Spectrum Sensing for Cognitive Radio using S-method based Joint Time-Frequency Representation

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***Abstract*—Cognitive Radio (CR) has emerged as a solution for spectrum crunch due to rise in large wireless digital ecosystem. Spectrum sensing(SS) is considered to be the brain beyond efficient utilization of spectrum without interfering the licensed Primary User (PU). In this paper, Time-Frequency Tool (TFT) based spectrum sensing is investigated as the novel non-parametric detection method. Here, variant quadratic time-frequency distribution, is obtained from Short time Fourier transform (STFT) called S-method time frequency tool is used for spectrum sensing. S-method is novel T-F distribution that overcomes the drawbacks of quadratic Wigner distribution and obtains energetic distribution. In this work spectrum sensing performance of S-method is compared with well researched Energy Detection (ED) technique in terms of detection probability. This paper also highlights importance of noisy signal analysis in the both time and frequency compared to the time or frequency domain only.**

Keywords- Cognitive radio,Spectrum sensing,Time-frequency representation (TFR),S-method

I. Introduction

The emerging trend in advanced wireless technologies and need for high speed wireless communication has created so called spectrum scarcity [1]. The licensed spectrum measurement analysis by various regulatory organizations in different countries revealed, that licensed spectrum is underutilized in a different time,frequency and geographical locations[2]. Cognitive Radio (CR) proposed by Joesph Mitola[3] is considered to be best platform for efficient utilization of underutilized spectrum without interfering primary user(PU). In this regard spectrum sensing is critical functionality CR, so that it continuously monitor wide spectral band for availability of used frequency bands. In the last decade number of spectrum sensing techniques have been investigated. Among them, energy detector (ED) is simple to implement and it does not require the prior information about the Primary User (PU) [4, 5]. However, it fails at low SNR condition. For better performance advanced techniques based on Cyclo-stationary and statistical signal properties using correlation sensing techniques have been used[4]. Though these techniques are robust at low SNR, implementation complexity is high and they are signal dependent[4]. To over come the effect multipath fading and hidden node problem cooperative sensing has been a candidate solution[6][7].

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Spectrum Sensing(SS) techniques are usually implemented considering signal and wireless channels to be stationary. Practically, signal and channel encountered at receiver are non-stationary. In last four decades Time-Frequency(T-F) tools have been widely used in solving non-stationary spectral analysis problems in radar signal processing,acoustic, seismic, biomedicine, knock detection in car engine and time-varying channel analysis in communication system [8]. Increase in dimensional freedom results in more enhanced signal depiction compared to noise, since noise is equally spread in T-F domain not the signal. Recently spectrum sensing based on Wigner-Ville distribution (WVD), Short-time Fourier transform (STFT) and Gabor transform have been proposed in[9][10][11]. Guibene *et al* [10] shows that spectrum sensing using T-F based methods provide more accurate and reliable in sensing compared conventional time or frequency based methods. Monfared *et al* [12] uses the compressive sensing to reduce the size of information matrix obtained using the T-F tools and captures the important features from T-F image to enhance the sensing. Wavelet transform(WT) is used in [13] to enhance wide band sensing and reduce the sensing time. A recent paper by Biagi*et al* incorporates Wigner-Ville transform for dynamic spectrum access and hardware implementation for CR[14]. These works concrete on WVD, WT and STFT based sensing techniques, which have their respective drawbacks. WVD provides better time-frequency resolution and concentrated energy density, but it suffers from cross-terms due to bilinear products, which may be guessed as signal energy. Whereas STFT does not have cross-term problem. But it can not guarantee simultaneous time and frequency resolution[8].

Recent work by Stankovic *et al* on time-frequency based fast maneuvering targets detection proposes S-method based T-F tool, that incorporates advantages of both STFT and WVD and overcoming drawbacks of both [15]. In the current work, we investigate the S-method based time-frequency tool proposed in Stankovic *et al* for spectrum sensing. Comparative analysis of energy detection(ED) and S-method spectrum sensing in terms probability detection versus SNR is conducted. Analysis of noisy signal in time-frequency domain also plotted to show the importance of T-F tool. Here we also analyze the probability of detection versus SNR with variation in the correction length. As this method is derived from STFT, its hardware implementation is also quite simple compared to traditional quadratic T-F tool[16].

Following this introduction,the remaining part of the paper is organized as under. Section II provides a brief overview of time-frequency distribution and also explains the novel S-method distribution. Section III presents the S-method based time frequency spectrum sensing. Comparative analysis and simulation results are presented in section IV. Whereas section V discusses the concluding remarks.

