Wireless Microphone Sensing Using Cyclostationary Detector

Hatem Yousry[1] Fatma Newagy[2] Salwa ElRamly[3] Magdi Ibrahim[4]

[1]Electronics Engineering Dept. [2,3&4] Electronics & Communications Dept.

[1]American University in Cairo [2,3&4] Ain Shams University

Cairo, Egypt Cairo, Egypt

(hatem_y@aucegypt.edu) (fnewagy@eng.cu.edu.eg) (salwa_elramly@eng.asu.edu.eg) (magdy_ibrahim@yahoo.com)

***Abstract*—— Spectrum sensing has been identified as a key enabling functionality to ensure that cognitive radios would not interfere with the primary users, by reliably detecting primary user signal. In this paper, the primary user signal is wireless microphone (WM) signal. The power of the WM signal is highly concentrated in the frequency domain. Due to this property, we focus on spectrum sensing in the frequency domain using cyclostationary detection (CD), which is robust against white Gaussian noise (WGN) and large degradation in performance under low signal-to-noise ratio (SNR) environment. We also examine the windowing effect on cyclostationary-based detector for a given sensing time and obtain the optimum thresholds in the region satisfying the probability of false alarm constraint. Furthermore, very low sensing time = 170μs has been achieved at low SNR=-10dB. In addition an analytical expression for Cyclic Spectral Density (CSD) of the WM signal is derived.**

Index Terms- Spectrum Sensing, Cyclostationary Detection (CD), FFT Accumulation Method (FAM), Spectral Correlation Density, Wireless Microphone, Cognitive Radio.

I. INTRODUCTION

Nowadays, Cognitive Radio (CR) proves to be a tempting solution to the spectral congestion problem by introducing opportunistic usage of the frequency bands that are not heavily occupied by licensed users [1-3]. As a matter of fact, recent measurements by Federal Communications Commission (FCC) have shown that 70% of the allocated spectrum in US is not utilized. Furthermore, the allocated spectrum experiences low utilization [4]. Since cognitive radios are considered lower priority or secondary users (SUs) of spectrum allocated to a primary user (PU), their fundamental requirement is to avoid interference to potential primary users. IEEE 802.22 standard is known as cognitive radio standard because of the cognitive features it contains.

One of the most distinctive features of the IEEE 802.22 standard is its spectrum sensing requirement [5]. IEEE 802.22 based wireless regional area network (WRAN) devices sense TV channels and identify transmission opportunities. Spectrum sensing (SS) aims to detect the presence or absence of a signal from a PU; which are TV or FM WM. The main challenge in SS is to quickly detect the signal in a very low SNR environment, and with high reliability.

The algorithms used for SS can be broadly classified into three types: Energy Detector (ED), Matched Filter Detector (MFD) and Cyclostationary Feature Detector (CFD) [6][7][8]. ED, where the received signal energy in a frequency band of interest is compared against a threshold to detect the presence of a primary, is the simplest and most popular detector [9][10][11]. The MFD correlates the received signal with a copy of the transmitted signal. Although it is computationally simple, it assumes knowledge of the primary's signal, which may not be feasible in general [8][12].

Cyclostationary feature detectors rely on the second order cyclostationary characteristics inherent in all communication signals, i.e., pilot sequences, carrier tones, etc [13] [14]; in addition it has to detect the wireless microphones and DVB-T as well [15][16]. The significant advantages of cyclostationary signal analysis when compared with alternative approaches lie in the wealth of information which may be represented by the spectral correlation of a signal. Although the presence or absence of a given signal may be indicated by the specific cyclostationary features detected, these features may also be used to determine key signal properties. Furthermore; the cyclostationarity based detection algorithms can differentiate noise from primary users' signals. This is a result of the fact that noise is wide-sense stationary (WSS) with no correlation while modulated signals are cyclostationary with spectral correlation due to the redundancy of signal periodicities [17]. Spectrum sensing using the Spectral Correlation Density (SCD) function and its application to IEEE 802.22 WRAN is discussed in [18]. Cyclostationarity features as a detection method for primary user transmissions has been investigated in [19]. Cyclostationary features are caused by the periodicity in the signal or in its statistics like mean and autocorrelation or they can be intentionally induced to assist spectrum sensing [20][21].

