such vacancies were found despite of the fact that most of the spectrum is licensed. This has led many authors to argue that the current spectrum regulation is highly suboptimal. The Dynamic Spectrum Access (DSA) vision tries to solve this problem and improve the efficiency of spectrum usage. So called secondary users look for unused spectrum bands and opportunistically use those in the case they do not sense any licensed signal (also sometimes referred as primary user signal, [3]).

The search for unused spectrum is based on various sensing techniques, see for instance, [8] and the references therein. Independently of the applied sensing method the spectrum sensing component has to choose among a pre-determined set of subbands the specific subband that should be sensed. The larger the covered bandwidth, the higher the energy consumption of the sensing system [9]. Therefore, systems that sense multiple Gigahertz bandwidth are realistic for spectrum sensing infrastructure but less reasonable for mobile devices.

In order to simplify the implementation complexity the authors propose in [10] to delay the next sensing action in the case a channel is found to be occupied. This dynamic adaptation of the time resolution of spectrum sensing lowers the amount of scanned occupied spectrum per time interval and thus improves the efficiency of the system. However, the performance of this method has not been evaluated for measured data and it is not clear if such theoretical gains can be achieved in practice. In addition to the duty cycle [4], [7], [10], several researchers have proposed to exploit deterministic behaviour and periodicities in spectrum occupancy data to more efficiently sense and later on select unoccupied channels for opportunistic use (see e.g., [11]–[13]).

In this paper we present a detailed comparison of adaptive spectrum sensing techniques and their evaluation based on measurement traces taken from an extensive spectrum occupancy study. We will present a periodicity analysis of our measurement data and show that most of the detected periods are rather long, i.e. of order of hours or higher and only few bands with periods in the order of tens of seconds or few minutes can be identified. One of the evaluated algorithms for adaptive sensing uses information about periods present in the primary user signals but our comparison shows that the number and the strength of exploitable shorter periods is rarely high enough to lead to any not negligible performance gain.

The remainder of this paper is structured as follows. In section II we shortly introduce our measurement setup. In section III we describe our periodicity analysis methodology and present some results. We continue in section IV with a more detailed explanation of adaptive spectrum sensing and explain four different algorithms. We present results of their comparison in section V and conclude the paper in section VI.

II. Measurement setup

The analysis presented in this paper is based on real data that was taken during an extensive spectrum occupancy measurement campaign (see [14] for details). The equipment was located on the roof of the International School Maastricht, Maastricht, Netherlands.

The measurement setup is based on an Agilent E4440A high performance spectrum analyser, which is remote controlled via Ethernet by a standard laptop. The detailed measurement

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Center frequency	Band 1: 770 MHz Band 2: 2250 MHz Band 3: 3750 MHz Band 4: 5250 MHz
Frequency span	1500 MHz
Resolution bandwidth	200 kHz
Number of measurement points	8192
Sweep time	1 s
Measurement duration	About 7 days per subband
Detector type	Average detector
Preamplifier	Up to 3 GHz: 28 dB gain

TABLE I
SPECTRUM ANALYSER CONFIGURATION USED THROUGHOUT THE MEASUREMENTS [14].

parameters are listed in table I. The selected resolution bandwidth of 200 kHz is a compromise between the frequency resolution and the maximum span which can be measured in one sweep. As one of the main goals of the reported measurement campaign was to investigate the spectrum occupancy behaviour over longer time periods we selected a lower frequency resolution in order to limit the required number of separate measurements. The results presented here are limited to the first two subbands because most real-life systems that might show periodicities are working in the frequency range between 20 MHz and 3 GHz. A more detailed description of the measurement setup and further measurement results were reported in [14].

III. Periodicities in spectrum occupancy data

In this section we shall describe our approach for periodicity analysis and present some results on the number of periodicities that can be found in the subset of our measurement data.

A. Analysis methodology

The spectral analysis is commonly used to analyse and find out periodic signals. We chose the classical Fourier transform after also comparing it against time-domain approaches such as [15] or more sophisticated spectral estimation techniques such as [16]. These approaches do not provide better performance for our sort of data but are computationally much more complex. Nevertheless, we are also aware of the limitations of the Fourier transform when non-linear time-series patterns should be detected. However, as we aim at exploiting periodic behaviour for more efficient spectrum sensing we do not consider more sophisticated approaches that are able to identify such complicated patterns.

