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Re:	802.16m-08/040 - Call for Comments and Contributions on the 802.16m System Description Document (SDD). **TGm SDD: SON**
Abstract	This contribution proposes the usage of methods for self-organizing fractional frequency reuse within IEEE 802.16m systems. An approach is also described.
Purpose	To review and adopt the proposed text in the next revision of the SDD.
Notice	
Release	
Patent Policy	

Self-organizing Fractional Frequency Reuse for 802.16m Systems

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1 Introduction

There are four basic approaches for interference mitigation within OFDMA-based cellular networks. Specifically, the following four approaches that can be combined and complement each other:

1. Interference randomization or averaging via subcarrier frequency hopping.
2. Interference avoidance by fixed or adaptive allocation of OFDMA frequency reuse patterns. OFDMA systems are very flexible and can support a variety of fixed and adaptive methods for frequency reuse.
3. Interference estimation and cancellation via advanced signal processing techniques (e.g. successive interference cancellation).
4. Interference mitigation by transmit and receive beamforming or precoding.

Fixed or adaptive fractional frequency reuse (FFR) provides a means to overcome interference especially cell edge interference. OFDMA systems supporting fractional frequency reuse (FFR) for interference mitigation divide frequency into several frequency partitions or subbands. In an FFR implementation mobile stations (MSs) at a cell center are allowed to operate using all available OFDMA subchannels but MSs at the cell edge are only allowed to use a fraction of the available OFDMA subchannels, that is a frequency partition. This frequency partition is allocated in such a way that MSs in adjacent cells' edges will simultaneously operate on different OFDMA frequency partitions. As a result cell-edge MSs have suppressed inter-cell interference and MSs around the cell center have the full frequency band usage (see Figure 1).

There are several approaches as how to schedule or distribute mobile stations to frequency partitions. The simplest one consists of randomly picking frequency partitions from a set of available frequency partitions. For self-organized networks frequency partitioning should not involve inter-BS coordination as is Section 20.1.1.2 of SDD. This contribution proposes baseline SDD text and describes an approach for self-organized networks that encompasses spectrum profiling, spectrum opportunity learning and spectrum opportunity management.

2 Proposed SDD Text

The proposed text below addresses FFR for self-organizing IEEE 802.16m networks. An approach for supporting self-organizing FFR is described in the remaining sections of this contribution.

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18.x Self-organizing Fractional Frequency Reuse

For self-organizing fractional frequency reuse three basic functions are supported:

1. Radio environment monitoring and awareness via spectrum profiling
2. Radio environment learning

3. Radio and/or network adaptation based on environment awareness and learning

These functions are divided between base stations and mobile stations: spectrum profiling by mobile stations and spectrum opportunity learning and management by base stations.

18.x.1 Spectrum Profiling by Mobile Stations

Spectrum profiling is the process of characterizing spectrum usage in a set of frequency partitions and maintaining an awareness of channel state and interference conditions within the frequency partitions. Spectrum profile data may include the following:

1. Estimates of received signal-to-interference plus noise power ratios.

2. Estimates of interference plus noise power.

3. Estimates of received signal power.

4. Decision bits that indicate whether a frequency partition is favorable for MS radio operation at a desired data rate.

For self-organizing FFR IEEE 802.16m mobile stations support spectrum profiling. A mobile station's serving BS specifies the frequency partitions to profile and the specified times instances or periodic time intervals for the spectrum profiling. MSs transmit their measured spectrum profile data to their serving BS using spectrum profile messages.

18.x.2 Spectrum Opportunity Learning and Management by Base Stations

Spectrum profiling only provides BSs information on the characteristics of a frequency partition (i.e. channel propagation conditions, interference conditions, and noise levels).

A spectrum opportunity may be defined simply as a frequency partition that supports MS radio operation at a desired data rate.

Spectrum opportunity learning concerns the mapping of data from spectrum profiling to information useful for FFR. Spectrum opportunity learning is based on spectrum profile messages from all of a BS's active MSs.

Spectrum opportunity learning is a BS-centric process for determining whether one or more candidate frequency partitions may be used for MS transmissions at a desired data rate. For FFR spectrum opportunity learning is implemented independently by each BS, no inter-BS communications are required.

For spectrum opportunity learning BSs construct and maintain a Spectrum Opportunity Map (SOM) for each frequency partition. Using spectrum profile messages BSs periodically update their SOMs. Entries in the SOM may contain information computed or learned from a number of uplink spectrum profile messages received over a time window.

Using their SOMs the BSs learn of spectrum opportunities and autonomously manage spectrum opportunities. For example, the SOM data and learned concepts may be used as input for scheduling MSs or allocating frequency partitions to MSs. Specific learning algorithms to use on SOM input are implementation dependent.

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3 Frequency Partitions for FFR

- Let N_{FFT} (a power of 2) denote the number of orthogonal subchannels associated with an OFDM symbol. The frequency set associated with the OFDM symbol is defined as

$$\mathsf{F} = \{f_k\}_{k=0}^{N_{FFT}-1} = \{f_k\}_{k=-N_{FFT}/2}^{N_{FFT}/2-1} \tag{1}$$

Here f_k denotes a subcarrier frequency. The N_{FFT} orthogonal subchannels are centered at the discrete frequencies in F, each having a bandwidth of $1/N_{FFT}T_S$ where T_S denotes the system sample period

- Set F contains the frequencies of all N_{FFT} subchannel signals associated with an OFDM symbol.
- We define a frequency or subband partitioning associated with an FFR implementation as

$$\mathcal{F} = \{F_1, F_2, ..., F_r\} \tag{2}$$

where integer $1 \leq r \leq N_{\text{used}}$ and $N_{\text{used}} < N_{FFT}$ denotes the number of used subcarriers.