Statistical spectral analysis can be described as the decomposition of a function into sinusoidal waveforms called spectral components; and to represent the function as a sum of weighted spectral components [22]. Cyclic spectral analysis deals with second order transformations of a function and its spectral representation. In the analysis of cyclostationary signals, two key functions are typically utilized. Time domain analysis of cyclostationary signals is performed using the Cyclic Autocorrelation Function (CAF); the frequency domain equivalent of the CAF is its Fourier transform, the Spectral Correlation Density (SCD) or Cyclic Spectral Density (CSD); for zero cyclic frequency these reduce to the conventional autocorrelation function and power spectral density (PSD) function. Successful exploitation of cyclostationarity typically requires knowledge of a cycle frequency. Cycle frequencies are the Fourier frequencies resulting from the Fourier-series representation of the almost-periodic moment or cumulant function [23]. Examples of exploitation of second-order cyclostationarity for detection and modulation classification are given in [24][25], in which knowledge of cycle frequencies is used to compute decision statistics. More recently, higher order cyclostationarity [24] has been applied to the modulation classification problem [25][26]. The various proposed algorithms require, in one way or another, detailed knowledge of the higher order moments and cumulants of the cyclostationary signals of interest [27].

The spectral correlation function is calculated based on the FFT Accumulation Method (FAM) [28]; which is one of the methods under time-smoothing classification which has good efficiency, computation wise. There are parameters involved that are used to trade-off resolution, reliability and of course computation reduction [29].

The rest of this paper is organized as follow. The basic concepts of cyclostationary detection model, the cyclostationary characteristics of wireless microphone signals , and the FFT accumulation method are discussed in section II. Section III presents the proposed wireless microphone detector. Simulation results are shown in section IV. Section V contains the conclusions.

II. Basic Concepts

Two basic concepts are reviewed in this section as follow:

A. *Cyclostationary Characteristics of Wireless Microphone (WM) Signals*

Most of the wireless microphone devices use analog frequency modulation (FM) and the signal bandwidth is less than 200 kHz. Let *m(t)* be the voice signal, then the transmitted FM signal *x(t)* can be generated by

$$x_{FM}(t) = A_c cos\,(2\pi f_c t + 2\pi k_f \int_0^t m(\tau) d\tau) \quad (1)$$

where A_c is the carrier amplitude [25]. The term f_c is the carrier frequency and the constant k_f is the sensitivity of the modulator. Also it could be in simplified form:

$$x(t) = A_c cos\,(2\pi f_c t + \varphi(t)) \quad (2)$$

where $\varphi(t)$ is the phase of FM signal.

Cyclostationary Feature could be extracted from Cyclic Spectral Density (CSD) $\hat{S}_x^\alpha(f)$ of FM WM signal ; which is the F.T of Cyclic Auto-Correlation (CAF) function $\hat{R}_x^\alpha(\tau)$.

$$\hat{R}_x^\alpha(\tau) \triangleq \frac{1}{T}\int_{-T/2}^{T/2} R_x(t,\tau)\, e^{-j2\pi\alpha t}\, dt \quad (3)$$

where R_x is the probabilistic auto-correlation function.

$$R_x(t,\tau) = R_x(t - \tau/2, t + \tau/2) = E\{x(t - \tau/2)\,,x(t + \tau/2)\} \quad (4)$$

$$x(t - \tau/2)\,.x(t + \tau/2) = \frac{A_c^2}{4}[\cos(w_1 + \varphi_1)\;.\cos(w_2 + \varphi_2)\,] \quad (5)$$

where $w = 2\pi f_c; w_1 = w(t - \tau/2) = wt - w\,\tau/2$; $w_2 = w(t + \tau/2)$; $w_1 - w_2 = -w\tau; w_1 + w_2 = 2wt$ *and* $\varphi_1 = \varphi(t - \tau/2)$; $\varphi_2 = \varphi(t + \tau/2)$.

$$R_x(t,\tau) = E\{x(t - \tau/2)\,,x(t + \tau/2)\}$$

$$= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} xy\; f_{x(t_1),x(t_2)}(x,y)\,dxdy \quad (6)$$

where x , y are jointly Wide Sense Stationary (WSS) Gaussian random variables, $f_{x(t_1),x(t_2)}(x,y)$ is the 2nd order probability density function (pdf) of *x(t)* and *E{.}*is the expectation function.

$$R_x(t,\tau) = E\{[\cos w_1 \cos\varphi_1 - \sin w_1 \sin\varphi_1].[\cos w_2 \cos\varphi_2 - \sin w_2 \sin\varphi_2]\} \quad (7)$$

