SPECTRUM SENSING USING CYCLOSTATIONARY SPECTRUM DENSITY FOR COGNITIVE RADIOS

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ABSTRACT

Cognitive radios (CR) are proposed to alleviate the spectrum scarcity problems facing wireless service providers. In US, the FCC is considering spectrum regulation changes by allowing unlicensed operation in the TV broadcast bands provided that no harmful interference is caused. In this paper, we discuss the spectrum sensing aspects of cognitive radios. We particularly focus on the detection method based on cyclostationary spectrum density (CSD) estimation. The advantage of CSD is its relative robustness against noise uncertainty compared with energy detection methods. CSD estimation is a two dimensional transformation; therefore it is computationally complex. We transform the algorithm from the two dimensional space to a one dimensional case, therefore making the real time implementation more feasible. Through analysis and simulation, we identify the features with highest SNR to be used for CSD based detection. Based on the simulation results, we further propose dedicated hardware implementation architecture for CSD estimation using field programmable logic array (FPGA). Our implementation can achieve greater than 90% detection probability on BPSK signals with SNR of -18 dB, when the probability of false alarm is less than 10%.

Index Terms—Cognitive Radio, Spectrum Sensing, Signal Detection, Cyclostationary Spectrum Density, FPGA

1. INTRODUCTION

With the rapid development of wireless communications, the increasing spectrum scarcity is becoming a forthcoming problem. However, recent studies have found the cause for the scarcity to be the out-dated fixed and inflexible spectrum allocation approaches. For example, a study conducted by Shared Spectrum through monitoring the spectrum occupancy in the frequency band from 30 MHz to 3000 MHz shows the average occupancy over multiple locations is merely 5.2%. The maximum occupancy is about 13% in New York City [1]. It can be seen that the spectrum scarcity is mostly caused by the fixed assignment to the wireless service operators, and there exist a lot of spectrum opportunities both spatially and temporally. Therefore the interest regarding allowing access to unutilized spectrum by unlicensed user (secondary user) has been growing in several regulatory bodies and standardization groups, e.g., FCC and 802.22 [2, 3].

In US, one appealing frequency band that promotes spectrum efficiency by allowing opportunistic spectrum usage is the TV band. In fact, the FCC approved a Notice of Proposed Rulemaking (NPRM) to allow new generation of wireless devices to utilize the vacant TV broadcasting channels in each region [2]. The vacant TV channels are often referred to as TV "white spaces" (TVWS). The rulemaking aims to enable broader wireless broadband coverage in US. The FCC was clear that any device certified to operate in such TV white space has to use new "smart radio" technology, such as cognitive radios. Cognitive radios are required not to cause harmful interference to the licensed users, in this case, the TV users. Therefore, a fundamental functionality of cognitive radio is to detect the presence of primary user in the vicinity, or "spectrum sensing", and select the vacant channel accordingly.

The growing interest on cognitive radios has led to a number of publications related to spectrum sensing. In [4] and [5], the detection performance based on energy detection method is analyzed for the cases of single user and multiple collaborative users. However, the energy detection method is not robust against noise uncertainty. In fact, as pointed out in [6], the minimum SNR required for reliable energy detection is -3.3 dB when the noise power variation is 1 dB. This limit, referred to as SNR_WALL, is well below the sensitivity requirement for spectrum sensing proposed for TV band. Other methods, such as match filtering and preamble detection, require strong prior knowledge about the primary user. Although performing well under low SNR scenario, these methods are not general enough, because each system eventually requires a match filter specifically designed for it [9]. The Cyclostationary Spectrum Density (CSD) based detection method offers a nice trade off between generality and robustness. The fundamental theory of CSD was presented in [7, 8], but the application of CSD recently attracted growing attention in the spectrum sensing research [9, 10]. For example,

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spectrum sensing based on CSD estimation is under consideration in the 802.22 working group as well.