II. Brief overview of Time-frequency representation [17]

Time-Frequency tools mainly used in analysis, processing, detection and parameter estimation of non stationary signals that is whose spectral characteristics vary with time. T-F tools are classified as linear and quadratic Cohen class type. Linear T-F include Short time Fourier transform (STFT), Wavelet Transform(WT) and Gabor Transform and quadratic type include Wigner-Ville distribution (WVD) and its variations[8]. First of that kind is STFT, that is derived from traditional Fourier analysis also called windowed Fourier transform. Other important important TF tool is Wigner distribution derived from quantum mechanics[8][17]. STFT suffers from poor time-frequency resolution, but it is free from cross terms. Whereas, Wigner distribution produces concentrated energy distribution at the cost of cross-terms. S-method TF representation combines the good properties of STFT and Wigner distribution. STFT as previously said windowed Fourier transform, that is obtained by applying Fourier transform to localized signal $x(t)$ using the sliding window function $w(t)$ [16]. STFT is defined in continuous domain as [16]

$$S(t,\omega)=\int^{\infty} x(t+\tau)w(\tau)e^{-j\omega\tau}d\tau. \tag{1}$$

In discrete domain it is defined at an instant n and frequency k as

$$S_N(n,k)=\sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} x(n+m)w(m)e^{-j\frac{2\pi}{N}mk}. \tag{2}$$

In the above case it is assumed that the number of discrete frequency points is equal to window length. In Equation.2 wide window covers the large signal samples over wide time interval that increases the frequency resolution at cost of time resolution[16]. Reverse phenomena can be found in the case of the narrow window.

To improve the TF concentration of non stationary signals, quadratic distribution are introduced. Most basic quadratic distribution is Wigner distribution, that was well defined in quantum mechanics was reintroduced to signals by Ville. So it is called Wigner-Ville distribution (WVD). Modified Discrete pseudo Winger distribution (WD) is defined as

$$WD(n,k)=\sum_{m=-\frac{N}{2}}^{\frac{N}{2}-1} w(m)w(-m)x(n+m)x^{\star}(n+m)e^{-j\frac{4\pi}{N}mk}. \tag{3}$$

in which *w(m)* is time window. As WD is quadratic product, it exhibits the cross-terms that limits the its application to multi-component signals [16]. So to overcome the cross-terms in WD, variant quadratic distribution with limitation on signal concentration are introduced in [8][17]. Because, concentration of auto terms and appearances of cross-terms are contradicted to each other. Stankovic et.al [17] discussed the novel method called S-Method (SM), that preserves the concentrated auto-terms as in WD and reduces significant cross terms as in STFT. SM derived using relationship between the STFT and pseudo-WD, which is given as

$$WD(n,k)=\sum_{i=-\frac{N}{2}}^{\frac{N}{2}-1} STFT(n,k+i)STFT^{\star}(n,k+i). \tag{4}$$

Using equation (3) SM time-frequency distribution is defined[17]

$$\begin{aligned} SM(n,k) &= \sum_{i=-L_d}^{L_d} P(i)STFT(n,k+i)STFT^{\star}(n,k+i) \\ &= |STFT(n,k))|^2+ \\ 2Re&\left[\sum_{i=1}^{L_d} P(i)STFT(n,k+i)STFT^{\star}(n,k+i)\right]. \end{aligned} \tag{5}$$

Where $P(i)$ is a finite window, $P(i)=0$ for $|i|>L_d$, with L_d being its width. By setting $P(i)=\delta(i)$ spectrogram is obtained and $P(i)=1$, pseudo-WD is obtained. It can produce the TF representation of a multi component signal such that the distribution of each component is, its pseudo WD, avoiding cross-terms, iff the STFTs of each component do not overlap in frequency plane [17].

III. S-Method based time frequency spectrum sensing

The received signal at CR receiver is defined as

$$r(t)=\begin{cases} & \text{if } w(t);..H_0 \\ & \text{if } s(t)+w(t);..H_1 \end{cases}$$

$s(t)$ is received PU signal and $w(t)$ is the noise signal at the receiver. Spectrum sensing is classified as binary hypothesis problem. If there is presence of primary user in received noisy signal than it is referred as hypothesis H_1 and absence of PU considered as hypothesis H_0. Time-frequency system model is depicted in Fig.1. First step in TFR based sensing is

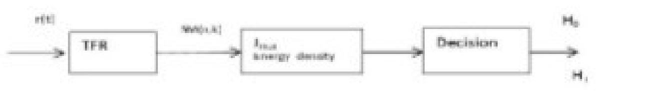

Fig. 1: System model for spectrum sensing

to find time-frequency based energy density using S-method. Equation.5 used to find TF representation of $r(t)$. Next is to calculate the test statistic for spectrum sensing using the energy density obtained in previous step. Last step is to compare the test statistic using predefined threshold to carry out likelihood ratio test to know the presence and absence of PUs. Difficult task is to finding the test statistic and predefined threshold based on fixed probability of false alarm. In this work test statistic is obtained using procedure given in the [17]. Path of maximum energy density is found by scanning along time and frequency plane and maximum of that path is used as test statistic for decision making. Test statistic is found by following steps as mentioned in[17].