- Each frequency partition F_i in $\mathcal{F}$ consists of N_i contiguous or non-contiguos subcarrier frequencies taken from F.
- Frequency partitions $F_1, F_2, ..., F_r$ may be overlapping or independent (disjoint) meaning that the equality $N_{\text{used}} = \sum_{i=1}^{r} N_i$ holds.

4 Overview of an FFR Technique for Self-Organizing Networks

- To better utilize spectrum 802.16m radios should operate opportunistically meaning they should be able to monitor and identify bands of unused or under used spectrum and adapt their signals to use this spectrum optimally.
- For self-organization 802.16m radios should be flexible, they should embody three fundamental characteristics:
  1. Radio environment awareness
  2. Radio environment learning
  3. Radio and/or network adaptation based on environment awareness and learning
- Two required steps for the proposed self-organizing fractional frequency reuse technique are as follows:
  1. Spectrum Profiling by Mobile Stations
     - Spectrum profiling may be defined as the process of characterizing spectrum usage in a frequency partition $\mathcal{F} = \{F_1, F_2, ..., F_r\}$ and maintaining an awareness of channel state and interference conditions within $\mathcal{F}$.
     - In a spectrum profiling process MSs assess and characterize their spectrum situation at BS specified times instances or at periodic time intervals (e.g. P-SCH, midambles, etc).
     - MS are best positioned to sense their local dynamic channel and interference conditions. MSs provide this information to their serving BSs.
     - Spectrum profiling data is gathered from a group of MSs spatially distributed within a network. Spectrum opportunity learning mechanisms do better with somewhat global knowledge of the RF environment.
  2. Spectrum Opportunity Learning and Management by Base Stations
     - Spectrum profiling only provides BSs information on the characteristics of a frequency partition $\mathcal{F}$ (i.e. channel propagation conditions, interference conditions, and noise levels).

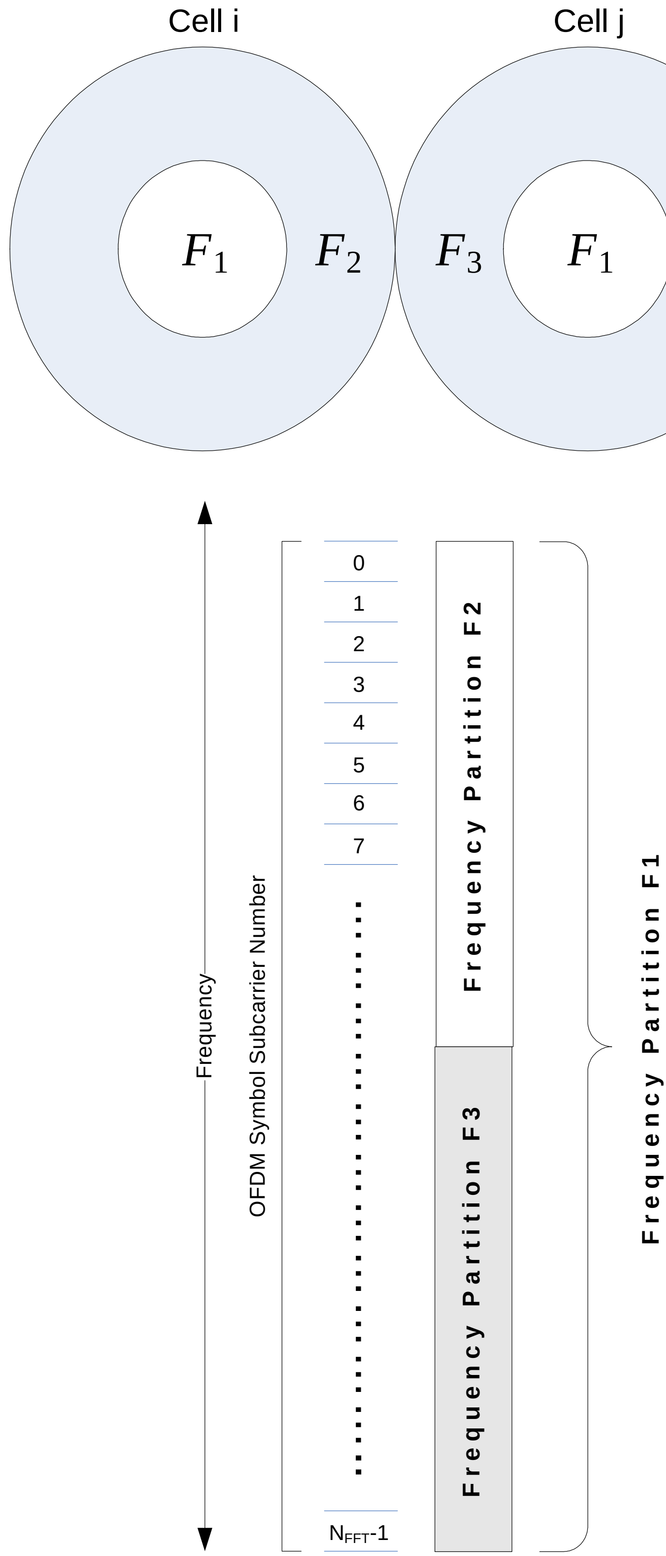

Figure 1: Simple example of frequency reuse within a OFDMA cellular network. The example shows three contiguous frequency partitions allocated to two non-sectorized cells. Sectorized cells will have more frequency partitions.