Most of the published results about spectrum sensing rely on theoretical analysis and numerical simulations. The results published by UC Berkeley's BWRC [9-11] give good insights on the challenges regarding the implementation of spectrum sensing and cognitive radio. In this paper, we evaluate the performance of CSD estimation from a practical implementation point of view. We also point out the potential limitations in the CSD based detection, which will determine the design of the signal processing functionalities in the spectrum sensing engine. In addition, we develop a feasible architecture for CSD based real time spectrum sensing, therefore field testing and performance evaluation can be made possible.

The rest of the paper is organized as follows. The system model under consideration is discussed in Section 2. In Section 3, we briefly discuss the principles of CSD estimation and why it can be used for spectrum sensing. In Section 4, we present the proposed algorithm transformation and the simulation results, in order to optimize the spectrum sensing performance. The implementation architecture derived from the simulation results is presented in Section 4. We conclude the paper and point out future work in Section 5.

2. SYSTEM MODEL

We are considering a cognitive radio to operate in the TV white space. Therefore we assume the licensed user (TV broadcasters) have fixed bandwidth of 6 MHz (in US). We also assume the licensed users may only occur at the finite number of center frequencies (TV channels). Figure 1 gives an example of spectrum sensing results showing that channels 16, 18 and 21 are TVWS, while channels 17, 19 and 20 are occupied. In addition, we assume our cognitive radio will only operate at a single available TV channel in the region. The problem considered in this paper is how to find the regional or temporal available channels. The issue of channel selection, on the other hand, is out of the scope of this paper.

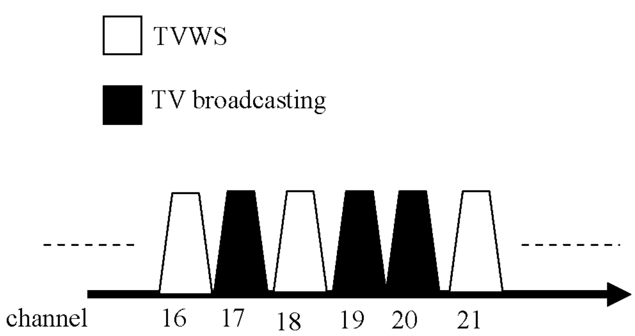

Figure 1. Spectrum sensing in TV band

The spectrum sensing problem can be modeled as hypothesis testing. We want to discriminate between these two hypotheses:

$$H_0: r(t)=n(t) \quad (1)$$

$$H_1: r(t)=x(t)+n(t) \quad (2)$$

The received signal, the primary user's transmit signal, and the noise, are denoted as *r(t)*, *x(t)*, and *n(t)*, respectively. For each TV channel, the cognitive radio needs to decide if it belongs to TVWS (H_0) or not (H_1) through spectrum sensing, before it decides to use any unused TV channels.

In the view of implementation, the spectrum sensing is performed with respect to one TV channel at a time. It will be ideal to perform broadband sensing that can cover multiple channels in each measurement; however the large difference in signal levels between TV stations will impose a very high dynamic range requirement. In addition, we choose an off-the-shelf TV tuner that only allows us to perform sensing on one TV channel at a time. The simplified hardware block diagram is shown in Figure 2. The compute intensive processing, such as the CSD estimation, is implemented on the FPGA. The sensing results are then forwarded to host computer for further processing.

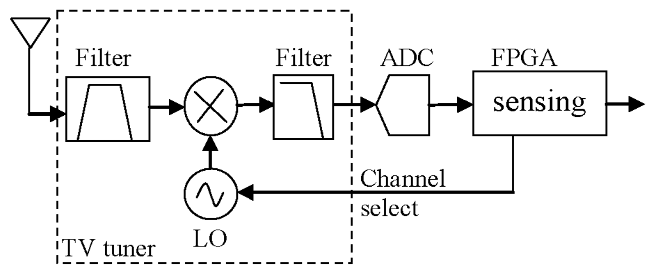

Figure 2. Spectrum sensing hardware diagram

3. PRINCIPLES OF CSD BASED SENSING

The spectrum sensing task is to detect a signal, often a weak signal, in the background noise. It is often assumed the primary signal *x(t)* has non-random components that can be exploited by cognitive radio to discriminate it from noise. These features include carrier wave, symbol period, and modulation type, etc [9]. The signal *x(t)* is said to be cyclostationary if its autocorrelation function $R_x(t,\tau)$ is periodical:

