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Throughput Analysis of Cognitive Radio Systems using Monte-Carlo Simulation

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Abstract: ***Orthogonal frequency division multiplexing (OFDM) is becoming the chosen modulation technique for wireless communications. OFDM can provide large data rates with sufficient robustness to radio channel impairments. Many research centers in the world have specialized teams working in the optimization of OFDM for countless applications. The transmit signals in an OFDM system can have high peak value s in the time domain since many subcarrier components are added via an IFFT operation. Therefore, OFDM systems are known to have a high PAPR (Peak -to-Average Power Ratio), compared with single-carrier systems. In fact, the high PAPR is one of the most detrimental aspects in the OFDM system, as it decreases the SQNR (Signal -to-Quantization Noise Ratio) of ADC (Analog-to-Digital Converter) and DAC (Digital- to-Analog Converter) while degrading the efficiency of the power amplifier in the transmitter. The PAPR problem is more important in the uplink since the efficiency of power amplifier is critical due to the limited batter y power in a mobile terminal. This research paper discusses several techniques that are being used to reduce the PAPR in an OFDM system***

Keywords: OFDM, PAPR, SQNR, clipping, pulse shaping

1. Vision of Cognitive Radio

The long term vision of cognitive radio technology is one in which handsets would automatically make use of underutilized spectrum across a broad frequency range, allowing the high bandwidth requirements of the future. If a radio were smart, it could learn services available in locally accessible wireless computer networks, and could interact with those networks in their preferred protocols, to have no confusion in finding the right wireless network for a video download or a printout. Additionally, it could use the frequencies and choose waveforms that minimize and avoid interference with existing radio communication systems. It might be like having a friend in everything that's important to your daily life.

2. History Leading to Cognitive Radio

The sophistication possible in a software-defined radio (SDR) has now reached the level where each radio can conceivably perform beneficial tasks that help the user, help the network, and help minimize spectral congestion. The development of digital signal processing (DSP) techniques arose due to the efforts of such leaders as Alan Oppenheim, Lawrence Rabiner, Ronald Schaefer, Ben Gold, Thomas Parks, James McClellen, James Flanagan, Fred Harris, and James Kaiser. These pioneers recognized the potential for digital filtering and DSP, and prepared the seminal textbooks, innovative papers, and breakthrough signal processing techniques to teach an entire industry how to convert analog signal processes to digital processes.

Meanwhile, the semiconductor industry, continuing to follow Moore's law, evolved to the point where analog functions implemented with large discrete components were replaced with digital functions implemented in silicon, and consequently were more producible, less expensive, more reliable, smaller, and of lower power.

During this same period, researchers all over the globe explored various techniques to achieve machine learning and related methods for improved machine behavior. Among these were analog threshold logic, which leads to fuzzy logic and neural networks, a field founded by Frank Rosenblatt. In networking, DARPA and industrial developers at Xerox, BBN Technologies, IBM, ATT, and Cisco each developed computer-networking techniques, which evolved into the standard Ethernet and Internet we all benefit from today. The researchers are exploring wireless networks that range from access directly via a radio access point to more advanced techniques in which intermediate radio nodes serve as repeaters to forward data packets toward their eventual destination in an ad hoc network topology. Cognitive radios are nearly always applications that sit on top of an SDR, which in turn is implemented largely from digital signal processors and general-purpose processors (GPPs) built in silicon.

3. Cognitive Radio Network Paradigms

Based on the type of available network side information along with the regulatory constraints, cognitive radio systems seek to underlay, overlay, or interweave their signals with those of existing users without significantly impacting their communication. The underlay paradigm allows cognitive users to operate if the interference caused to non cognitive users is below a given threshold. In overlay systems, the cognitive radios use sophisticated signal processing and coding to maintain or improve the communication of non cognitive radios while also obtaining some additional bandwidth for their own communication. In interweave systems; the cognitive radios opportunistically exploit spectral holes to communicate without disrupting other transmissions.