- A spectrum opportunity may be defined simply as a band or frequency partition F_i in $\mathcal{F}$ favorable for MS radio operation at a desired data rate. A spectrum opportunity exists if a radio can transmit using some combination of its operating parameters with minimal interference to other MSs.
- Spectrum opportunity learning or identification is the process of determining whether one or more frequency partitions F_i in $\mathcal{F}$ may be used for MS transmissions at a desired data rate. It concerns the mapping of MS and BS transmissions to frequency partitions F_i.
- Spectrum opportunity learning may be based on a combination of inputs that may include spectrum profiling data, radio operating policies, and radio operating time and location. Spectrum opportunity learning by a BS should include input from all of its MSs.
- Given inputs spectrum opportunity learning is realized independently by each BS. For self-organizing networks no active negotiation between BSs via a distributed algorithm or protocol is required.
- Given spectrum profiling data in the form of an uplink message from a served MS each BS constructs and updates a Spectrum Opportunity Map (SOM). Entries in the SOM may be derived from the collected spectrum profiling data of all MSs associated with a BS. Entries in the SOM may contain information learned from a number of uplink messages for all MSs. That is, the SOM is learned an updated based on messages collected over a time window.
- Spectrum opportunity management concerns spectrum opportunity coordination.
- Given BS commands derived from spectrum opportunity learning an MS may adapt its operating frequency, transmit power, modulation, coding, network protocols, etc.

5 MS Spectrum Profiling

5.1 Overview of Spectrum Profiling

- A spectrum profiler allows networked 802.16m radios to achieve improved spectrum efficiency by means of embedded RF monitoring and measurements needed for radio adaptation to dynamic spectrum conditions. A spectrum profiler portrays a radio's RF spectrum environment using physical layer measurements such as the following:

  1. Estimates of the received signal to interference plus noise power ratio P_{SINR}
  2. Estimates of interference plus noise power P_{IPN}
  3. Estimates of received signal power P_S
  4. Decision rule bits δ that indicate whether a spectrum opportunity exist at a specified false alarm probability.

- A spectrum profiler's measurements may be used as inputs for spectrum opportunity learning. A spectrum profile provides detailed spectrum usage information that can be exploited for spectrum efficiency, spectrum planning, frequency hopset adaptation, and waveform adaptation.

- A spectrum profiler may provide these measurements for a programmable frequency partitioning such as $\mathcal{F} = \{F_1, F_2, ..., F_r\}$. For each F_i in $\mathcal{F}$ channel conditions and interference/noise (narrowband, wideband, impulsive and mixed) can be monitored and characterized by a spectrum profiler.

- A spectrum profiler may provide these measurements at periodic (e.g. superframe of frame-based) or random time intervals and in accordance with a specified search algorithm. The search algorithm may change based on application needs.

- A spectrum profiler may be used as a key component for the following adaptive radio applications:
  - Link Data Rate Adaptation
  - Transmit Power Control
  - Noise/Interference Avoidance
  - Interference Mitigation
  - Channel Access Control
  - Efficient Bandwidth Utilization
  - Coexistence management with other radios and equipment

5.2 Signal Processing for Spectrum Profiling

Figure 2 shows a conceptual block diagram of a Spectrum Profiler. Referring to Figure 2 the components are now described.

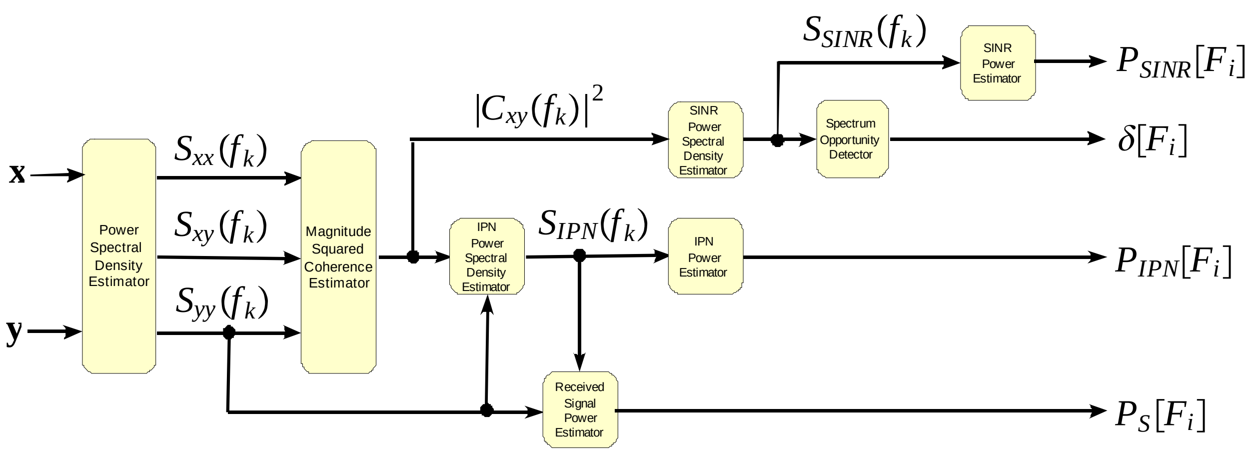

Figure 2: Conceptual block diagram of a Spectrum Profiler

5.2.1 Power Spectral Density Estimator

- Let **x** denote a known wideband reference sequence such as a preamble or a midamble and **y** the received channel-corrupted version of **x.** The length of the sequences is N_{FFT} which equals a power of two.

