This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE INFOCOM 2010 proceedings

The Feasibility of a Fast Fourier Sampling Technique for Wireless Microphone Detection in IEEE 802.22 Air Interface

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Abstract— **The speed and accuracy of spectrum sensing techniques are essential factors in the performance of cognitive radio networks. The limitations imposed by computational complexity and limited monitoring time window impede the success of spectrum sensing operation performed by cognitive radio nodes. Compressive sensing technique is viewed as a novel approach to solve scalability problems in some signal processing operations. One popular application of compressed sensing is sizable image recovery. This technique can be used in spectrum sensing applications to reduce the barriers of current spectrum sensing computational requirements. The success of this technique will result in faster sensing operations, less complex sensing modules, or wider spectrum sensing capabilities. The coming IEEE 802.22 air interface standard aims to provide wireless services in wireless regional area network using TV spectrum white spaces. This standard is considered as the first standard that is based on cognitive radio approach. Spectrum sensing is a critical functionality that needs to be performed by 802.22 compliant devices. While, the standard does not specify any spectrum sensing method, it requires the sensing operation to be performed within timing and accuracy constraints. This work in progress is investigating the feasibility of using one of the compressive sensing techniques named Fast Fourier Sampling to detect wireless microphone signals for IEEE 802.22 air interface.**

Keywords-compressive sensing; spectrum sensing; wireless microphones; IEEE 802.22; cognitive radio

I. INTRODUCTION

In November 2008, the Federal Communications Commission (FCC) in the United States issued a report and order (R&O) that permits unlicensed devices to use vacant bands (white spaces) in the TV spectrum (TV channels 5-13 in the VHF band and 14-51 in the UHF band) [1]. This permission opens a plethora of new possibilities and stimulates wireless communication innovations to provide better wireless broadband connectivity and new array of internet based products and services.

The IEEE 802.22 is considered the first wireless standard that uses cognitive radio technology to operate in TV white spaces. The standard aims to provide wireless broadband services to wide rural areas. The good non-line-of-sight (NLOS) propagation characteristics, reasonable antenna size and limited industrial noise and ionospheric reflections are among the attractive features of TV spectrum that facilitate large coverage [2]. A typical IEEE 802.22 network consists of a base station and a number of client stations known as customer premise equipment (CPE). The network strives to avoid interfering with three types of primary users, namely; Analog TV, Digital TV and Wireless Microphones (WM). One technique to protect these primary users is spectrum sensing. Several studies have evaluated different spectrum sensing techniques to detect these three signals (Analog, digital TV and WM signals) [3-4].

The detection of WM signals in particular is impeded by several technical challenges [5]. The WM signals do not have unique modulation scheme. However, FM modulation tends to be the de Facto modulation scheme for WM. Additionally, the frequency separation between WM signals is not clearly defined. Therefore, multiple WM may appear in one or more TV channels [6]. Another challenge may face energy based detectors is the ability to distinguish between WM signals and spurious tones in the sensed band.

Several studies have investigated the detection of WM signals [6,8,9]. Most of the studies based on energy detection method have shown better detection performance when FM deviation factor is smaller due to higher spectral power density [7]. A study by Rutgers University and Thomson Corporate Research has examined the energy detection method to detect WM signals [8]. They have used two different voice source models; the colored noise and tone signals. Philips research labs have examined the performance of energy detectors based on 2048-point FFT [6]. Their lab experiments have shown a probability of detection that exceed 90% for signals as low as -116 dBm. Table I summarizes the performance of WM detectors in [6,8].

Table 1. Wireless Microphone Detectors Performance Summary

Detector Type	P_{MD}	P_{FA}	Sensing time	SNR	Voice source
Energy Detector [8]	0.1	0.1	10	-24.8	Tone
	0.1	0.1	10	-27	Colored noise
	0.1	0.01	10	-23.8	Tone
	0.1	0.01	10	-26	Colored noise
Welch Periodogram [6]	0.1	0.001	5	>-22	Tone
	0.1	0.1	5	-23.4	Tone
	0.1	0.1	10	-25	Tone

The size and sampling rate of energy detectors is constrained by the computing power and sensing time window. A novel method to reduce the required number of samples for signal sensing is compressive sensing [10]. There are several methods for signal reconstruction and some has been envistigated for spectrum sensing applications. This work presents the initial study results for using Fast Fourier Sampling technique which is based on the theory of streaming algorithms [11].