Companding is another popular distortion based scheme for PAPR reduction in OFDM system. In [5], Wang et al. proposed a scheme based on µ-law companding to reduce the PAPR of OFDM signal. In µ-law companding scheme the peak value of the OFDM signal before and after companding remains same, which keeps peak power of the OFDM signal unchanged but the average power of the OFDM signal after companding increases and therefore the PAPR of the OFDM signal gets decreased. But due to increase in the average power of the OFDM signal the error performance of µ-law companding scheme degrades.

The underlay paradigm encompasses techniques that allow secondary communications assuming that they have knowledge of the interference caused by its transmitter to the receivers of the primary users. Specifically, the underlay paradigm mandates that concurrent primary and secondary transmissions may occur as long as the aggregated interference generated by the secondary users is below some acceptable threshold. In the underlay paradigm, the secondary user enters the primary spectrum only when its activity will not cause considerable interference or capacity penalty to the primary user. Measure of interference requires knowledge about multiuser CQI. Measurement challenges for underlay paradigm are:

- Measuring interference at NC receiver
- Measuring direction of NC node for beam steering
- Both easy if NC receiver also transmits, else hard.
- Underlay typically coexists with licensed users.

Licensed users paid for their spectrum so they don't want underlay, Insist on very stringent interference constraints which severely limits underlay capabilities and applications. That is the main challenge for underlay policy.

The overlay paradigm allows the coexistence of simultaneous primary and secondary communications in the same frequency channel as long as the secondary users somehow aid the primary users, for example, by means of advanced coding or cooperative techniques. In particular, in a cooperative scenario the secondary users may decide to assign part of their power to their own secondary communications and the remaining power to relay the primary user's transmission. The enabling premise for overlay systems is that the cognitive transmitter has knowledge of the non-cognitive users' codebooks and its messages as well. A non-cognitive user message might be obtained by decoding the message at the cognitive receiver.

On the one hand, the information can be used to completely cancel the interference due to the non-cognitive signals at the cognitive receiver by sophisticated techniques, like dirty paper coding (DPC). On the other hand, the cognitive users can utilize this knowledge and assign part of their power for their own communication and the remainder of the power to assist (relay) the non-cognitive transmissions. By careful choice of the power split, the increase in the non-cognitive user's signal-to-noise power ratio (SNR) due to the assistance from cognitive relaying can be exactly offset by the decrease in the non-cognitive user's SNR due to the interference caused by the remainder of the cognitive user's transmit power used for its own communication.

4. Basic Theory of Spectrum Sensing

General Model for Spectrum Sensing Suppose that we are interested in the frequency band with carrier frequency fc and bandwidth W and the received signal is sampled at sampling frequency fs. When the primary user is active, the discrete received signal at the secondary user can be represented as:

$$y(n) = s(n) + u(n),$$

Which i s t he output under hypothesis H1. When the primary user is inactive, the received signal is given by

$$y(n) = u(n),$$

and this case i s referred to as hypothesis H0 .We make the following assumptions.

- (AS1) the noise u (n) is a Gaussian, independent and identically distributed (iii) random process with mean zero and variance E [|u (n) |2] = σ2u;
- (AS2) the primary signal s (n) is an iid random process with mean zero and variance E [|s (n) |2] = σ2s;
- (AS3) the primary signal s (n) is independent of the noise u (n).