For the spectral analysis we interpret all measurements taken at a single frequency bin during the complete measurement duration as a time series assuming that the measured signal is stationary over the whole duration. First, we normalize the data and estimate the power spectral density for each time series measured in a single 200 kHz channel. In this case we use the Fourier transform of the autocorrelation function instead of the Fourier transform of the time series itself because uncorrelated noise components of the measured signal will not contribute to the autocorrelation at higher lags so that the present periodicities are slightly better estimated in the case of the autocorrelation function.

During the measurement campaign, the deployed spectrum analyser performs auto-calibration actions on aperiodic time basis that are triggered by changes in the environment such as, e.g., temperature variations. These realignments lead to the fact that the inter-sample time is not perfectly constant. However, as the difference to a perfect inter-sample time is rather small we do not correct this. Additionally, it also enables the system to detect periodicities which are multiples of the sampling frequency because the signal phase will change from one sample to another. A further consequence is that perfectly periodic signals do not lead to a single peak in the Fourier transform but contribute to multiple Fourier coefficients around a local maximum.

A very high Fourier coefficient documents that the analysed time series has a strong periodic component with the corresponding frequency. As we are also interested in signals that show multiple periodicities, we do not only select the strongest Fourier coefficient but save the 15 strongest ones for each frequency bin. The value of 15 was chosen after comparing different values. It ensures that all major maxima are considered and not too many coefficients are selected that do not represent a noticeable periodicity. In order to avoid that we select 15 coefficients around the global maximum (typically one day period) but miss all or most of the further local maxima, we apply a windowing technique and do not choose additional coefficients around an already selected coefficient. Hence, we reduce the impact of the sampling period jitter. The window size is proportional to the frequency represented by a Fourier coefficient. Additionally, we apply a minimum window size and do not consider periods longer than 60 % of the whole measurement duration of about seven days since we are interested in finding periods of few minutes. The lower limit for considered periods is determined by the average inter-sample time of 1.8 sec, which consists of the configured sweep time of 1 sec, further delay caused by data transmission between the spectrum analyser and the laptop, and the mentioned instrument realignments. The rather high inter-sample time leads to the fact that very short periods such as, e.g., the TV blanking interval cannot be detected. These periodicities are not of interest in our approach as we expect that it is significantly more complex to exploit such very short periods in commercial products because of the high requirements on synchronization and sensing speed.

B. Results on the periodicities

Figure 1 shows an overview of all the detected periodicities for the measurement data comprised within subband 1 in the Netherlands. Each dot represents one Fourier coefficient and its size is proportional to its value (we applied an upper limit to its size if its value was too large). The y-axes has a logarithmic scale and represents the duration of a full period. Horizontal lines that can be identified in the plots show that the same period is present in the time series at numerous

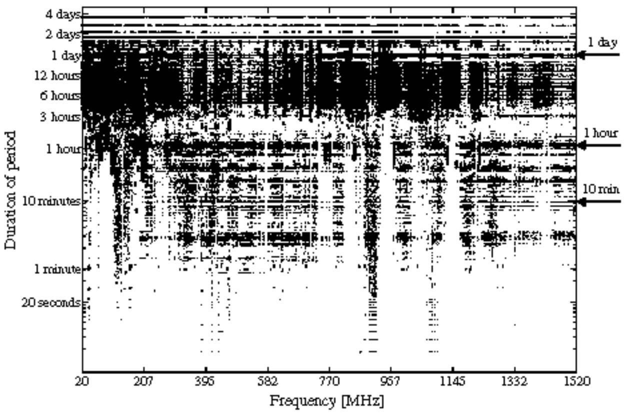

Fig. 1. Periods represented by the 15 strongest FFT coefficients for each frequency bin (subband 1: 20 MHz - 1520 MHz).