- Let T_S denote sampling period and recall the OFDM symbol frequency set

$$\mathsf{F} = \{f_k\}_{k=0}^{N_{FFT}-1} = \{f_k\}_{k=-N_{FFT}/2}^{N_{FFT}/2-1} \tag{3}$$

  Discrete frequency

$$f_k = \frac{k}{N_{FFT}T_S} = \frac{2k}{N_{FFT}} f_{\mathrm{NF}} \tag{4}$$

  lies within the spectral band $B = [0, f_{\mathrm{NF}}]$ where $f_{\mathrm{NF}} = 1/2T_S$ is the Nyquist frequency. Note that as N_{FFT} increases frequency resolution within $B = [0, f_{\mathrm{NF}}]$ increases and when T_S decreases bandwidth B increases.

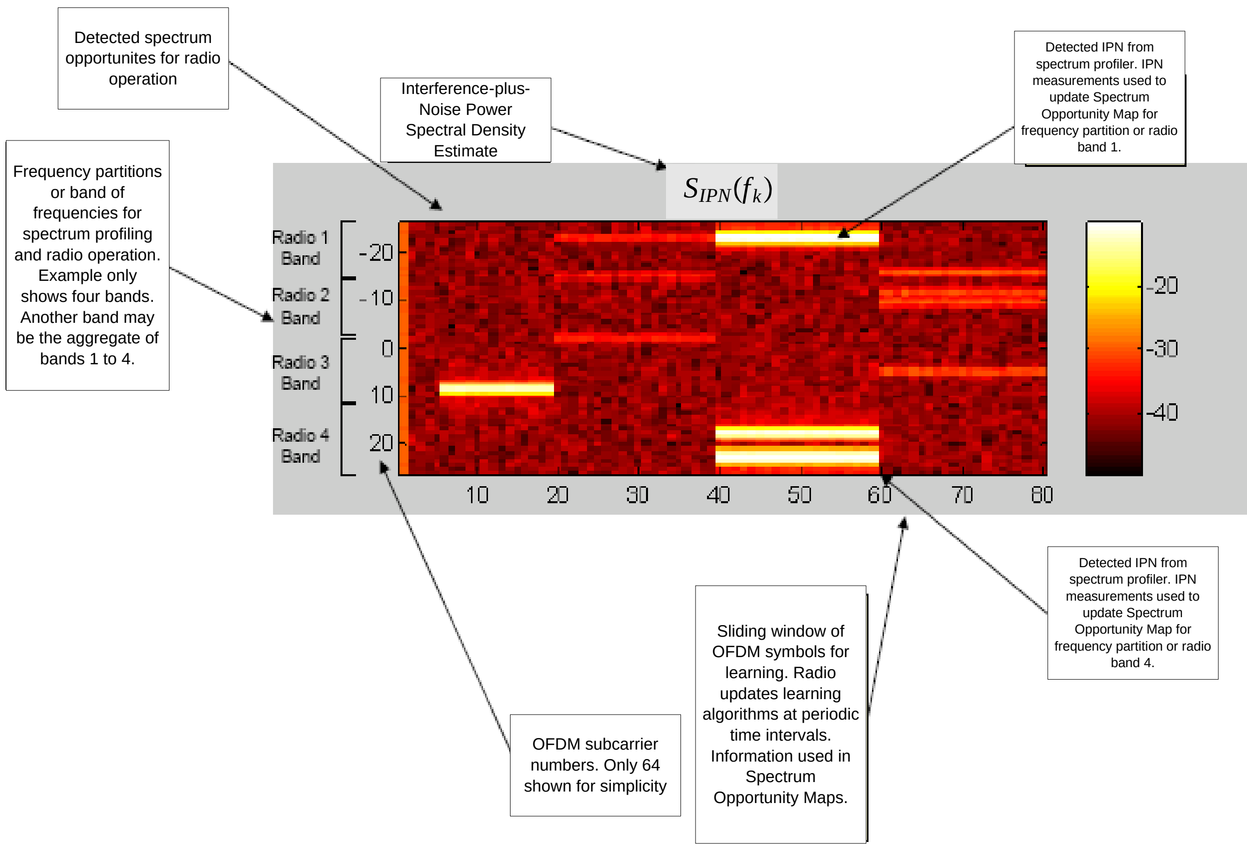

Figure 3: A spectrogram computed by the Spectrum Profiler. A spectrogram is a frequency vs. time vs. power display where the frequency is represented on y-axis and time on the x-axis. The power is expressed by the color.

- For each received $\mathbf{y}$ and f_k in F the Power Spectral Density Estimator computes a PSD estimate

$$\begin{aligned} S_{yy}(f_k) &= \frac{T_S}{N_{FFT}} \left| \sum_{n=0}^{N_{FFT}-1} y[nT_S] e^{-j\frac{2\pi kn}{N_{FFT}}} \right|^2 \\ &= \frac{T_S}{N_{FFT}} \left| FFT(\mathbf{y}) \right|^2 \end{aligned} \tag{5}$$

- To improve the Power Spectral Density Estimator's performance estimates $S_{yy}(f_k)$ should be smoothed or averaged. Let $t > 0$ denote the preamble or a midamble number, $\tilde{S}_{yy}[t]$ a smoothed estimate, and $S_{yy}(f_k, t)$ the PSD estimate computed from the tth preamble or a midamble. A simple exponentially weighted smoothing algorithm such as the following may be easily implemented:

$$\tilde{S}_{yy}[t] = \tilde{S}_{yy}[t-1] + \alpha \left(S_{yy}(f_k, t) - \tilde{S}_{yy}[t-1] \right) \tag{6}$$

  The parameter $0 \leq \alpha \leq 1$ controls the degree of smoothing. When α approaches 1 smoothing increases and when α approaches 0 smoothing decreases.