In the following sections, a brief description of the Fast Fourier Sampling algorithm is provided in section II. Section III reports the initial simulation results for using the fast Fourier sampling algorithm to detect WM signals. Section IV discusses the results of the simulation and future work is proposed in section V.

II. Fast Fourier Sampling Overview

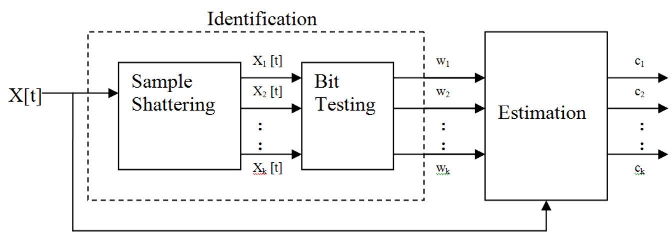

Figure 1. Fourier Sampling algorithm block diagram

In digital systems, signal spectrum can be decomposed into a number of equi-spaced frequencies (orthogonal functions) as shown in equation 1. The coefficients a_k of these frequencies are retrieved using Discrete Fourier Transform DFT as shown equation 2:

$$x(t)=\frac{1}{\sqrt{N}}\sum_{j=0}^{N-1}a_j e^{2\pi i\omega_j t/N}, \qquad t=0,1,2,\ldots,N-1 \tag{1}$$

$$a_j=\frac{1}{\sqrt{N}}\sum_{t=0}^{N-1}x(t).e^{-2\pi i\omega_j t/N}, \omega_j\in(0,1,2,\ldots,N-1) \tag{2}$$

where N is the number of samples.

The complexity of this transform is $O(N^2)$. This computational complexity is reduced O(NlogN) using FFT algorithm. While FFT provides a dramatic complexity reduction, the complexity of calculating large number of N remains a challenge in current computing systems that operate under severe power and chip real estate limitations such as wireless mobile devices. Nevertheless, FFT appears to be inefficient when we are interested in detecting only m << N frequencies in the received signal spectrum. In this case, it is possible to use less number of samples to detect the most m "energetic" frequencies in the spectrum and approximate the spectrum using a non-uniform IFFT as shown in equation 3.

$$y(t)=\frac{1}{\sqrt{N}}\sum_{k=1}^{m}a_k e^{2\pi i\omega_k t/N} \tag{3}$$

One computational algorithm proposed to calculate this approximation is called Fast Fourier Sampling (FFS). The algorithm is first presented in [12] and then enhanced in [13]. This section provides a brief overview of the algorithm based on the tutorial published in [11]. FFS produces spectral approximation using time and storage of:
m.poly(ε^{-1}, log (δ^{-1}),log(N)) where $\varepsilon>0$ is approximation quality factor, $\delta>0$ is probability of failure.

This algorithm is performed in three stages that are iterated for a fixed number of times (see figure 1):

1- Frequency identification stage
2- Coefficient estimation stage
3- Updating the set of frequencies and coefficients

The Identification stage constructs a list of frequencies that are likely to carry a significant amount of received spectrum energy. The identification is achieved in two stages. First is by "Sample Shattering" which aims to separate significant frequencies from each other and pass them through a sub-band decomposition filter bank. The separation is performed by time dilation of signal samples by a factor σ which results in frequency permutation by factor σ^{-1} where σ^{-1} is the multiplicative inverse of σ that satisfies $\sigma.\sigma^{-1}$ mod(N) =1. This argument can be expressed mathematically in equation 4:

$$y(t)=x(\sigma t) \quad \text{for all t} \quad \Leftrightarrow \quad Y(\omega)=X(\sigma^{-1}\omega) \quad \text{for all } \omega \tag{4}$$

The bit test examines the output of filter banks to determine the major K frequencies (or less) at the output of filter bank. This bit testing detects the dominant frequencies using two frequency filters; g^{even} and g^{odd}.