1) S(n,k) is time-frequency representation of $r(t)$, where $k = 0, 1, ..., M-1$ and $n = 0, 1, ..., N-1$.
2) Considering that instantaneous frequency of a primary signal s(n) is continuous, define a path in time-frequency plane as an array of N frequency indices *w(n)*, with $0 \leq w(n) \leq M$ for every t.
3) Than obtain ensemble of W_D of such paths of having the property $|w(n) - w(n-1)| \leq D$,for some specified value of D for all n. Where D is maximum allowed frequency step for two consecutive time instants.
4) $w_m(n)$ is one observed path belonging to W_D and sum the T-F representation along this path, that results as
$$J_m = \sum_{n=0}^{N-1} S(n, w_m(n)). \tag{6}$$
5) Same calculation done for all ensemble paths of W_D and maximum of them represented by J_{max}, which is used as test criteria for hypothesis testing. J_{max} is defined as
$$J_{max} = \max_{w(m) \in W_D} J_m = \sum_{n=0}^{N-1} S(n, w_{max}(n)). \tag{7}$$

Primary signal is detected if

$$J_{max} > \gamma_{TF}$$

where γ_{TF} is predefined threshold value,that is obtained using same statistic procedure for only noise case by Monte Carlo simulation. In this paper, threshold value is calculated by simulation for probability false alarm (P_{fa}) equal to 10% [18].

IV. Comparative analysis and simulation results

Performance of proposed method is compared with traditional frequency domain energy detection method(ED). Model and threshold setting for ED is obtained from [5][19]. In this paper two class of primary signals, that are used in Project 25(P25) which is suite of standards for digital radio communications for use by federal, state, province and local public safety agencies in North America [20][21]. First case, Compatible 4 level frequency modulation (C4FM) that transmit digital data over a 12.5 kHz channel [20] used as primary signal. Second primary signal used for testing is Compatible quadrature phase shift keying (CQPSK), that transmits siganl over 6.25KHz channel. For both signals settings are done as for the P25 standard.

Fig.2 (a-d) are the time-frequency plots of clean primary signals and noisy primary signals at -10 dB SNR. Using S-method with $L = 16$ and hamming window of size of 32 with Primary signal samples of $N = 512$ are used to plot the T-F representation. Clean primary signal without any additive noise represented by Fig.2(a) and (c), clearly shows the concentrated plot of pure C4FM and CQPSK. Fig.2(b) and (d) shows the noisy primary signals in which noise is spread over all the time-frequency plane. Joint time-frequency based sensing overcomes noise uncertainty problem encountered in ED, as noise equally spread in both the plane.

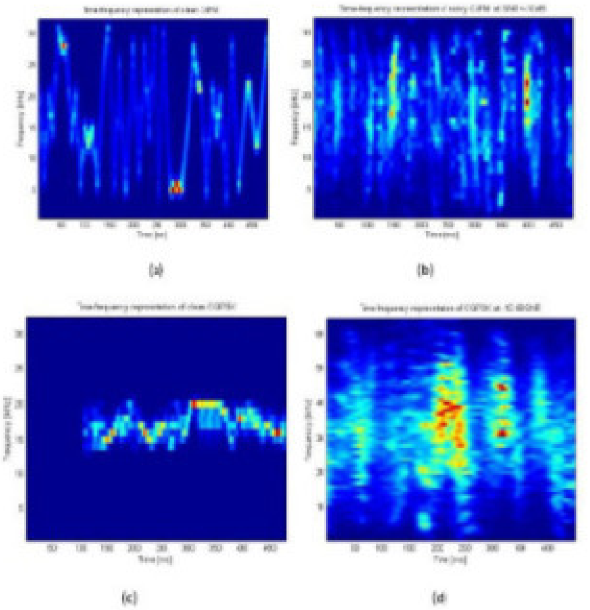

Fig. 2: Time-frequency representation of Primary signals (a) Noisy free C4FM signal (b) C4FM signal at SNR= -10 dB (c) Noise free CQPSK (d) CQPSK signal at SNR= -10 dB