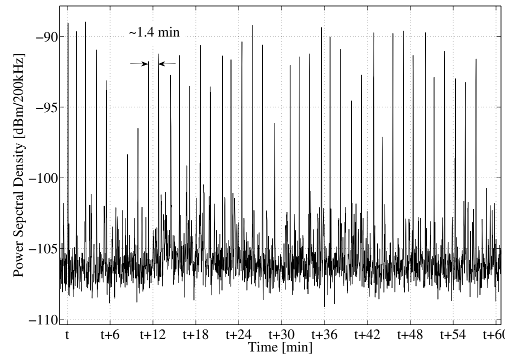

Fig. 2. Extract of the time series of about one hour length measured at 465.7 MHz.

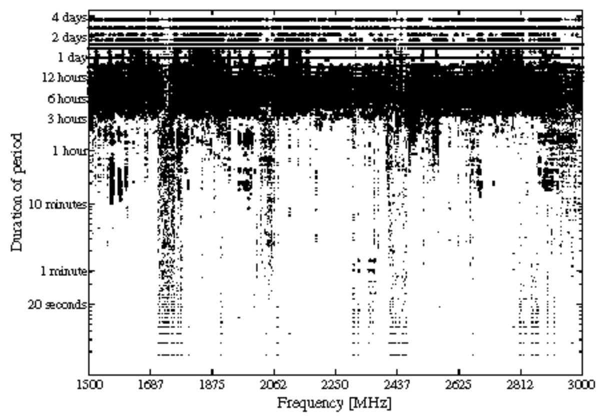

Fig. 3. Periods represented by the 15 strongest FFT coefficients for each frequency bin (subband 2: 1.5 GHz - 3 GHz).

different frequencies[1]. Such lines are present, e.g., at periods of 10 min, 1 hour or also at 1 day. Especially the period of one day leads to high Fourier coefficients for nearly all frequencies. Another result is that services seldom show periods below five minutes. Furthermore, few of those services can be identified within specific bands such as the GSM-bands. However, the corresponding Fourier coefficients are rather small indicating that these short periods are not strong.

Figure 2 shows an extract of the time series measured at 465.7 MHz, which is one of the rare examples that shows a strong short period[2], which is about 1.4 min long. In contrast, very long periods such as 24 h are caused by a general trend which is also present in free bands because man-made noise level is higher during daytime than during the night time.

Figure 3 shows the periodicities found in the second subband (1.5-3 GHz). Similarly to band one, only very few periods shorter than ten minutes are found. Additionally, some major services can be identified by the presence of these short periods. The GSM1800 uplink around 1700-1800 MHz and the UMTS downlink around 2000-2100 MHz both do not exhibit strong periodicities overall but their shorter periods are even weaker. Also the ISM-band at 2.4 GHz and some radionavigation signals used in aviation around 2.8 GHz are unveiled by the presence of these shorter periods. Additionally, the same statement as for subband 1 can be made: The same periodicities are present in numerous signals so that several horizontal lines are displayed.

[1]The applied windowing technique might cause that the same Fourier coefficients are chosen because the directly adjacent coefficients to a local maximum are not selected. However, the spectrum still has to look very similar to lead to the situation that nearly the same coefficients are selected and that also the size of the plotted dots is often very similar.

[2]The periodicity is most probably caused by the transmit pattern of a pager service. However, such services use only 20 kHz of bandwidth and the resolution bandwidth of 200 kHz may cover multiple services licensed for adjacent narrowband channels.

IV. Adaptive Spectrum Sensing

The primary goal of the adaptive spectrum sensing is to lower the amount of spectrum to be sensed based on the fact that spectrum that was previously busy is very likely busy at present [9]. Therefore, a good strategy for adaptive spectrum sensing consists in identifying those channels with the highest probability of being free. In this paper we compare four different such methods. All of them are based on a set of probabilities that describe a binary occupancy state machine for each single channel but use different historical information. The whole measurement trace of more than 330000 samples ($\approx$7 days) per time series was evaluated in order to determine the respective probabilities for each channel.