The Estimation stage receives the list of identified frequencies and estimates their corresponding coefficients. The estimation of a_k is performed by demodulating the signal by w so that we can estimate the zero frequency instead. Then we randomly dilate the signal to separate any frequencies around zero frequency (the time dilation fixes zero frequency and shuffle other frequencies). After separation, we use a low pass filter to pass the zero frequency and the output is considered an estimation of the frequency coefficient c_w. This operation can be expressed mathematically using equation 1.7

$$a_k=\sqrt{N}e^{2\pi i\omega_k/N}\sum_{j=0}^{K-1}h(j)x(t-\sigma j)e^{2\pi i(\omega_k\sigma K/N)j/K} \tag{5}$$

The third stage adds the findings of a_k,ω_k to the previous findings and updates the total set by retaining the frequencies with largest coefficients. Then the algorithm subtracts the estimated spectrum from the sampled one and repeats the three stages for a predetermined number of times.

The incoherency and spectrum sparsity are important conditions for the applicability of compressed sensing technique. For IEEE 802.22, it is a valid assumption to expect sparse spectrum in rural areas which provides a great opportunity for compressed sensing technique to be used.

III. Simulation Results

This section reports the initial simulation results to examine the ability of FSS detecting WM signals. Most of wireless microphones use the frequency modulation (FM). Therefore, WM signals can be modeled as:

$$s(t)=A_c\cos\left[2\pi f_c t+2\pi\Delta\int_0^t m(\tau)d\tau\right] \tag{6}$$

where :

A_c the carrier amplitude f_c the carrier frequency

Δ the frequency sensitivity (Deviation factor)

$m(\tau)$ the modulating signal

The wireless microphone signals simulation method in [16] suggests three signal models as shown in Table 2. Note that the modulating signal m(t) is modeled as a single frequency. The simulation method suggests two environment conditions:

1- Outdoor environment: modeled as additive white Gaussian noise (AWGN) channel.
2- Indoor environment: modeled as Rayleigh fading channel as specified in [16].

Table 2. The Simulation Parameters of WM Signal Models

	Silent	Soft Speaker	Loud Speaker
M(t) frequency [kHz]	32	3.9	13.4
FM deviation factor [kHz]	$\pm$ 5	$\pm$ 15	$\pm$ 32.6

Figure 2 shows the power spectral density of the three WM signals with identical power level used generated in AWGN channel with signal to noise ratio (SNR) of 20 dB. The carrier frequency is 3 MHz and sampling frequency is 18 MHz. The sampling frequency allows sensing 3 channels (6 MHz channels) at a time as per IEEE 802.22 requirements [2, 3]. The bandwidth of WM signals does not exceed 200 kHz.

The FSS simulation is done using the AAFFT_0.9 code developed by Mark Awin [14]. The simulation parameters are listed in Table 3. More details about the simulation parameters can be found in [14].

Table 3. Fast Fourier Sampling Simulation Parameters

AAFFT Parameter	Value
Signal Size	2^22
Num_FreqID_CoefEst_Iterations	5
Num_Rep_Terms	1
Working_Rep_Terms	1
Max_KShattering_Sample_Points	128
Num_KShattering_Sample_Points	128
Exhaustive_Most_Sig_Bits	0
Max_FCE_Sample_Points	512
Num_FCE_Sample_Points	512
Norm_Estimation_Max	9
Norm_Estimation_Num	9
Max_FCE_Medians	9
Num_FCE_Medians	9
Roots_Coef	8
Naive_Bulk_Cutoff	1
Naive_Coef_Est_Cutoff	1
Num_Fast_Bulk_Samp_Taylor_Terms	8
FFCE_Roots_Coef	8
Num_Fast_Freq_Coefnt_Est_Taylor_Terms	8
FFCE_Iterations	5

In the simulation, the FSS is used to detect a single WM signal at 3 MHz under different environment conditions (AWGN and Rayleigh Fading) with SNR values from 10 to -24 dB. The simulation scenarios have been repeated for 1000 times. At each iteration, the FSS provides the most energetic single frequency and its associated estimated coefficient.