- For each $\mathbf{x}$ and f_k in F the Power Spectral Density Estimator computes the power spectral density estimate $S_{xx}(f_k)$ using an FFT.

- Using $S_{xx}(f_k)$ and $S_{yy}(f_k)$ the Power Spectral Density Estimator computes cross-power spectral density estimate $S_{xy}(f_k)$.

5.2.2 MS-Coherence Estimator

- Given the PSD estimates

$$\{S_{xx}(f_k)\}_{k=-N_{FFT}/2}^{N_{FFT}/2-1}, \; \{S_{yy}(f_k)\}_{k=-N_{FFT}/2}^{N_{FFT}/2-1} \text{ and } \{S_{xy}(f_k)\}_{k=-N_{FFT}/2}^{N_{FFT}/2-1} \tag{7}$$

  the Magnitude-Squared (MS) Coherence Estimator computes

$$\left\{ |C_{xy}(f_k)|^2 \right\}_{k=-N_{FFT}/2}^{N_{FFT}/2-1} \tag{8}$$

  where

$$0 \leq |C_{xy}(f_k)|^2 = \frac{|S_{xy}(f_k)|^2}{S_{xx}(f_k) S_{yy}(f_k)} \leq 1 \tag{9}$$

  denotes the magnitude-squared coherence estimate at discrete frequency f_k.

- The MS-Coherence estimate $|C_{xy}(f_k)|^2$ quantifies the similarity or dependence between sequences $\mathbf{x}$ and $\mathbf{y}$.

- Time-domain cross-correlations also provide signal similarity measures but $|C_{xy}(f_k)|^2$ may be more useful because:

  1. $|C_{xy}(f_k)|^2$ provides similarity measures at discrete frequencies f_k
  2. $|C_{xy}(f_k)|^2$ is independent of any time delay between signals $\mathbf{x}$ and $\mathbf{y}$.

5.2.3 SINR, IPN and Received Signal Power Estimators

- MS-coherence estimates are appropriate for spectrum-adaptive communications since they may provide both SINR and interference estimates.

- For each received signal $\mathbf{y}$ and each f_k in $\mathcal{F}$ the SINR Estimator computes the ratio of received signal-of-interest power to received interference-plus-noise power:

$$S_{SINR}(f_k) = \frac{|C_{xy}(f_k)|^2}{1 - |C_{xy}(f_k)|^2} \tag{10}$$

- For each received signal $\mathbf{y}$ and f_k in $\mathcal{F}$ the IPN Power Spectral Density Estimator computes the PSD of the received interference-plus-noise (IPN):

$$S_{IPN}(f_k) = \left(1 - |C_{xy}(f_k)|^2\right) S_{yy}(f_k) \tag{11}$$

- The PSD estimate measured at the output is

$$\begin{aligned} S_{yy}(f_k) &= S_{ss}(f_k) + S_{IPN}(f_k) \\ &= |H(f_k)|^2 S_{xx}(f_k) + S_{IPN}(f_k) \end{aligned} \tag{12}$$

- The received signal PSD estimate is then

$$S_{ss}(f_k) = S_{yy}(f_k) - S_{IPN}(f_k) \tag{13}$$

- As defined above a frequency partitioning associated with an FFR implementation is

$$\mathcal{F} = \{F_1, F_2, ..., F_r\} \tag{14}$$

  where integer $1 \leq r \leq N_{\text{used}}$ and $N_{\text{used}} < N_{FFT}$ denotes the number of used subcarriers. Each frequency partition F_i in $\mathcal{F}$ consists of N_i contiguous or non-contiguos subcarrier frequencies taken from F.

- The SINR Power Estimator computes the received signal-of-interest to interference-plus-noise (IPN) power ratio over an F_i in $\mathcal{F}$ from the summation

$$P_{SINR}[F_i] = \frac{1}{N_i} \sum_{k \in F_i} S_{SINR}(f_k) \tag{15}$$

- The IPN Power Estimator computes the received interference-plus-noise power over an F_i in $\mathcal{F}$ from the summation

$$P_{IPN}[F_i] = \frac{1}{N_i} \sum_{k \in F_i} S_{IPN}(f_k) \tag{16}$$

- The Received Signal Power Estimator computes the received interference-plus-noise power over an F_i in $\mathcal{F}$ from the summation

$$P_S[F_i] = \frac{1}{N_i} \sum_{k \in F_i} S_{ss}(f_k) \tag{17}$$

5.3 Some Estimator Computation Notes

- Sequence $\mathbf{x}$ should designed so that $S_{xx}(f_k)$ is constant and non-zero for all f_k. If $S_{xx}(f_k)$ is zero $|C_{xy}(f_k)|^2$ will be singular and corrupt subsequent signal processing operations.

- If $\mathbf{x}$ is known and constant $S_{xx}(f_k)$ can be computed off-line and stored in memory.