1) Reference case: No historical information available to decide if the channel will be free or not: The reference technique does not use any historical information and thus cannot select channels, which were found to possess an especially high probability of being free. Instead it randomly selects the channels to be sensed next. The probability of selecting a channel which will be free is thus $p_{ref}(free) = \mathbb{E}(1 - DC_i)$, where $p_{ref}(free)$ is the probability that the channel selected by the reference method will be free, DC_i is the duty cycle as measured at channel i and $\mathbb{E}(1-DC_i)$ is one minus the average duty cycle over all channels.

2) Duty cycle based method: The duty cycle based method will always choose the channel which had the lowest duty cycle during the period which is covered by the available historical data $p_{DC}(free) = 1 - \min(DC_i)$.

3) First order Markov chain: The inter-sample time of our measurement traces is about 1.8 sec. We assume that most connection durations are longer than such a short period. Therefore, the probability that the channel state switches between state *free* and state *occupied* will be much lower than the probability to stay in the current state. Since we consider in this paper the state of the previous sample only, such a system can be represented using a first order Markov chain. We determine the probability $\rho = p_{Markov}(occupied_t|free_{t-1})$ to switch from state *free* at time index $t-1$ to state *occupied* at time index t from our measurement traces. Afterwards, we combine it with the duty cycle information to $p_{Markov}(free_t|occupied_{t-1}) = \rho \cdot (1-DC)/DC$.

The probability $p_{Markov}(free, t|t-1, i)$ of a channel i to be free at the time index t now depends on the former state of the channel:

$$p_{Markov}(free, t|t-1, i) = \begin{cases} 1-\rho_i & \text{if } state_i(t-1) \text{ is } free \\ \frac{\rho_i \cdot (1-DC_i)}{DC_i} & \text{if } state_i(t-1) \text{ is } occupied \end{cases}$$

Therefore, we select the best channel at each time index and average over all considered time indices (10000 samples $\approx$ first five hours of our measurement): $p_{Markov}(free) = \mathbb{E}_t[\max_i(p_{Markov}(free, t|t-1, i))]$.

4) Method exploiting periodicity: Although we already saw that shorter periods were rarely detected in our measurement data we evaluate the benefit that could be reached when adapting the sensing based on this information. The model is similar to the Markov-case except that we consider a time shift of τ sample durations instead of using the knowledge of the previous sample. We determine τ as the period below five minutes with the highest Fourier coefficient. If such a period is not present for some frequency bins, we base our probability calculation for these frequencies only on the duty cycle.

V. Results

The four aforementioned strategies describe the probabilities that a single selected channel will be free. In the next step we evaluate the probability that a bandwidth > 200 kHz will be sensed free. In this context we differentiate two cases. In the first case the sensed bandwidth does not have to be consecutive so that either the found free channels could be used by different transmissions or certain intermediate channels have to be avoided by, e.g., nulling the respective subcarriers in a multi-carrier system [17]. A possible usage scenario could also be based on a centralized architecture with a central instance allocating the free channels to different secondary users. The second case requires that the free bandwidth is consecutively

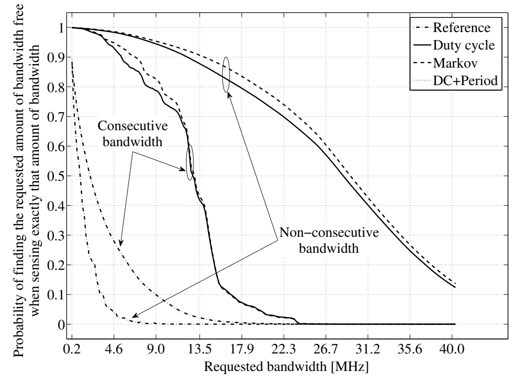

Fig. 4. Comparison of the four methods for adaptive spectrum sensing for the UMTS uplink band.

useable in a secondary fashion so that also single carrier systems could benefit from it.

We determined the binary state (*free* or *occupied*) of the sample data using energy detection. The required occupancy decision threshold is -107 dBm such as proposed for 200 kHz channels in the spectrum sensing requirements summary of the IEEE 802.22 standardisation group [18]. Using this threshold we calculate the duty cycle as the time fraction during which the energy detection resulted in state *occupied* and determine the further probabilities for the Markov chain- and the period-based models.