After some calculations, we get that

$$R_x(t,\tau) = \frac{A_c^2}{2}.E\{(a(t,\tau)cos(w\tau) + b\,(t,\tau)\,sin(w\tau) + c\,(t,\tau)\,cos(2wt) - d\,(t,\tau)\,sin(2wt))\} \quad (8)$$

where

$$a(t,\tau) = \cos\left[\varphi\left(t + \frac{\tau}{2}\right) - \varphi\left(t - \frac{\tau}{2}\right)\right]$$

$$b(t,\tau) = \sin\left[\varphi\left(t + \frac{\tau}{2}\right) - \varphi\left(t - \frac{\tau}{2}\right)\right]$$

$$c(t,\tau) = \cos\left[\varphi\left(t + \frac{\tau}{2}\right) + \varphi\left(t - \frac{\tau}{2}\right)\right]$$

$$d(t,\tau) = \sin\left[\varphi\left(t + \frac{\tau}{2}\right) + \varphi\left(t - \frac{\tau}{2}\right)\right]$$

But the probability density function (pdf) is even for WSS Gaussian random process, which means that:

$$b(t,\tau) = d(t,\tau) = 0 \quad (9)$$

thus

$$R_x(t,\tau) = \frac{A_c^2}{2}E\{[a\,cos(w\tau) + c\,cos(2wt)]\} \quad (10)$$

The exponential form of $a(t,\tau) = \frac{e^{j(\varphi_1-\varphi_2)} + e^{-j(\varphi_1-\varphi_2)}}{2} = Re\{e^{i(\varphi_1-\varphi_2)}\}$ and $c(t,\tau) = \frac{e^{j(\varphi_1+\varphi_2)} + e^{-j(\varphi_1+\varphi_2)}}{2}$

$$R_x(t,\tau) = \frac{A_c^2}{2}\left[Re\{e^{j(\varphi_1-\varphi_2)}\}\cos(w\tau) + \frac{1}{2}\left(e^{j(\varphi_1+\varphi_2)}\cos(2wt)\right) + \frac{1}{2}\left(e^{-j(\varphi_1+\varphi_2)}\cos(2wt)\right)\right] \quad (11)$$

Using equation (3) we can get CAF Function:

$$\hat{R}_x^\alpha(\tau) = \frac{1}{T}\frac{A_c^2}{2}\int_{-T/2}^{T/2}\left([Re\{e^{j(\varphi_1-\varphi_2)}\}\cos(w\tau) + \frac{1}{2}\left(e^{j(\varphi_1+\varphi_2)}\cos(2wt)\right) + \frac{1}{2}\left(e^{-j(\varphi_1+\varphi_2)}\cos(2wt)\right)]\right)\,e^{-j2\pi\alpha t}\,dt \quad (12)$$

The phases φ_1 and φ_2 are joint WSS Gaussian random variables; where the characteristic function of them [30]:

$$\psi_r(\omega_1,\omega_2) = E\left[e^{j(\varphi_1\omega_1+\varphi_2\omega_2)}\right] = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} e^{j(\varphi_1\omega_1+\varphi_2\omega_2)}\,dt \quad (13)$$

ψ_r is the two dimensional Fourier transform (F.T) conversion of the pdf of φ_1 and φ_2. If the parameter $\omega = \frac{2\pi}{period}$; for periodic function of period $=2\pi$; thus $\omega = \omega_1 = \omega_2 = 1$.

$$\psi_r(1,1) = \lim_{T\to\infty}\frac{1}{T}\int_{-T/2}^{T/2} e^{j(\varphi_1+\varphi_2)}\,dt \quad (14)$$

$\psi_r(1,1)$ is the joint characteristic function of φ_1 and φ_2.

$$\hat{R}_x^\alpha(\tau) = \frac{A_c^2}{2}\left(\psi_r(1,-1)\cos(w\tau) + \frac{1}{2}(\psi_r(1,1)\cos(2wt)) + \frac{1}{2}(\psi_r(1,1)^*\cos(2wt))\right).(e^{-j2\pi\alpha t}) \quad (15)$$

$e^{-j2\pi\alpha t}$ is the cyclic weighting factor. As multiplying the signal by it will shift the spectral contents by $\pm\alpha/2$

Assume $A_c^2 = 1$;

$$\hat{R}_x^\alpha(\tau) = \begin{cases} \frac{1}{2}Re\{\psi_r(1,-1)e^{-j2\pi f_c\tau}\}, & if\ \alpha = 0 \\ \frac{1}{4}\psi_r(1,1), & if\ \alpha = 2f_c \\ \frac{1}{4}\psi_r(1,1)^*, & if\ \alpha = -2f_c \\ 0, & Otherwise \end{cases} \quad (16)$$

CSD is the F.T of cyclic auto-correlation function $\hat{R}_x^\alpha(\tau)$

$$\hat{S}_x^\alpha(f) = \int_{-\infty}^{\infty}\hat{R}_x^\alpha(\tau)\,e^{-j2\pi f_0\tau}\,d\tau \quad (17)$$

$$\hat{S}_x^\alpha(f) = \begin{cases} \frac{1}{4}[\Psi_r(f + f_c) + \Psi_r(f - f_c)], & if\ \alpha = 0 \\ \frac{1}{4}[\Psi_r(f)]e^{\pm j2\varphi_0}, & if\ \alpha = \pm 2f_c \\ 0, & Otherwise \end{cases} \quad (18)$$

where Ψ_r is the F.T of ψ_r.