- Estimate $S_{xy}(f_k)$ can be computed efficiently from $S_{xx}(f_k)$ and $S_{yy}(f_k)$. Thus for each received frame only $S_{yy}(f_k)$ (which is required for OFDM systems) needs to be computed using Welch's method.

- Performance of the spectrum profiler depends upon implementation factors:

  - Receiver characteristics such as sensitivity
  - Spectrum profile window size equal to N
  - Average and peak values within the window
  - Spectrum profiling scan rate
  - Thresholds on discriminating interference/noise from signals

5.4 Spectrum Opportunity Detector

- For any discrete frequency f_k in F_i the MS-Coherence estimate can be written as

$$|C_{xy}(f_k)|^2 = \frac{\sigma_x^2}{\sigma_x^2 + S_{IPN}(f_k)/\,|H(f_k)|^2} \tag{18}$$

  where $S_{xx}(f_k) = \sigma_x^2$, $H(f_k)$ denotes the channel transfer function and $S_{IPN}(f_k)$ the PSD of the received interference-plus-noise (IPN).

- Note that MS-coherence estimates aggregate information on both channel quality and interference-plus-noise power. As the ratio $S_{IPN}(f_k)/\,|H(f_k)|^2$ increases (decreases) $|C_{xy}(f_k)|^2$ decreases (increases). We can therefore use $|C_{xy}(f_k)|^2$ as a measure to detect spectrum opportunities for each f_k in a received spectral band $B = [0, f_{\mathrm{NF}}]$. The MS-coherence estimate also simplifies the mathematical formulation of a signal detector implementation.

- The problem of detecting spectrum opportunities can be stated as a statistical hypothesis test with null and alternative hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$. A spectral opportunity for each f_k in F_i is detected using the hypothesis test

$$\begin{aligned} \mathcal{H}_0 &: |C_{xy}(f_k)|^2 = 0 \text{ (Spectrum opportunity does not exist)} \\ \mathcal{H}_1 &: |C_{xy}(f_k)|^2 > 0 \text{ (Spectrum opportunity exists)} \end{aligned} \tag{19}$$

- Following table summarizes the possible decisions and errors:

Truth	Decision Accept $\mathcal{H}_1$	Decision Reject $\mathcal{H}_1$
$\mathcal{H}_0$	Type I Decision Error	Correct Decision
$\mathcal{H}_1$	Correct Decision	Type II Decision Error

(20)

5.4.1 Error Probabilities for Spectrum Opportunity Detection

- Let random variable $T(f_k)$ denote a test statistic at frequency f_k in F_i and τ a critical value for $T(f_k)$. The probability of a Type I decision error (spectrum opportunity false alarm) is defined as

$$P_{\mathrm{FA}} = \Pr\{\text{Accept } \mathcal{H}_1 | \text{Truth } \mathcal{H}_0\} = \Pr\{T(f_k) \geq \tau | \text{Truth } \mathcal{H}_0\} \tag{21}$$

  The probability of a Type II Decision Error (missed spectrum opportunity detection) is defined as

$$P_{\mathrm{MD}} = \Pr\{\text{Accept } \mathcal{H}_0 | \text{Truth } \mathcal{H}_1\} = \Pr\{T(f_k) < \tau | \text{Truth } \mathcal{H}_1\} \tag{22}$$

- The difference $1 - P_{\mathrm{MD}}$ is the probability of detecting a spectrum opportunity.

5.4.2 Test Statistic for Spectrum Opportunity Detection

- A design requirement for a Spectrum Opportunity Detector is to minimize the missed detection probability P_{MD} for a false alarm probability P_{FA} as small as possible.

- To meet the design requirement a Spectrum Opportunity Detector may use the test statistic

$$T(f_k) = (m-1)\frac{|C_{xy}(f_k)|^2}{\left(1 - |C_{xy}(f_k)|^2\right)} = (m-1)S_{SINR}(f_k) \tag{23}$$

5.4.3 Probability Distribution of the Test Statistic

- Under $\mathcal{H}_0$ test statistic $T(f_k)$ has an Fdistribution $F_{1-P_{\mathrm{FA}}}(2, 2(m-1))$ with 2 and $2(m-1)$ degrees of freedom. Probability P_{FA} is chosen from the interval $[0, 1]$.

- Positive integer $m > 0$ denotes the number of signal segments used to compute $|C_{xy}(f_k)|^2$ (e.g. when computing $|C_{xy}(f_k)|^2$ using Welch's method m sections of a sequences $\mathbf{x}$ and $\mathbf{y}$ are used to compute m periodograms that are averaged).

5.4.4 Decision Function for Spectrum Opportunity Detection

- The decision function for the Spectrum Opportunity Detector is defined as

$$\delta(f_k) = \begin{cases} 1 & \text{if } T(f_k) \geq \tau = F_{1-P_{\mathrm{FA}}}(2, 2(m-1)) \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

- Given a specified false alarm probability of P_{FA} the Spectrum Opportunity Detector rejects the null hypothesis $\mathcal{H}_0$ at discrete frequency f_k when $\delta(f_k)$ outputs a 1.

- Decisions $\delta(f_k)$ may be combined.. For example, using equal weighted decision combining (majority voting) the Spectrum Opportunity Detector may uses the decision function

$$\delta[F_i] = \begin{cases} 1 & \sum_{f_k \in F_i} \delta(f_k) > \left\lceil \frac{N_{ii}}{2} \right\rceil \\ 0 & \text{otherwise} \end{cases} \tag{25}$$

  Other decision combining methods may also be used.