The histogram of identified frequencies for the 1000 iterations is shown in figure 3. Figure 4 lists the histogram of the estimated coefficients. The histogram plots are useful tools to examine the algorithm stability and accuracy across different SNR values. The frequency identification stage is considered successful if the identified energetic frequency is within 200 kHz range (The maximum bandwidth of WM signal) of the carrier frequency (3 MHz). The success rate of the identification stage in AWGN and Rayleigh channel is provided in Figure 5. Figure 6 shows the success rate of the coefficient estimation stage of the successful identified frequencies. The coefficient estimation for false frequency estimation is not counted.

This algorithm has used 68256 samples out of 2^22 (%1.63) and found to be %170 faster than FFTW (highly optimized C subroutine library for computing discrete Fourier transform.

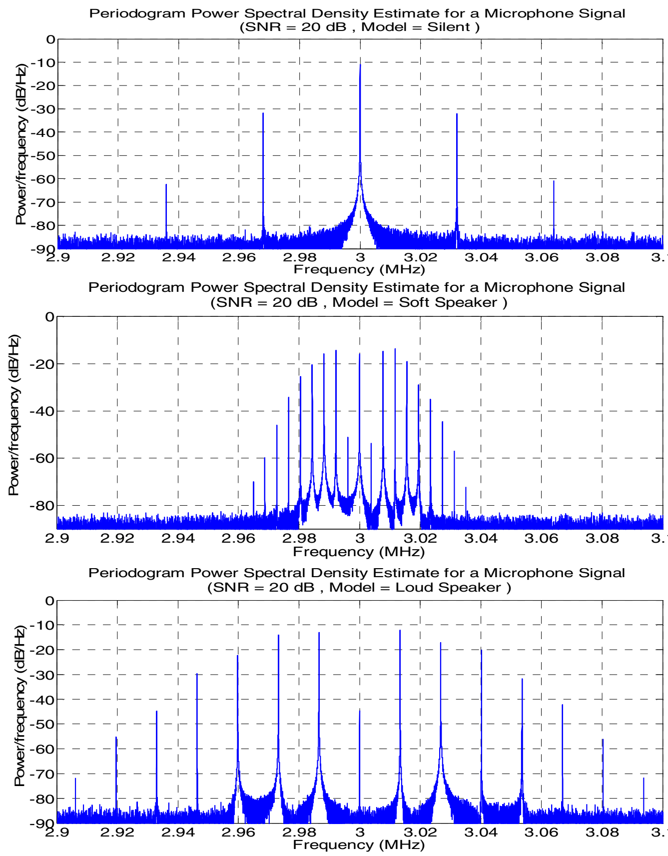

Figure 2. The power spectral density of three WM signal models (Silent, Soft Speaker, Loud Speaker)

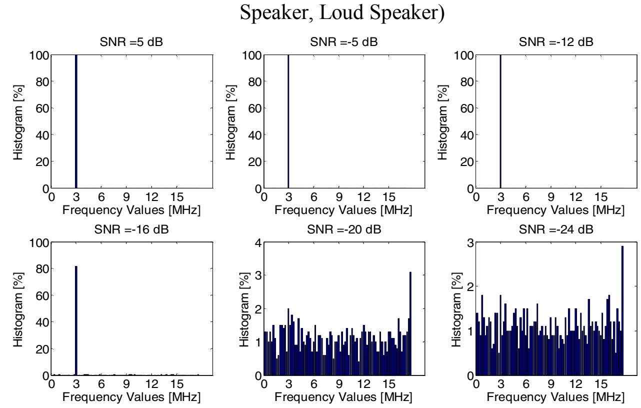

Figure 3. Histogram of the frequency identification output for 1000 tests (The energetic frequency is 3 MHz)