Thus, the cycle spectrum consists of only the two cycle frequencies $\alpha = \pm 2f_c$ and the degenerate cycle frequency$\alpha = 0$. For $\alpha = 0$, cyclic autocorrelation is the conventional autocorrelation function. The conventional power spectral density (PSD) function is defined by the Fourier transform of the autocorrelation function, $\hat{S}_x^0(f)$.

We focus on Spectral Correlation Function (SCF) feature resulting from carrier frequency embedded in the primary signals. By using (18), a FM WM signal at frequency f_c was found at (f = ±f_c, α =0) and (f = 0, α =±2 f_c), the latter two are the cyclostationary features of FM WM signal.

B. FFT Accumulation Method (FAM)

The FFT accumulation method (FAM) [29] incorporates the idea of time smoothing using a Fourier transform to arrive at a computationally efficient digital implementation of the SCD function using N samples from a finite observation interval of duration Δt.

FAM consists of capturing in a time length N a piece of the incoming signal $x_{FM}[n]$ which is the result of x_{FM} (t) sampled at f_s. Estimation of the SCD is performed over this time length. This computation is performed iteratively over consecutive pieces in the time domain until acceptable results for a summation of several CSDs satisfy the application, in terms of time of computation and objective to meet [14].The complex demodulates $X_N\left(n, k+\frac{\gamma}{2}\right)$ and $X_N^*\left(n, k-\frac{\gamma}{2}\right)$; where k is the discrete frequency and γ is the discrete cycle frequency over period N as illustrated in Fig.1.

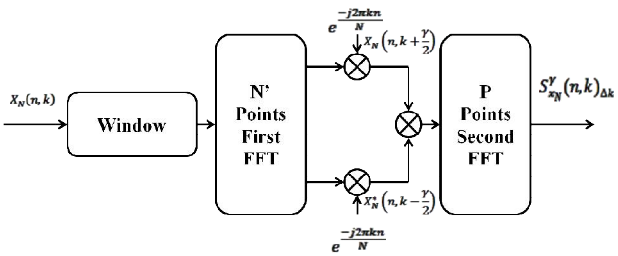

Figure 1. FAM block diagram

First, windowing of data is done using a window $w(n)$, which control the smoothing of the input data, and its general form is called Kaiser window and is defined by

$$w(n)=\begin{cases}\dfrac{I_0[\beta\sqrt{1-\frac{(n-\alpha)^2}{\alpha^2}}]}{I_0(\beta)} & 1\le n\le N \\ 0 \quad otherwise & \end{cases} \qquad (19)$$

where $\alpha = N/2$, β is the shape parameter, and $I_0(\beta)$ is the zero – order modified Bessel function of the first kind.

Different window types are obtained depending on the value of the parameter β; e.g., β=0 for rectangular window and β = 1.33 for Bartlett, β = 3.86 for Hanning, β = 4.86 for Hamming, and β = 7.04 for Blackman [24].

The complex demodulates of $X_N\left(n, k+\frac{\gamma}{2}\right)$ and $X_N^*\left(n, k-\frac{\gamma}{2}\right)$ are estimated by means of a sliding N' point FFT, followed by a down-shift in frequency to the baseband. Here, $X_N\left(n, k+\frac{\gamma}{2}\right)$ is the $(k+\frac{\gamma}{2})^{th}$ component of the N' point FFT output (in baseband) of the n^{th} N' point window. That is, n is a time index corresponding to consecutive N' point windows that are used in the FAM. The N' point FFT is hopped over the data in blocks of K samples. The value of K is generally chosen to be $N'/4$ (i.e., 75% overlap between adjacent segments) as it allows for a good compromise between computational efficiency and minimizing cyclic leakage and aliasing. Next, the element-wise product between the sequences $X_N\left(n, k+\frac{\gamma}{2}\right)$ and $X_N^*\left(n, k-\frac{\gamma}{2}\right)$ is formed and time smoothed by a P-point second FFT. The value of N' depends on the frequency resolution required, and is given by $N' = f_s/\Delta f$. The value of P is given by $P = \frac{f_s}{K\Delta\gamma}$, where f_s denotes sampling frequency and Δf and $\Delta\gamma$ denote the frequency resolution and cyclic frequency resolution, respectively. A block diagram of the FAM implementation is shown in Fig.1.