5.4.5 Critical Value Computation

- Given a false alarm probability P_{FA} and the number of signal segments used to compute $|C_{xy}(f_k)|^2$ the inverse of the F distribution function $F_{1-P_{\mathrm{FA}}}(2, 2(m-1))$ can be used to compute critical value τ.
- Computations for a number of τ values can be computed off-line and results stored in look-up tables indexed by false alarm probabilities P_{FA}.

6 BS Spectrum Opportunity Learning (SOL) and Management

6.1 Learning Algorithms

- Spectrum profiling only provides information on the characteristics of a channel or subchannel (i.e. channel propagation conditions, interference conditions, and noise levels).
- Spectrum opportunity learning concerns the design of algorithms that convert information from spectrum profiling to information useful for FFR.
- Learning algorithms may be used for tasks such as signal detection, identification, classification and prediction (e.g. detection/identification of interference or network traffic patterns).
- Spectrum opportunity learning may be based on factors such as a 16m radio's application (voice or data transmission), its operating environment, its operational time and/or geographic location.
- Spectrum opportunity learning may occur at different levels and/or time periods:
  1. It may learn based on every possible radio and network parameter that it observes or is given by other elements within a network
  2. It may learn based on only RF spectrum data that is observed by its Spectrum Profiler. Most of the research work is currently focused on learning based on only obtained RF spectrum data. Higher-layer (Layer 2 and 3) learning based on network data is also a research focus.
- Learning algorithms may be broadly categorized as supervised, unsupervised or reinforcement based:
  - Supervised Learning Algorithm
    * Learning data: $(\mathbf{x}, \mathbf{y})$ where $\mathbf{x}$ and $\mathbf{y}$ are sample sequences of input and output signals associated with an unknown signal map or transfer function to be learned. Sequence $\mathbf{x}$ is typically known.
    * Main Usages: Signal prediction, system identification, classification
    * Example Radio Usage Task: Channel transfer function estimation or prediction for radio data rate and transmit power adjustments.
  - Unsupervised Learning Algorithm
    * Learning data: Sample sequence $\mathbf{y}$ of a signal of interest (e.g. an interference signal at some frequency).
    * Main Usages: Signal characterization, structure learning via clustering algorithms, pattern recognition and classification.
    * Example Radio Usage Task: Dynamic histogram construction for estimating the probability of interference occurring at a certain frequency, power, etc. in a MS's spectral field of view. BS may dynamically change an MS frequency or frequency hop algorithm based on input of estimated probabilities.

  - A reinforcement learning algorithm is more complex and differs from a supervised and unsupervised learning algorithm in several ways. The main difference is that a reinforcement learning algorithm requires interaction with other radios within a network. Supervised and unsupervised learning algorithms may work with or without interaction. Reinforcement learning is performed based on positive/negative feedback messages from the other networked radios. Positive/negative feedback messages are sent to a learning radio in response to an action that it executes (e.g. a power increase). The goal of reinforcement learning may be to learn a procedure, plan, or policy: which radio action(s) to choose given the state of its external environment (i.e. channel and/or network). A simple example is closed-loop power control.

- Learning algorithms may be used by a 16m radio in performing tasks such as signal, interference and network traffic pattern detection and classification; discovering RF spectrum usage opportunities, predicting their duration times and frequency usage patterns; situation assessment (e.g. the status of nearest neighbors based on their RF emissions); concept formations based on channel and network states; radio and network variable selections; and predictions (e.g. motion prediction of mobile radio, channel state, interference, etc.).

- Radio learning may be accomplished in two basic ways: single-radio learning and multi-radio learning.

- Single-radio learning is performed by a 16m radio independently, data from other radios or network elements are not used.

- Multi-radio learning occurs within a network and may implemented as multiplied, divided and interactive learning.

  - For multiplied learning there are two or more learners, each of them learns independently of the others. There may be interactions among the learners, but these interactions just provide data which may be used in the other learners' learning processes. The individual learners may use the same or a different learning algorithm.
  - For divided learning a learning algorithm is divided among two or more learners. The division of the learning algorithm is not a part of the learning process itself. The radios involved in divided learning have a shared overall learning goal. The division may be according to functional aspects of an algorithm, radio location, radio capabilities, etc. An individual learner involved in divided learning may also act as specialist who is just responsible for a specific subset of activities that form part of the overall learning process. Learner interaction is required for aggregating the results of the learning activities.
  - Interactive learning is a more dynamic activity that concerns the intermediate steps of the learning process. Interaction is used for data exchange and for executing a cooperative search for a solution to a learning task. Interaction is an essential part and ingredient of the learning process.

6.2 Examples of SOL

- Dynamic histogram construction for estimating the probability of interference occurring at a specified frequency partition and/or power level. A 16m radio may dynamically adapt (e.g. a frequency hop algorithm) based on this knowledge.

- The status of a nearby network or cell based on RF emissions of the users. A 16m radio protocol may use this knowledge for its operation.

- Selection of radio and/or network parameters based on learned RF spectrum usage patterns as a function of time and location.