Next the Receiver operating characteristics (ROC) performance analysis is done as per the emerging cognitive standard IEEE 802.22. As Per the standard, the worst case SNR at which sensing is done for ED is -21 dB with sensing time of 2 seconds [18]. Probability of detection (P_d) is obtained for SNR ranging from -30 dB to 5 dB by fixing P_{fa} to 10%. We consider noise uncertainty of 1 dB for simulation. For this simulation, signal samples of N=256 is taken to obtain TF representation using S-method, number samples acquired are as below sensing time requirement IEEE 802.22 standard. Hamming window of width 32 and L_d=8 are used for S-method implementation. Fig(3) and(4) shows the plot of P_d vs SNR for the both type of primary signals. ROC curves depict that, when detection of Probability of ED zero below -10 dB with noise uncertainty of 1 dB, S-method provides significant P_d around 0.1 to 0.2 at low SNR of below -10 dB. Fig.5 shows S-method performance by varying correction term L. In the figure it is seen, by increasing the L probability detection improves. This is because by increasing L, T-F representation improves towards the more energetic Wigner distribution. When signals are represented in T-F domain number samples rises to 256 X 256 size, that can be handled within the standards requirement. Sensitivity of joint time-frequency method can be enhanced by incorporating robust feature extraction methods. It can assist the dynamic spectrum accessing capability of CR by locating the instantaneous frequency location of PU, as explained in [14]

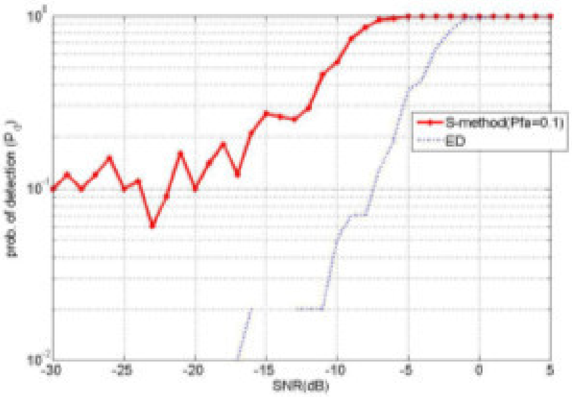

Fig. 3: Probability detection vs SNR for CQPSK as Primary signal

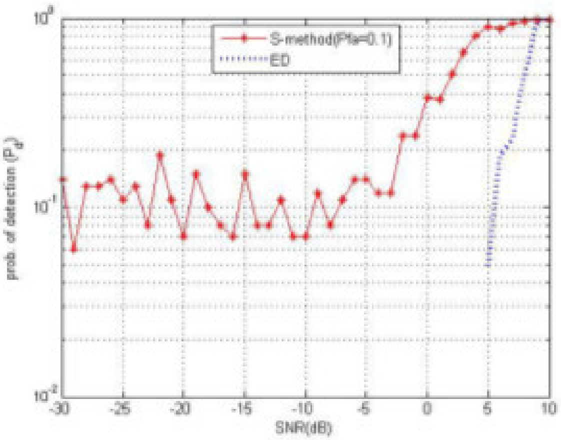

Fig. 4: Probability detection vs SNR for C4FM as Primary signal

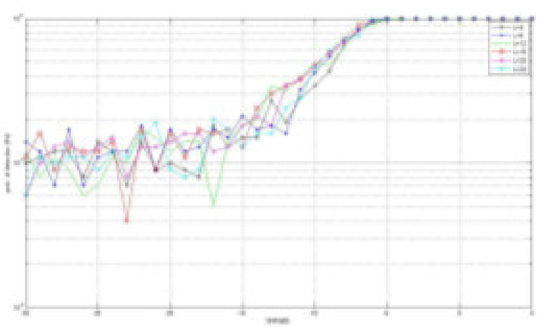

Fig. 5: Probability detection vs SNR for CQPSK signal with changing L

V. CONCLUSION

The joint time-frequency based spectrum sensing using S-method is analysed. S-method, which is combines the good characteristics of STFT and WD overcomes the problem of cross-terms appearing in time-frequency representation. As S-method is obtained from STFT, hardware implementation is feasible compared to quadratic WD. Comparison analysis of S-method spectrum sensing is done with traditional frequency domain energy detection, which shows the better performance in terms of detection at low SNR. Joint time-frequency based sensing can be used in distributed manner to enhance sensitivity cognitive radio detecting primary user and also to locate the primary user position and frequency.

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