III. THE PROPOSED WIRELESS MICROPHONE DETECTOR

Modulated signals (e.g., BPSK, FM, FSK, MSK, QAM, PAM) are characterized by built-in periodicity or cyclostationarity. The spectral correlation function contains phase and frequency information related to timing parameters in modulated signals (carrier frequencies, pulse rates, chipping rates in spread spectrum signaling, etc.). The proposed method is described as shown in Fig.2.

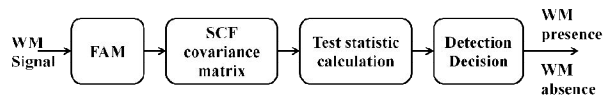

Figure 2. Block diagram of the proposed detection method.

There are four stages in this method. First the spectral correlation function of the received signal is generated by FAM method. After that the covariance matrix is searched in the second stage. Based on the searching results, a test static is calculated in the third stage, and then the detection decision is made in the last stage.

The detection decision is generally described under the test of the following two hypotheses:

$$\begin{aligned} &H_0: y[n] = g[n] && \textit{signal absent} \\ &H_1: y[n] = x[n] + g[n] && \textit{signal present} \\ &\quad n=1, 2,\ldots\ldots, N; && \qquad (20) \end{aligned}$$

where $y[n]$ is received sampled signal, $x[n]$ is transmitted sampled signal, $g[n]$ is the additive white Gaussian Noise (AWGN) with zero mean and variance δ^2, and N is the number of observation samples which depends on the sensing (detection) time and the signal bandwidth.

Probability of detection, P_D, defines, at the hypothesis H_1 (signal present), the probability of the sensing algorithm having detected the presence of the primary signal $(P\{Y>\lambda| H_1\})$. Probability of false alarm, P_{FA}, defines, at the hypothesis H_0 (signal absent), the probability of the sensing algorithm claiming the presence of the primary signal $(P\{Y>\lambda| H_0\})$.

The Spectral Auto-coherence (also called Spectral Coherence (SC)) of $x(t)$ at cyclic frequency α and spectrum frequency f is defined as

$$C_x^\alpha(f) \triangleq \frac{S_x^\alpha(f)}{\sqrt{S_x^0(f+\alpha/2)S_x^0(f-\alpha/2)}} \qquad (21)$$

Note that $|C_x^\alpha(f)| \in [0,1]$.The difference between the SCD and the SC is that the SC gives a normalized measure of cross-correlation between frequency shifted versions of $x(t)$ at frequencies $f-\alpha/2$ and $f+\alpha/2$. It follows from the definition that the SC is identically zero for all $\alpha \neq 0$ if and only if $x(t)$ contains no second order periodicity[18].

In our proposed algorithm we search for the symmetry feature of the SCF considering that stationary noise exhibits no spectral correlation; so that this feature can be detected by analyzing a spectral correlation function [18]; there are several test statistics that are using this feature [31][32].

In light of this; our new test statistic is:

$$\frac{S_x^0(f)}{S_x^\alpha(f)} \underset{H_0}{\overset{H_1}{\gtrless}} T_{th} \qquad (22)$$

where $S_x^0(f)$ is the conventional power spectral density (PSD) at $\alpha = 0$ at the center of SCD covariance matrix. Thus the decision rule depends on the calculation of SCD and its covariance matrix (CM).

The threshold T_{th} is first calculated when no signal is present, i.e., when $y(t) = n(t)$. When the signal is white and there is a pure noise case, the power of the covariance matrix will be concentrated in the central elements and the off-central terms should be approximately flat, these elements will take the background noise level. However, when the wireless microphone signal is present the received signal is no longer white and the signal power will increase the sum of the magnitude of the central elements of the covariance matrix, so that the test statistic will exceed the threshold. One of our objectives is to find the optimum T_{th} value while satisfying the P_{FA} = 10%.