- Measurements provided by a Spectrum Profiler may be used to learn the following:

  - For each frequency partition F_i in $\mathcal{F}$ power levels and average usage durations.
  - For each frequency partition F_i in $\mathcal{F}$ average and peak values within a partition and ratios of peak interference power to mean or RMS power.
  - Interference duty cycles, interference traffic patterns and spectrum usage patterns. For example, in a lightly loaded network duty cycles may be slow.
  - Thresholds for discriminating interference/noise from signals may be computed or learned.
  - Interference and received signal power characterization via counting methods (e.g. peak counting, level cross counting, range counting, from-to-counting, range-mean counting, and range pair-range counting).
  - Change-point detection is an area of statistical inference and signal processing that links together control theory, estimation theory and hypothesis testing. Simply stated a change-point in an observed random signal is defined as the moment in time when some probabilistic characteristics of the signal change. Probabilistic changes in a random signal can be additive or multiplicative. Additive changes imply changes in the mean of a random signal. Multiplicative changes result when a random signal is transformed by a linear or nonlinear map resulting in spectral, variance or correlation changes in the signal. The change-point detection problem is to detect a change-point in a signal via a statistical hypothesis test, estimate an unknown parameter or parameters of interest that the change-point depends on and to invoke a control or action based on the change-point detected and the parameter estimation.

6.3 Spectrum Opportunity Maps

- For fractional frequency reuse each BS maintains a Spectrum Opportunity Map (SOM) for each frequency partition F_i in $\mathcal{F}$. The BS uses the data in its SOMs to manage spectrum opportunities; the data is used as input for scheduling MSs and allocating frequency partitions. SOMs are useful when multiple spectral opportunities are available. They help a BS choose a "good" spectrum opportunity from a candidate set. They may help coordinate partition changing and switching. Specific algorithms to use on SOM input are implementation dependent.

- During a spectrum profiling interval (e.g. P-SCH or preamble, midamble) each MS obtains spectrum profiling data for one or more frequency partitions F_i in $\mathcal{F}$. The MSs transmit this data to their serving BS in an uplink spectrum profile message. An example of a spectrum profile message derived from spectrum profiling data is as follows:

Message Fields

MS_ID	F_i	$\delta[F_i]$	$P_{SINR}[F_i]$	$P_S[F_i]$	$P_{IPN}[F_i]$
8 bits	2 bits	1 bit	8 bits	8 bits	8 bits

Example Format of Spectrum Profiling Message

- Note that some of fields may be transmitted via other types of uplink messages. For example, the SINR estimate may be transmitted via another uplink fast feedback channel message.

- Given a spectrum profile message the serving BS updates its SOM. Entries in the SOM may be computed and/or learned from spectrum profiling data collected from all MSs.

- The following is an example of a Spectrum Opportunity Map for frequency partition F_i in $\mathcal{F}$. A base station should store and maintain one SOM for each F_i in $\mathcal{F}$.

SOM for Frequency Partition F_i in $\mathcal{F}$						
MS_ID	**SOInd**	**Time**	**Prob**	**AvgSigPower**	**AvgIntPower**	**AvgSINR**
ID_0	1	T_0	P_0	SP_0	IP_0	$SINR_0$
ID_1	0	T_1	P_1	SP_1	IP_1	$SINR_0$
ID_2	1	T_2	P_2	SP_2	IP_2	$SINR_2$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
ID_M	1	T_M	P_M	SP_M	IP_M	$SINR_M$

- The **MS_ID** column contains MS identifiers ID_i. MSs may be added or deleted from the SOM at BS chosen time intervals.

- The **SOInd** column contains spectrum opportunity decisions $\delta[F_i]$ as defined above. Recall that $\delta[F_i]$ indicates whether a spectrum opportunity in frequency partition F_i exists based on a specified detection or false alarm probability P_{FA}. The BS may specify the false alarm probability P_{FA} in a prior downlink message. It may also be fixed or learned. These are implementation decisions. A value of 1 indicates that the frequency partition F_i is candidate frequency partition for usage by specific MS. A value of 0 indicates that no spectral opportunity exists in frequency partition F_i.

- The **Time** column contains entries T_i which denote the accumulative amount of time that a spectrum opportunity has existed for an MS in frequency partition F_i. These values are easily obtained from the run length of a sequence of **SOInd** values equal to one.

- The **AvgSigPower** column contains values SP_i which represent the average received power of received signal transmissions in frequency partition F_i. The average received signal power $SP_i$is computed from received signal power values $P_S[F_i]$.

- The **AvgIntPower** column contains the average interference powers IP_i as observed by a MS in frequency partition F_i. The average interference power is computed by averaging received values $P_{IPN}[F_i]$.

- The **AvgSINR** column contains values $SINR_0$ that represent the average SINR power as observed by a MS in frequency partition F_i. The average power is computed from received values $P_{SINR}[F_i]$.

- The **Prob** column contains values P_0 that denote the probability that a frequency partition F_i in $\mathcal{F}$ provides a spectrum opportunity. Let $P_i = \Pr(F_i)$ denote the probability that a frequency partition F_i in $\mathcal{F}$ provides a spectrum opportunity. Decisions $\delta(F_i)$ may be used to generate estimates of $\Pr(F_i)$ by averaging binary decision values $\delta(F_i)$ over a window of time (e.g. a sequence of superframes or frames). Choosing a window size for the moving average is important design parameter. The window size can also be parametrized.

- Dynamic histogramming can be implemented by combining the $\Pr(F_i)$ values for each frequency partition. More specifically, for the partition set $\mathcal{F} = \{F_1, F_2, ..., F_r\}$ a plot of the values $\Pr(F_i)$, $i = 1, 2, \ldots, r$, versus partition set index numbers will give the probability that each F_i in $\mathcal{F}$ provides a spectrum opportunity for an MS. Probabilities $\Pr(F_i)$ and SOMs may also be used by networked BSs or MSs as feature vectors for frequency usage pattern recognition algorithms.

7 References

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