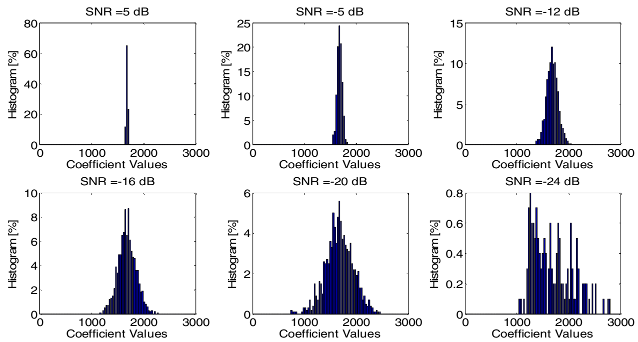

Figure 4. Histogram of coefficient estimation output for 1000 tests (The coeffiecient value is 1683.4)

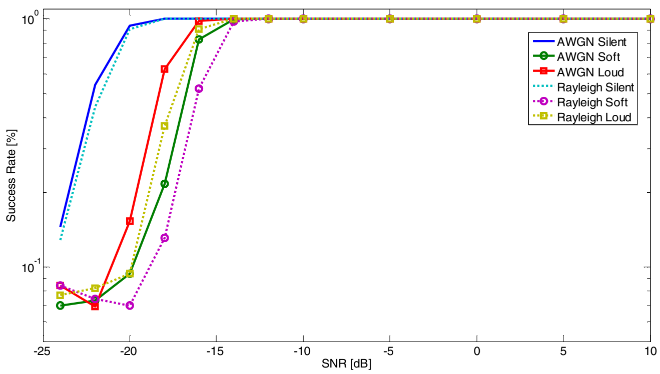

Figure 5. Success rate of frequency identification stage

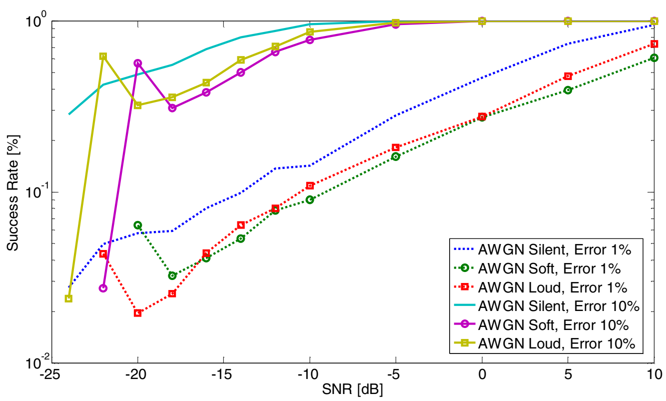

Figure 6. Success rate of coefficient estimation of a correctly identified frequency

IV. Discussion

The success rate plots in figure 5 and 6 uncover interesting heterogeneity in the algorithm performance at different stages. While the frequency identification performance deteriorates rapidly, the coefficient estimation stage performance degrades gradually as the SNR value decreases. The histogram of identified frequencies and estimated coefficients explains this behavior. In figure 3, the frequency identification stage shows a good stability in identifying the carrier frequency. The performance degrades partially at SNR=-16 dB and then it fails completely at -20 dB where the identification stage act almost as a uniform random number generator. In figure 4, the coefficient estimated value follows a Gaussian distribution with increasing variance as the noise in the wireless channel increases (SNR value decreases). This distribution is expected as a result of the additive white Gaussian noise. This distribution is reflected in the performance behavior as a gradual decay in coefficient estimation success rate.

Another observation found in the result is the algorithm is the identification stage sustainability against Rayleigh fading since the success rate show a slight degradation in the performance (around 1 dB). However, the coefficient estimation performs poorly under Rayliegh fading (not shown in figures). This poor performance in coefficient estimation is expected from FSS technique which acts as an energy detector in the frequency domain. The energy detectors have been found to act poorly in Rayleigh fading channel [4].

Typical energy detectors show better performance in detecting soft WM than loud WM signals [6,9] because they perform better in detecting narrow band signals (higher spectral energy density) than wideband ones. However, the energy of the frequency "spikes" in the signal is the main performance factor for FSS algorithm and not the signal bandwidth. This explains the third observation found in the performance across different WM signal models. The loud microphone signals are better detected than soft microphone signals by the algorithm because of the higher frequency spikes in the loud WM speaker as compared to the soft WM speaker. The stronger the frequency spikes the better the detection of the signal by the algorithm.