A. Analysis of the UMTS uplink band

As a first example we investigate the UMTS uplink band, which is allocated to 1899.9-1979.7 MHz in the Netherlands. Figure 4 shows two groups of lines, one for the case of non-consecutive and one for the case of consecutive bandwidth. We evaluated the probability to find up to 40 MHz free bandwidth in the case exactly the same amount of bandwidth is sensed. This means that if the adaptive sensing applies one of the described four methods, it will find the requested free bandwidth without sensing a single occupied channel with the depicted probability. If further channels are sensed the probability of finding free bands will obviously increase.

The graphs for the reference method start at the value for a single channel, which is one minus the average duty cycle. This probability is rather high showing that the UMTS uplink band was not highly utilized during our measurement campaign. When comparing the two lines for the reference case it is surprising that the probability is higher in case of consecutive bandwidth. This is against the intuition because a continuous block of free bandwidth is expected to appear more seldom. However, although the best combination of certain channels leads to a higher probability of finding free bandwidth, the cases of consecutive bandwidth lead on average to a higher probability of success. This could, e.g., be caused by the wideband nature of WCDMA signals.

If historical information is used the probability of finding free spectrum can considerably be increased. When looking

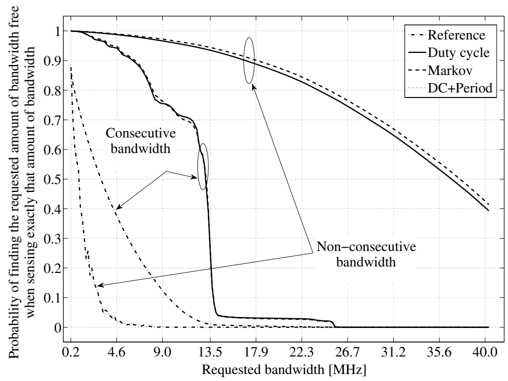

Fig. 5. Comparison of the four methods for adaptive spectrum sensing for the GSM1800 uplink band.

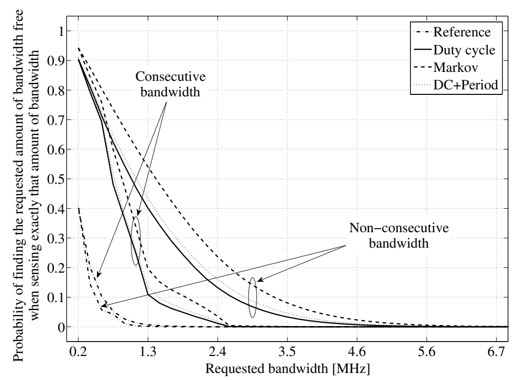

Fig. 6. Comparison of the four methods for adaptive spectrum sensing for the GSM uplink band.

for consecutive bandwidth of 9 MHz the probability can be increased by about 70 %. The differences between the methods benefitting from historical information are rather small, e.g., the curves for the approach using only duty cycle information and the approach using periodicity information cannot be clearly distinguished. The periodicity analysis does result in nearly no periods below five minutes for the UMTS uplink band so that only very few periods can be exploited for the adaptive sensing. The Markov model is slightly better than the purely duty cycle based approach so that our expectation that most transmissions last longer than our inter-sample time is correct.

B. Analysis of the GSM1800 uplink band

The next example is the GSM1800 uplink band which is allocated to 1710.1-1784.9 MHz. Figure 5 shows a similar plot as discussed for the UMTS uplink band. The clear drop in probability of finding consecutive bandwidth around 13.5 MHz in the cases where historical information is used shows that this seems to be the largest consecutive amount of spectrum, that was free for a significant amount of our measurement time. The duty cycle of single selected GSM1800 channels, which also use 200 kHz bandwidth, is rather high although on average this band is not highly utilized. However, when investigating the distance between the few highly utilized channels it can be confirmed that the largest amount of consecutive spectrum that is free with a high probability is about 13.5 MHz wide. Thus, the approaches using historical information can reliably find such opportunities. The existence of multiple such free bands of few MHz width leads again to the situation that the reference model performs better for consecutive bandwidth.