$$R_x(t,\tau) = R_x(t+T,\tau) \quad (3)$$

Therefore the autocorrelation function $R_x(t, \tau)$ can be expanded using Fourier series, whose coefficient is determined by:

$$R_x^\alpha(\tau) = \frac{1}{T}\int_T R_x(t,\tau)e^{-j2\pi\alpha t}dt \quad (4)$$

If the signal is cyclostionary with period T, the equation (4) will be non-zero when evaluated at α=1/T. For a stationary process such as noise, equation (4) will be zero-valued for all $\alpha \neq 0$. Taking the Fourier transform with respect to τ results in the cyclostationary spectrum density (CSD), or the spectral correlation function:

$$S_x^{\alpha}(f) = \lim_{\Delta t \to \infty} \lim_{T \to \infty} \int_{-\Delta t/2}^{\Delta t/2} X_T(t, f + \frac{\alpha}{2}) X_T^*(t, f - \frac{\alpha}{2}) dt \quad (5)$$

The term $X_T(t,f)$ stands for the short time Fourier transform of x(t) with bandwidth 1/T. The CSD is a two dimensional transform that consists of two variables: the cyclic frequency α and the spectral frequency f. In our implementation, the CSD estimation is performed digitally using fast Fourier transform (FFT) and spectral correlation. Therefore equation (5) is only evaluated at a set of discrete frequency pairs ($\{\alpha_k, f_j\}$). In addition, the practical estimation can only be performed within limited time duration. So the CSD is estimated by performing a sliding N point FFT, and then correlating the appropriate spectral components, i.e.,

$$S_x^{\alpha_k}(f_j) = \frac{1}{NM} \sum_{i=1}^{M} X_i(f_j + \frac{\alpha_k}{2}) X_i^*(f_j - \frac{\alpha_k}{2}) \quad (6)$$

It is easy to see that when the cyclic frequency α_k is zero, the CSD will be degenerated to the power spectrum density (PSD). The application of CSD to spectrum sensing is because the noise only contributes to the PSD levels, while the signal with some distinct cyclostationarities can contribute to certain CSD levels. Therefore it is possible to detect weak signals buried in noise in the low SNR scenario. In [9], authors show the difference between CSD and PSD under low SNR and high SNR conditions.

4. CSD ALGORITHM TRANSFORMATION AND SIMULATION RESULTS

The implementation architecture of CSD estimation is determined through algorithm transformation and simulation.

4.1. Algorithm Transformation

From (6), it can be seen that the number of correlations needed is largely determined by the size of the FFT. The ideal CSD estimation in (5) will require an FFT of infinite number of samples. We choose a 4K-point FFT as it provides a good comprise between estimation quality and hardware cost. On one hand, large size FFT results in more accurate CSD estimation. On the other hand, FFT with large data size will not only be expensive in hardware cost, but it might also require longer averaging time for CSD estimation.