The initial simulation results lead the authors of this work to see potentials in using this technique for spectrum sensing for cognitive radio applications in general and for IEEE 802.22 standard in particular. The frequency identification performance complies to the IEEE 802.22 spectrum sensing sensitivity requirement for WM signals which is -12 dB SNR for a conservative sensing device with a noise factor of 11 dB. The frequency identification of Silent WM signals tolerates up to -22 dB SNR, while the detection limit is around -17 dB for loud and soft speaker signals.

The simulation results have shown considerable spectrum sensing complexity reduction as compared to results [6], The work in [6] uses a sampling rate of 7.5 MHz to process one channel using 2048 FFT. For sensing time of 5 to 10 ms, around so 37.5 to 75 ksamples is needed to scan 1 channel. That means around 112.5 to 225 ksamples for 3 channels as compared to 68256 samples for FFS algorithm ~%40 to %70 reduction in number of processed samples. However, it is important to mention that the energy detector accuracy in [6] outperform FFS algorithm, yet the results presented in this work comply to IEEE 802.22 time constrains at far less processing complexity.

V. Future Work

The successful implementation of compressed sensing techniques for spectrum sensing in wireless cognitive networks can improve the network performance in many ways. Using fewer samples to sense the spectrum may lead to faster spectrum sensing allowing more spectrum range to be scanned within the same sensing time window. Compressive sensing may reduce the computational complexity of spectrum sensing, hence reducing the cost of computing devices.

The FSS technique has several unique advantages as well as technical challenges that need to be investigated in future work. The followings are some of the unique features:

1- Parallelism: with the semiconductor industry trend towards multicore and multiprocessor architecture, investing in parallel algorithms is an appealing call. Some stages of the FFS technique can be parallelized by decomposing them into several processes running independently such as the bit testing operation and coefficient estimation for each identified frequency. Future work will attempt implementing a parallelized version of the code using OpenMP on multicore with shared memory architecture.
2- Parameterizable: the frequency identification section can be parameterized. This means that a specific range of frequencies of interests can be defined in the bit testing section so that spectrum sensing can be targeted for predefined sub-bands of interests rather than scanning for the whole spectrum range from zero frequency to half of the sampling frequency including bands that are already known to be occupied. This feature can be used to build adaptive FFS algorithm to scans bands based on wireless activity.
3- Streaming algorithm: which is, by definition, designed for minimal memory resources to process large stream of data.
4- The computational resources required by the algorithm are approximately proportional to the number of frequencies used in approximation (m). Therefore, the Fourier Sampling can be potentially exponentially faster than FFT.

Beside these attractive features, several technical challenges need to be solved for feasible FSS implementation. Some are listed below:

1- Building a random sampling unit: A study have proposed two implementations of the random sampling unit using an array of data converter or analog registers [17]. The collected samples used in FFS do not depend on the signal or algorithm progress. Therefore, it is possible to decide in advance (before algorithm execution) the sampling time instants. However, a study to determine the minimum time difference between the samples is needed (not only number of samples) for a given channel condition (SNR) in order to estimate the implementation cost. It is expected for the time difference to decrease for less SNR values to achieve the same detection performance.
2- The effect of limited bit size and quantization error propagation on the algorithm stability and accuracy.
3- Further implementation experiments will be conducted in the future to evaluate FSS performance under nonlinear signal distortions, spurious RF spikes and multiple CPE signals of different power in the scanned spectrum.
4- The performance of FSS based detector is based on the number of representation terms used in the approximation (m). Monitoring wireless channel activity helps in picking the appropriate m value needed for each scanning cycle.

ACKNOWLEDGMENT

The authors thank Dr. Mark Iwen for sharing AAFFT code with the research community. Many thanks to OSCER center at the University of Oklahoma for providing the technical support and computational resources needed to perform the simulation tests in this work. Special thanks to Dr. Henry Neeman for all his support and useful technical advices. Thanks to Dr. Christos Komninakis for sharing his Rayleigh fading simulation model.

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