Two probabilities are of interest for spectrum sensing: probability of detection, which dense, under hypothesis H1, the probability of the algorithm correctly detecting the presence of primary signal; and probability of false alarm, which defines, under hypothesis H0, the probability of the algorithm falsely declaring the presence of primary signal. From the primary user's perspective, the higher the probability of detection, the better protection it receives. From the secondary user's perspective, however, the lower the probability of false alarm, there are more chances for which the secondary users can use the frequency bands when they are available. Obviously, for good detection algorithm, the probability of detection should be as high as possible while the probability of false alarm should be as low as possible. We focus on the complex-valued PSK signal and CSCG noise case. Based on the PDF of the test static, the probability of detection can be approximated by

$$P_d(\epsilon, \tau) = \mathcal{Q}\left(\left(\frac{\epsilon}{\sigma_u^2} - \gamma - 1\right)\sqrt{\frac{\tau f_s}{2\gamma + 1}}\right).$$

For a target probability of detection,

$$P_d = \mathcal{Q}\left(\frac{1}{\sqrt{2\gamma + 1}}(\mathcal{Q}^{-1}(\bar{P}_f) - \sqrt{\tau f_s}\gamma)\right).$$

5. Monte Carlo Simulation

Monte Carlo methods (or Monte Carlo experiments) are a broad class of computational algorithms that rely unrepeated random sampling to obtain numerical results; typically one runs simulations many times over in order to obtain the distribution of an unknown probabilistic entity. The name

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comes from the resemblance of the technique to the act of playing and recording your results in a real gambling casino. They are often used in physical and mathematical problems and are most useful when it is difficult or impossible to obtain a closed-form expression, or infeasible to apply a deterministic algorithm. Monte Carlo methods are mainly used in three distinct problem classes: optimization, numerical integration and generation of draws from a probability distribution.

In physics-related problems, Monte Carlo methods are quite useful for simulating systems with many coupled degrees of freedom, such as fluids, disordered materials, strongly coupled solids, and cellular structures (see cellular Potts model). Other examples include modeling phenomena with significant uncertainty in inputs, such as the calculation of risk in business; and, in math, evaluation of multidimensional definite integrals with complicated boundary conditions. In application to space and oil exploration problems, Monte Carlo–based predictions of failure, cost overruns and schedule overruns are routinely better than human intuition or alternative "soft" methods. The modern version of the Monte Carlo method was invented in the late 1940s by Stanis law Ulam, while he was working on nuclear weapons projects at the Los Alamos National Laboratory. It was named by Nicholas Metropolis, after the Monte Carlo Casino, where Elam's uncle often gambled. Immediately after Ulam's breakthrough, John von-Neumann understood its importance and programmed the ENIAC computer to carry out Monte Carlo calculations. Monte Carlo methods vary, but tend to follow a particular pattern:

1) Define a domain of possible inputs.
2) Generate inputs randomly from a probability distribution over the domain.
3) Perform a deterministic computation on the inputs.
4) Aggregate the results.

For example, consider a circle inscribed in a unit square. Given that the circle and the square have a ratio of areas that is $\pi/4$, the value of π cane approximated using a Monte Carlo method:

1) Draw a square on the ground, and then inscribe a circle within it.
2) Uniformly scatter some objects of uniform size (grains of rice or sand) over the square.
3) Count the number of objects inside the circle and the total number of objects.
4) The ratio of the two counts is an estimate of the ratio of the two areas, which is $\pi/4$. Multiply the result by 4 to estimate π.

In this procedure the domain of inputs is the square that circumscribes our circle. We generate random inputs by scattering grains over the square then perform a computation on each input (test whether it falls within the circle). Finally, we aggregate the results to obtain our final result, the approximation of π. If the grains are not uniformly distributed, then our approximation will be poor. Secondly, there should be a large number of inputs. The approximation is generally poor if only a few grains are randomly dropped into the whole square. On average, the approximation improves as more grains are dropped.

6. Conclusion

This research paper gives a brief introduction to cognitive radio technology. In addition to that it has been established in this paper that Monte- Carlo simulation could help in the spectrum sensing aspect of cognitive radio. This aspect of Monte- Carlo simulation could be extended for white space detection in modern cognitive radio systems. This particular application of Monte- Carlo simulation is though useful but is applicable when other variables such as sampling rate, signal to noise ratio of the system is known in advance for the Monte-Carlo algorithm to effectively determine the spectrum sensing scenario.

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