After estimating the computation requirement and the maximum clock speed that our FPGA can perform, we realize that it is very difficult to perform real time CSD estimation over the entire two-dimensional plane of cyclic frequencies and spectral frequencies. It is also unnecessary to perform such exhaustive operation. If we assume the input signal is a digitized IF signal centered at F_c with bandwidth B, the regions that an ideal CSD estimation will have non-zero magnitude locate in the four shaded areas as shown in Figure 3. Therefore we could limit the CSD estimation only in these support regions. If the bandwidth is small compared with the sampling frequency, this could significantly reduce the number of correlations performed in CSD estimation. Moreover, we want to further reduce the number of correlations by reducing the two dimensional space to be one dimensional. The advantage of such operation is two fold. Firstly, the number of operations will be reduced such that real time processing is more feasible. Secondly, the search space for signal detection is much smaller and easy to handle. In [12], the authors also presented a method to generate one dimensional profile of CSD by performing projection. However, this transformation only affect the post processing on the 2D CSD estimation results without alleviating the computation burden. In this paper, instead, we will only perform the CSD estimation along the axis of zero cyclic frequency and the axis of zero spectral frequency. In other words, we will only estimate the CSD values of $S_x^{\alpha}(0)$, and the PSD values of $S_x^{0}(f)$. Through this transformation, we reduce the maximum number of correlations to be performed from N^2 to 2N. Geometrically, among all the straight lines in the plane, these two axes intersect the most with the four potential support regions. Therefore, we could anticipate the least loss of features by transforming the CSD estimation into the two one-dimensional cases as described. The PSD values are useful when we try to identify the type of the system under good SNR condition. For example, we can classify a primary signal to be analog TV (NTSC) signal when the power level at video carrier frequency is significantly higher than other frequencies.

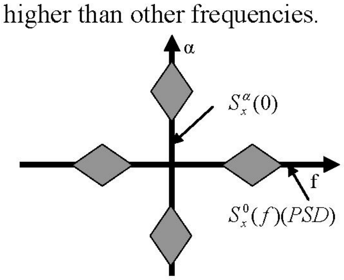

Figure 3. Support regions of CSD and the proposed 1D transformation

4.2. Features Comparison

In Figure 4, we show the CSD estimation performed only along the zero spectral frequency, denoted by $S_x^{\alpha}(0)$. The test signal is a digital intermediate frequency (IF) signal modulated by BPSK symbols. The symbol frequency is denoted as F_{sym}, while the sampling frequency and the IF frequency are both normalized with respect to F_{sym}. The sampling frequency is chosen to be $16\times F_{sym}$. The signal to noise ratio is set to 10 dB such that the features can be clearly identified. We show the magnitude of the $S_x^\alpha(0)$ estimation under two different carrier frequencies, namely F_c equals to $3\times F_{sym}$ and $3.01\times F_{sym}$. For both simulations, the size of FFT is set to 256 and the observation time is equal to 512 symbol periods.

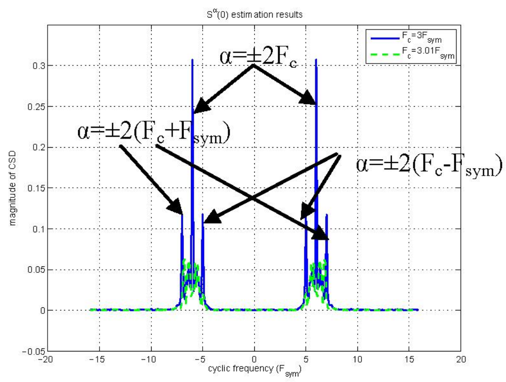

Figure 4. CSD estimation along the axis of zero cyclic frequency

When F_c equals to $3\times F_{sym}$, the CSD estimation clearly shows non-zero values (features) at the characteristic cyclic frequencies of 1) twice of the carrier frequencies ($\alpha=\pm2\times F_c$), and 2) the combination of twice of the double carrier frequency and twice of the symbol frequency ($\alpha=\pm2\times(F_c\pm F_{sym})$). This observation matches the simulation and analysis results presented in the literature [8]. However, if the carrier is changed by as little as $0.01\times F_{sym}$, we notice that all these features disappear. The CSD only has some small non-zero values compared with the 1st case. The reason for the features to disappear is that the carrier frequency no longer coincides with a frequency bin in the FFT results. Therefore the featured cyclic frequencies no longer belong to the set of discrete cyclic frequencies $\{\alpha_k\}$. This imposes a stringent limit on the CSD feature detection using FFT implementation: in order to detect strong cyclic features, the featured cyclic frequency (α_f), sampling frequency (F_s), and the size of FFT (N) need to be chosen such that the featured cyclic frequency is exactly one of the discrete cyclic frequencies that CSD are evaluated at:

$$\alpha_f \in \{\alpha_k\}, \alpha_k = k\frac{2F_s}{N}, k = 0, \pm1, \ldots, \pm\frac{N}{2}-1. \quad (7)$$