IV. Simulation Results

In order to evaluate the performance of the proposed spectral correlation based detection method, simulations were carried out in AWGN environment. We assume that the signal is FM WM with a carrier frequency f_c = 2 MHz and a frequency deviation Δf. The FM WM signal spectrum generally concentrates within a small frequency band which is less than 200 kHz from 6 MHz channel bandwidth. Moreover, there are apparent peaks contained in the CSDs of the various FM WM signal models (Silent, Soft speaker, and Loud speaker). In this paper thus far, we present results for 15 kHz frequency deviations, representing soft speaker WM user [33]. The received signal is sampled at 12MHz to N=2048 samples depending on the observation time, i.e. sensing time (170µsec). And then one of three window shapes is applied to the received signal; which is the rectangle window (β=0), Hamming window (β=4.86), or Kaiser window (β=10). The spectral correlation function of FM wireless microphone signals is generated using the FAM method. Figure 3 shows the SCF function with rectangle window at different noise levels. In Fig. 3.a there are four clear peaks of the signal at ($f=\pm f_c$, α=0) and (f=0, $\alpha=\pm 2f_c$). This is the defined cyclostationary feature of FM WM signal. As SNR decreases, the peak values of the FM WM signal are whelmed by the noise as shown in Fig.3.b where the SNR = -4 dB. It is hard to detect the unique cyclic frequency because the background noise increase and the visibility of peaks and intersection lines decreases. At no signal case as shown in Fig. 3.c all noise power is concentrated at the center of the covariance matrix at α=0, while the other areas at $\alpha \neq 0$ have approximately the same power level and there is no visible peaks at all because the signal has no second order periodicity, from that the optimum threshold value T_{th} is found by measure the P_{FA} versus T_{th} values. The optimum T_{th} value is chosen to satisfy the P_{FA} = 10% condition. As seen in Fig. 4, P_{FA} = 10% is achieved at T_{th} =0.018 for β =0, T_{th} =0.0207 for β =4.86, and T_{th} =0.02 for β =10. After the T_{th} value is estimated, the detector uses it in the decision process.

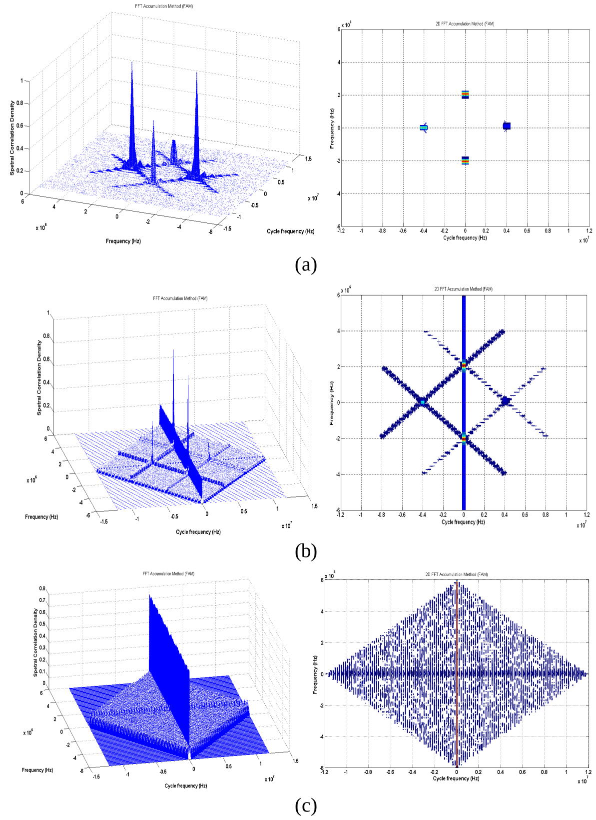

Figure 3. (a) CSD of the WM signal (noiseless), (b) CSD of WM signal at SNR=-4dB, (c) CSD of noise only, Soft Speaker.

Finally, the probability of detection (P_D) is calculated against different values of SNR. Figure 5 shows the probability of missed detection ($P_{MD}=1-P_D$) versus SNR using FAM method at P_{FA}=10% and sensing time = 170µsec for different windows to the received signal.

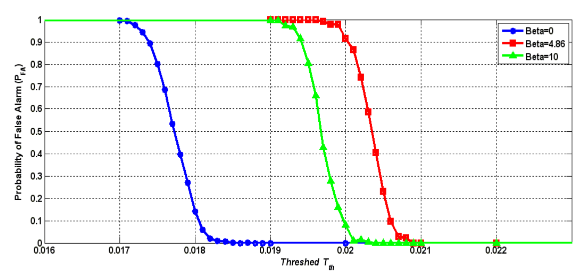

Figure 4. P_{FA} versus threshed values T_{th}.