The number of periods below five minutes that were found during the periodicity analysis for this band is significantly higher compared to the UMTS uplink band. However, most of these periods were found for bands with low duty cycles so that the probabilities could hardly be further improved. Therefore, the advantage of the period-based approach is again too small to be visible and can be neglected.

C. Analysis of the GSM uplink band

The GSM uplink is regulated to work at 880.1-913.9 MHz in the Netherlands. Figure 6 shows the already discussed type of plot for this third example. The probability of finding a single free channel in the reference case of about 42 %, which corresponds to the average duty cycle in this band throughout the whole measurement, shows that this band is used more regularly than the other two examples. The higher utilization can also be seen from the fact, that the maximum consecutive bandwidth which is found with 50 % probability with the best adaptive technique is only about 1.1 MHz. However, the duty cycle of 42 % in the GSM band still shows that spectrum opportunities are present, which can be explained by the fact that GSM networks are designed to exhibit high efficiency during the peak hours with the certain call blocking probability and the duty cycle discussed here includes all measured data. Additionally, GSM is based on a cellular structure that implies certain frequency reuse patterns [19].

The periodicity analysis found several periodicities within this band and the high duty cycles lead also to the situation that the method based on duty cycle only performs worse than for the other spectrum bands. Nevertheless, the benefit that can be achieved when exploiting information about periods present in the spectrum usage data is only in the order of a couple of percent. Additionally, the Markov-model still leads to superior performance.

D. Comments on further examples

Another popular spectrum band is the ISM-band[3] between 2.4 and 2.5 GHz although we consider only the part up to 2.4835 GHz because the most popular ISM-band systems WLANs and Bluetooth are limited to this subband. The results are similar to what was discussed for the other bands. Exploitable periods are mostly detected for frequencies with low duty cycles so that the duty cycle based approach performs already very well. WLANs are very wideband systems so that also for this band the spectrum opportunities are not very

[3]Industrial, scientific, and medical.

fragmented. A free 20 MHz channel can be found with nearly 50 % probability when using historical information.

When investigating the cellular downlink bands we have to differentiate the two major multiple access schemes used for cellular systems. UMTS is based on CDMA and thus base stations continuously send management information using the broadcast code. Thus, as long as a base station is active in the surrounding of the measurement location it will lead to very high duty cycles. As a consequence no periods below five minutes were found in this band. However, not all licensed UMTS channels were used at our measurement location so that few 5 MHz channels were free. The GSM downlink bands were used with duty cycles above 80 % when applying energy detection based on the threshold -107 dBm. However, also in these cases the historical information can greatly improve the spectrum sensing although simply the amount of available free spectrum is strictly limited.

VI. Conclusion

In this paper we reported about the analysis of adaptive sensing techniques. We have investigated data from an extensive measurement campaign and thus all presented results are based on real-life measurements. We described an approach how to determine the most dominant periodicities in such spectrum usage data and showed that rarely periods shorter than five to ten minutes can be found. Additionally, the results show that the period of 24 h is identifiable nearly for all frequencies.

Based on the measurement data we have proposed four methods for selecting the channels that should be sensed first such that the probability that they are free is high. In addition to the reference scheme based on random selection we exploited historical information in form of the duty cycle and present periods. Additionally, we used a first order Markov chain to model the spectrum occupancy. As expected based on the low number of found periods the benefit achievable by exploiting periodicity information is strictly limited. Moreover, the Markov chain is superior in most cases and also the purely duty cycle based model performs very well. As the duty cycle based model performs especially well for rarely used bands, which are also the most attractive ones for DSA capable systems, more complex models are rarely required.

The advantage of adaptive sensing based on historical information is significant and can increase the probability that the bandwidth chosen for sensing is free by up to 70 % compared to a random sensing scheme. Thus the overhead required to provide enough memory and computational power to implement such an adaptive scheme is well spent because the adaptive sensing process will be much more efficient.

We will further enhance the schemes in our future work and investigate the impact of the detection threshold. We will also evaluate how much historical information is needed during the model building process in order to estimate the required amount of memory for such an adaptive scheme.

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