From Figure 4, it can also be seen that the features at the double carrier cyclic frequency ($\alpha=\pm2\times F_c$) are more distinct than the features at the other cyclic frequencies. The effectiveness of a feature *F* for the discrimination between two hypotheses can be measured by Fisher criterion, defined as

$$C_F = \frac{|E(F\,|\,H_1) - E(F\,|\,H_0)|^2}{Var(F\,|\,H_1) + Var(F\,|\,H_0)}. \quad (8)$$

The Fisher criterion can be viewed as a generalized SNR representation. The more distinct a feature is, the higher C_F value it should posses. In order to show the significance of the feature at the double carrier, we create two test signals. One of them is a baseband signal centered at DC, and the other is an IF signal. Among the set of cyclic frequencies mentioned in previous paragraph, we select two featured cyclic frequencies of IF signal for simulation: $\alpha=2F_c$ and $\alpha=2(F_c\text{-}F_{sym})$. For the baseband signal, the non-zero CSD values locate at cyclic frequencies of $\pm2\times F_{sym}$ [8]. We select the positive one to be compared with the features selected for IF signal. The Fisher criterion is estimated through multiple Monte Carlo simulations. The test signals used for simulation is the same as the BPSK modulated signal used in Figure 4, except that the carrier frequency is set to 0 for baseband signal. In Figure 5, the Fisher criterion measure of the three CSD features is plotted with respect to various signal-to-noise ratios (SNRs). It can be seen that the feature of $|S_x^{\alpha=2(F_c-F_{sym})}(0)|$ for the IF signal has much lower C_F values than the other two features. Although having similar C_F values, the feature of $|S_x^{\alpha=2F_c}(0)|$ for the IF signal still has higher C_F than the $|S_x^{\alpha=2F_{sym}}(0)|$ feature of the baseband signal. In addition, a detector can combine the estimated CSD values at multiple cyclic frequencies to improve the performance. For example, we can combine $|S_x^{\alpha=2F_C}(0)|$ and $|S_x^{\alpha=2(F_C-F_{sym})}(0)|$ together for the detection of the IF signal, while it's not possible to do so for the baseband signal.

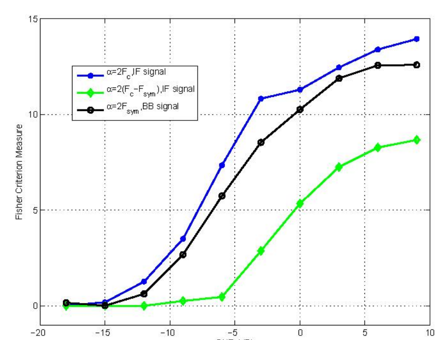

Figure 5. Fisher criterion comparison of selected features

Through this simulation, we can conclude that the double carrier cyclic frequency is the most distinct feature in CSD based feature detection. However, if the signal of interest is at baseband, this feature is degenerated because the cyclic frequency corresponding to double carrier is simply zero. Therefore, the signal of interest should not be translated to baseband. Instead, the signal should be centered at an intermediate frequency.