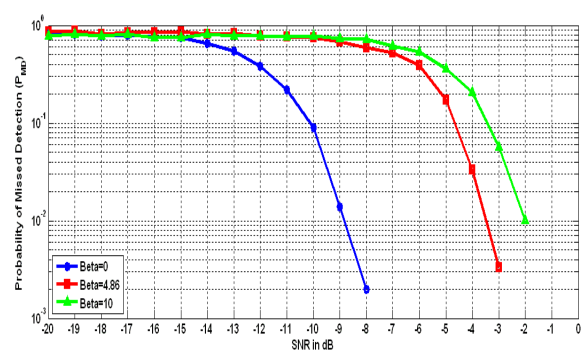

Figure 5. The probability of missed detection versus SNR for different windows applied to the received signal (P_{FA}=10%)

It is clear from Fig. 5 that the rectangle window (β=0) achieves a $P_{MD} = 0.1$ at SNR= -10dB, Hamming window (β=4.86) at SNR= -4.7dB and Kaiser window (β=10) at SNR= -3.5dB. So that the rectangular window at β =0 is achieved the smallest SNR=-10dB at $P_{MD} = 0.1$ for sensing time =170μsec.

V. CONCLUSIONS

In this paper we proposed and investigated techniques for detection of FM WM signals in a cognitive radio (CR) environment. First, an analytical expression for Cyclic Spectral Density (CSD) of the FM WM signal is derived; Second, a new detection decision method, depends on the SCF, was implemented and its threshold value was estimated for P_{FA}=10%. Third, different windowing shapes were tested and the P_{MD} for each shape was calculated. The rectangle window has the lowest SNR= -10dB at P_{MD} =0.1 and P_{FA}=10% for a sensing time equals170μsec. Moreover, there is a trade-off between the P_{MD} and sensing time. By increasing the sensing time the frequency resolution and cyclic frequency resolution will increase, hence P_D will increase and P_{MD} will decrease as well. So that it is expected to achieve lower SNR if the sensing time is increased. The advantage of the proposed detection scheme is that spectrum sensing sensitivity could be improved by choosing the suitable window shape that achieves the lowest SNR at the shortest sensing time and satisfies the P_{FA} constraint; simulation results show that the rectangular window outperforms the other windows, even in the low SNR environment. Finally, using the proposed approach, WM signals can be detected quickly and reliably.

REFERENCES

[1] J. Mitola III, "Cognitive Radio: An Integrated Architecture for Software Defined Radio," Ph. D. Thesis, Royal Institute of Technology, Sweden, May 2000.

[2] S. Haykin, “Cognitive radio: brain-empowered wireless communications,” *IEEE J. Select. Areas Commun.*, vol. 3, no. 2, pp. 201–220, Feb. 2005.

[3] C. Cordeiro, K. Challapali, and D. Birru, “IEEE 802.22: An introduction to the first wireless standard based on cognitive radios,” *Journal of communications*, vol. 1, no. 1, Apr. 2006.

[4] Federal Communications Commission, “Notice of proposed rulemaking and order: Facilitating opportunities for flexible, efficient, and reliable spectrum use employing cognitive radio technologies,” ET Docket No. 03-108, Feb. 2005.

[5] M. Marcus, “Unlicensed cognitive sharing of TV spectrum: the controversy at the federal communications commission,” *IEEE Commun. Mag.*, vol. 43, no. 5, pp. 24–25, 2005.

[6] S. Shellhammer, “Spectrum sensing in IEEE 802.22,” Proc. of *IAPR Workshop on Cognitive Information Processing*, Jun. 2008.

[7] A. Sahai and D. Cabric, “Spectrum sensing: Fundamental limits and practical challenges,” in *Proc. IEEE Int. Symp. New Frontiers in Dynamic Spectrum Access Networks (DySPAN)*, Baltimore, MD, Nov. 2005.

[8] T. Yucek and H. Arslan, "A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications", *IEEE Communications Surveys & Tutorials*, Vol. 11, Issue:1, pp. 116-130, First Quarter 2009.

[9] H. Urkowitz, “Energy detection of unknown deterministic signals,” *Proc. IEEE*, vol. 55, pp. 523–531, Apr. 1967.

[10] H. Chen, W. Gao, and D. G. Daut, ”Spectrum Sensing for Wireless Microphone Signals,” *IEEE SECON Workshop*, pp. 1-5, June 2008.

[11] H. Kim and K.G. Shin, “In-band Spectrum Sensing in Cognitive Radio Networks: Energy Detection or Feature Detection? ,” *in Proceedings of the 14th Annual International Conference on Mobile Computing and Networking (ACM* MobiCom), pages: 14-25, September, 2008.

[12] H. Tang, “Some physical layer issues of wide-band cognitive radio systems,” in *Proc. IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, Maryland, USA, Nov. 2005, pp.151–159.