In addition, further analysis and simulation show that the location of the center frequency can affect the signal detection performance. We denote the center frequency of the signal to be detected as F_c. Based on our first observation, F_c needs to satisfy

$$F_c = k\frac{F_s}{N}, \quad (9)$$

where F_s is the sampling frequency, N is the size of FFT, and k is an integer. We also assume the signal to have one dimensional constellation such as PAM, therefore the signal can be represented as

$$x(n) = s(n)\cos(2\pi k \tfrac{n}{N}) \quad (10)$$

The baseband transmit signal *s(n)* is approximately modeled as a wide sense stationary (WSS) process, with zero mean, and power of σ^2. Then the FFT output *X[m]* is

$$X[m] = \sum_{n=0}^{N-1} \frac{s_n}{2}\left(e^{-j2\pi n(m-k)/N} + e^{-j2\pi n(m+k)/N}\right) \quad (11)$$

The CSD evaluated at double carrier cyclic frequency is

$$S_x^{2F_c}(0) = E\{X[k]X^*[-k]\} \quad (12)$$

Combine (11) and (12), after some manipulation, we can have

$$S_x^{2F_c}(0) = \frac{\sigma^2}{4}\left(N + \sum_{n=0}^{N-1} e^{-j8\pi nk/N} + \sum_{n=0}^{N-1} e^{-j4\pi nk/N}\right) \quad (13)$$

Only the last two terms are dependent on k, so the frequency of IF can be determined. When k=0, the signal becomes a baseband signal, therefore is excluded from consideration. It can be seen that the last summation will be zero except when k=N/2. In this case, the center frequency is located at $F_s/2$. However, a bandpass signal centered at $F_s/2$ cannot be sampled at F_s without aliasing; therefore we can ignore the third term since it is always zero. The second term will be evaluated to zero except when k=N/4, which means the IF frequency is $F_s/4$. Therefore (13) can be simplified to

$$S_x^{2F_c}(0) = \begin{cases} \dfrac{N\sigma^2}{2}, k = \frac{N}{4} \\ \dfrac{N\sigma^2}{4}, k \neq 0, \frac{N}{4}, \frac{N}{2} \end{cases} \quad (14)$$

So if the IF frequency is set at ¼ of the sampling frequency, the CSD feature should have the highest C_F values comparing to other IF frequencies.

This analysis results are verified by simulating the Fisher criterion measure of the double carrier cyclic frequency feature, when the IF frequencies are set at ¼, 3/16, and 5/16 of the sampling frequency. The simulation results are shown in Figure 6, where the Fisher criterion measure corresponding to the $F_s/4$ IF is the highest. The other two cases have almost identical measures using Fisher criterion. It is also worth noticing that the difference in the Fisher criterion measure gets larger when SNR of the signal becomes lower, which will benefit the detection of weak signals in spectrum sensing.

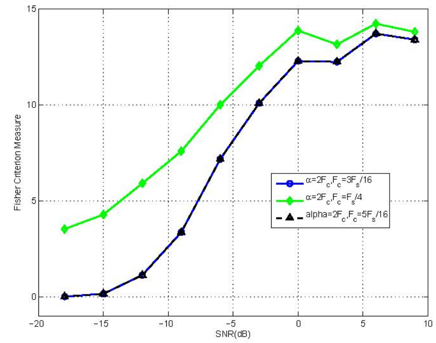

Figure 6. Fisher criterion comparison of different IF frequencies

5. HARDWARE IMPLEMENTATION

The simulation and analysis results obtained in Section 4 show that in order to optimize the performance of CSD based feature detection for spectrum sensing, we need to

1) have prior knowledge of the feature cyclic frequencies, and choose appropriate FFT size such that they are included in the discrete set of cyclic frequencies in digital CSD implementation;
2) shift the signal of interest to an IF frequency instead of baseband; and
3) set the IF frequency to be ¼ of the sampling frequency if possible.

The relatively static spectrum occupancy of the TV broadcast signals makes it possible to meet all of the three requirements. The block diagram of the implementation that performs these tasks is shown in Figure 7.

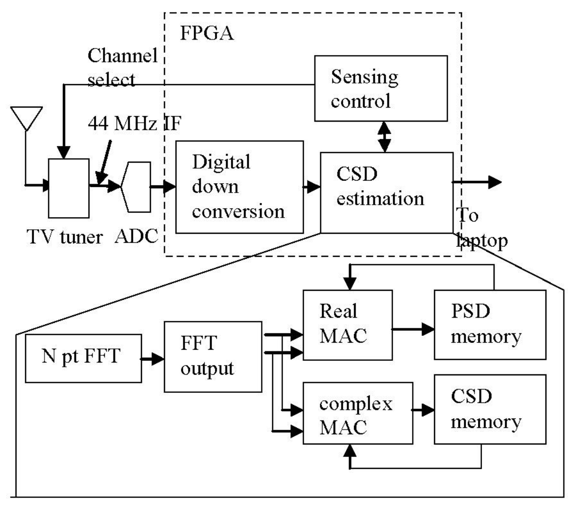

Figure 7. FPGA implementation of CSD estimation

Due to the legacy design compatibility, the TV tuner generally outputs its signal at 44 MHz IF. We then convert the IF signal to digital using high speed data converter. A digital down converter (DDC) is needed to down-sample the signal, and subsequently shift the signal to be centered at ¼ of the reduced sampling frequency. Another functional block can be included in the DDC is the sample rate converter (SRC) such that the sampling frequency may be converted to 4 times of the IF frequency.

After the algorithm transformation described in section 4.1, the CSD estimation becomes fairly straightforward. After the N point FFT, the correlation operation is performed in every clock cycle with respect to the two spectral components read from the FFT output memory. The two spectral components are *X[m]* and *X[-m]*, respectively. The PSD is estimated using the real MAC (multiply-and-accumulate), while CSD is estimated using the complex MAC, because CSD values have to be averaged coherently. The CSD based feature detection will be performed by post processing on a computer, which collects the data from the PSD and CSD memories. The CSD estimation is implemented on a Xilinx Virtex4 SX35 device. The implementation complexity is summarized in Table 1. In Figure 8, we show the receiver operating characteristics (ROC) curves for detecting BPSK signals with different IF frequencies simulated on the hardware implementation. Under low SNR (-18dB) condition, when the false alarm rate is less than 10%, the probability of detection is greater than 90% when IF is ¼ of the sampling frequency. However, the probability of detection falls to below 30% when IF is 3/16 of the sampling frequency under the same conditions.

Table 1. CSD implementation summary

Max. clock frequency	112 MHz
Block RAM	54
DSP48	42
Total slices	3712

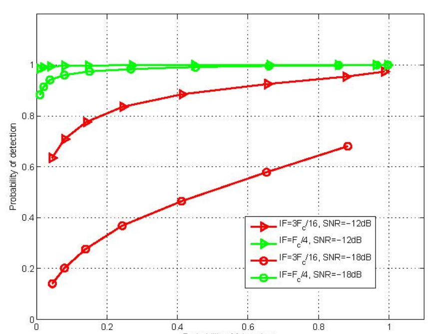

Figure 8. ROC curves for detecting signals with different IF

6. CONCLUSIONS AND FUTURE WORK

In this paper we present the design and implementation of a CSD estimation engine for the purpose of spectrum sensing in cognitive radios. This work is motivated by optimizing the performance of CSD based feature detection, such that it can be feasible to detect weak primary signals. To alleviate the compute burden in estimating CSD, we reduce the two dimensional processing space of CSD estimation to two one dimensional cases: the PSD case, and the zero spectral frequency case. However, we try to minimize the loss of features during this transformation. Our simulation results show the tight requirement on the sampling frequency, FFT size, and feature cyclic frequencies. In addition, we also analyze and simulate different cyclic features. We propose that the signal should be an IF signal at $F_s/4$, such that the double carrier frequency feature can achieve the highest metric in the measure of Fisher criterion.

This implementation is most suitable when the spectrum sensing is performed with respect to one channel at a time. The broadband spectrum sensing remains to be very challenging. In addition, the problem of general purpose signal identification is still unsolved. Our future work will continue to tackle these hard problems, identify and attack the technological problems while proposing necessary regulatory policy changes, such that cognitive radios can become reality.

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