[13] H.-S. Chen, W. Gao, and D. G. Daut, “Signature based spectrum sensing algorithms for IEEE 802.22 WRAN,” in *Proc. IEEE Int. Conf. Communications (ICC)*, Jun. 2007.

[14] A. Mossa, V. Jeoti, “Cognitive radio: Cyclostationarity-based classification approach for analog TV and wireless microphone signals,” In Proc. of the *IEEE CITISIA* 2009, pp. 107-111, Malaysia, July 2009.

[15] K. Kim, I. A. Akbar, K. K. Bae, J.-S. Um, C. M. Spooner, and J. H. Reed, “Cyclostationary approaches to signal detection and classification in cognitive radio,” in Proc. *IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Dublin, Ireland, Apr. 2007, pp. 212–215.

[16] A. Tkachenko, D. Cabric, and R. W. Brodersen, “Cyclostationary feature detector experiments using reconfigurable BEE2,” in Proc. *IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Dublin, Ireland, Apr. 2007, pp. 216–219.

[17] A. Al-Dulaimi, N. Radhi, “Cyclostationary Detection of Undefined Secondary Users”, *IEEE Computer Society* September 2009.

[18] A. Fehske, J. Gaeddert, and J. Reed, “A new approach to signal classification using spectral correlation and neural networks,” in Proc. *IEEE Int. Symposium on New Frontiers in Dynamic Spectrum Access Networks*, Baltimore, Maryland, USA, Nov. 2005, pp. 144–150.

[19] M. Ghozzi, F. Marx, M. Dohler, and J. Palicot, “Cyclostationarity based test for detection of vacant frequency bands,” in Proc. *IEEE Int. Conf. Cognitive Radio Oriented Wireless Networks and Commun. (Crowncom)*, Mykonos Island, Greece, June 2006.

[20] P. D. Sutton, K. E. Nolan, “Cyclostationary Signatures in Practical Cognitive Radio Applications”, *IEEE Journal on Selected Areas in Communications*, Vol. 26 No. 1 2008.

[21] K. PO and J. Takada “Signal Detection Based on Cyclic Spectrum Estimation for Cognitive Radio in IEEE 802.22 WRAN System” *Technical report of IEICE.81.*

[22] N. Han, S. H. Shon, J. H. Chung, and J. M. Kim, “Spectral correlation based signal detection method for spectrum sensing in IEEE 802.22 WRAN systems,” in Proc. *IEEE Int. Conf. Advanced Communication Technology*, vol. 3, Feb. 2006.

[23] J. Lund´en, V. Koivunen, A. Huttunen, and H. V. Poor, “Spectrum sensing in cognitive radios based on multiple cyclic frequencies,” in Proc. *IEEE Int. Conf. Cognitive Radio Oriented Wireless Networks and Commun. (Crowncom)*, Orlando, Florida, USA, July/Aug. 2007.

[24] W.A Gardner, “The spectral correlation theory of cyclostationary time series,” *Signal processing*,Vol.11,pp.13-36,1986 [*EURASIP*].

[25] W.A. Gardner, “Spectral correlation of modulated signals: Part I-analog modulation,” *IEEE Transactions on Communications*, VOL. COM-35. NO. 6, JUNE 1987, pp.584-594.

[26] W. A. Gardner, “Exploitation of spectral redundancy in Cyclostationary signals,” *IEEE Signal Process. Mag.*, vol. 8, no. 2, pp. 14–36, Apr. 1991.

[27] W. A. Gardner, Statistical Spectral Analysis A Non-probabilistic Theory, Prentice Hall, 1988.

[28] G. Yu-Long, C. Yan, “Modification and Digital Implementation of FAM algorithm for Spectral Correlation”, *IEEE Wireless Communication and Signal Processing*, 2009.

[29] R. Roberts, W. Brown, H. Loomis, “Computationally efficient algorithms for cyclic spectral analysis”, *IEEE Signal Processing Magazine*, April 1991, 38–49.

[30] A. Leon-Garcia, Probability and Random Processes for Electrical Engineering, Addison-Wesley, 1994.

[31] A. V. Dandawaté and G. B. Giannakis, “Statistical tests for presence of cyclostationarity,” *IEEE Trans. Signal Processing*, vol. 42, pp. 2355–2369, Sept. 1994.

[32] S. Lim, et al, “The detection and classification of the Wireless Microphone signal in the IEEE 802.22 WRAN system,” in *Proceedings Asia-Pacific Microwave Conference (APMC, 07)*, pp. 1-4, Dec. 2007.

[33] C. Clanton, M. Kenkel and Y. Tang, "Wireless Microphone Signal Simulation Method," *IEEE 802.22-07/0357r0*, July 2007.