A Novel Approach for Spectrum Sensing in Cognitive Radio

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ABSTRACT
Cognitive radio has become an adequate approach to solve the inefficiency of the spectrum utilization by accessing the radio spectrum strategically. In this paper, adaptive multistage wiener filter is used for the detection purpose. With the designing of such filter, detection performance is boosted because of picking up of the signal report and abolishing the additive noise. Meanwhile, in this scheme estimation of the complex matrices as well as the eigenvalue from covariance matrices is not required. Thus this system achieves a low computational complexity. Unlike conventional algorithms, neither noise power estimation nor prior knowledge of primary user signal is needed.All these qualities make the proposed algorithm robust to noise uncertainty and suitable for unseeing detections. Simulation results illustrates how reliably the unused spectrum can be detected with an acceptable trade-off. In other words, the fundamental aim is to increase detection probability and minimizing the complexity .

Keywords
Cognitive, spectrum, frequency bands

1. INTRODUCTION
Cognitive Radio (CR) [1] is a favorable technology which works to improve spectrum efficiency by accessing the under-utilized frequency bands. Spectrum sensing is one of the key enabling functionality in cognitive radio networks which reliably identify signals from licensed primary radios to avoid any kind of intervention. Finding the vacant bands and selecting the most efficient of all available options is main character of cognitive. To withstand the affects of noise uncertainty, several approaches have been emerged that require no prior knowledge of noise power. [2][3]. In wireless communication systems, wideband spectrum[4]–[6] can be divided into smaller non overlapping subbands. Eventually, spectrum sensing can be accessed independently in each subband. Out of various energy detection techniques, Energy detection [4] is applied to wideband case by performing narrowband detection in a particular subband at a time. A wavelet transform based method is proposed in [5], which calculates the power spectral density over a wideband frequency range. Optimal multiband joint detection operates simultaneously over multiple frequency bands at a time, where the optimum set of detection thresholds is designed from wideband considerations [6].This paper presents wideband spectrum sensing from a novel perspective. The proposed strategy accomplishes spectrum sensing synchronously over the all the available frequency bands rather than sensing a single subband each time. Firstly, it calculates the number of occupied subbands, and afterwards, it predict the correct place of employed sub bands as well as the vacant ones. The exploited characteristic is that the energy of the employed sub band is the imposition of noise and signal, whereas energy of the empty subband is only assisted by noise. Subsequently, energy of the employed subband is more than that of the vacant one. If there is a prior information about the number of employed subbands,then the particular subbands with the maximum energy are more feasible to be the occupied ones. Thus the evaluation of the number of occupied sub bands becomes a critical issue which can refer to the subject of source enumeration. Akaike information criterions as well as minimum description length are the primitively raised approaches to address this problem by exploiting the information of eigenvalues of covariance matrix [7]. Following the procedures of designing of the Adaptive Multistage Wiener filter (A-MSWF), a computational efficient method without calculation of covariance matrix or eigenvalue decomposition (EVD) [8], which motivates us to estimate the number of occupied subbands.

2. SYSTEM MODEL
It is assumed that a wideband CR system operates over W non overlapping narrow subbands, among which K subbands are occupied by primary users (PUs) [6]. Fig. 1 depicts a wideband channel usage pattern at a particular time within a particular area. There are M uniform linear arrays in the cognitive receiver [9]. The antenna spacing is $t = \lambda/2$, where λ denotes PU signal wavelength.

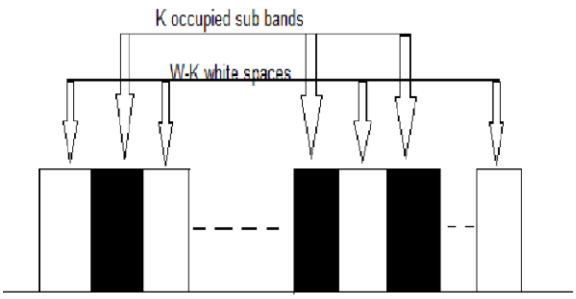

Fig 1: Schematic illustration of a wideband channel

The received signal from antenna arrays can be given as

$$p_m(\sum_{i=1}^{K} \bar{r}_i(k) v(\theta_i) + \varepsilon_m(k) \quad m = 1,2 \ldots\ldots M \quad (1)$$

Where

$$v(\theta)_{i}=[1, e^{j2\pi \sin(\theta_i)/\lambda}, \ldots\ldots\ldots e^{j2\pi d(M-1)\sin\theta_{i/\lambda}}]^T$$

(2)

$(.)^T$ stands for transpose and θ_i represents the incident angles.

$\bar{r}_i(k)$ denotes the received PU signals including the effects of channel response, i.e. fading, path loss, time dispersion $\varepsilon_m(k)$ is the background noise,which is modeled as an independent identical distribution additive white Gaussian noise (AWGN) with mean-zero and variance σ^2. The PU signals are uncorrelated with the noise. More compactly, (1) can be rewritten in matrix notation as

$$p(k)=V(\theta_i)\bar{r}(k)+\varepsilon_m(k), \tag{3}$$

where

$$V(\theta)=[v(\theta_1),v(\theta_2),\dots\dots v(\theta_n)] \tag{4}$$

is the direction matrix and p(n)=[$p_1(k),p_2(k),\dots p_M(k)$]

$$\bar{r}(k)=[\bar{r}_1(k),\bar{r}_2(k),r_3(k)\dots..\bar{r}_K(k)]^T,$$

$$\varepsilon(k)=[\varepsilon_1(k),\varepsilon_2(k),\varepsilon_3(k)\dots\varepsilon_M(k)]^T$$

The covariance matrix of received signals can be denoted as

$$C_p=E[p(k)p^H(k)]$$

$$=V(\theta)C_sV^H(\theta)+\sigma^2 I \tag{5}$$

$$=V(\theta)\,E[\tilde{r}(k)\tilde{r}^H(k)]\,V^H(\theta)+\sigma^2 I$$

Where I is the identity matrix,E[.] and (.) stands for expectation operator and Hermitian transpose, respectively. Nonetheless, in experimental operations, the covariance matrix can only be estimated by a finite number of samples, which can be expressed as

$$\hat{C}_s=\frac{1}{N}\sum_{n=1}^{N}s(k)s^H(k), \tag{6}$$

Where N denotes the number of samples.

3. PROPOSED SPECTRUM SENSING SCHEME

According to (1), firstly we define a new observation data as

$$p_0(k)=[p_1(k)p_2(k)p_3(k)\dots\dots..p_{M-1}(k)]^T \tag{7}$$

and a new reference signal as

$$q_0(k)=s_M(k)=\tilde{r}^T(k)1+\varepsilon_M(k) \tag{8}$$

where 1=[1,1,1…….1]^T.

That is to say, the first M-1 antenna arrays and the last one provide the observation data and reference signal of a successive refinement procedure, respectively,similar to the MSWF [10].The cross-correlation between the observation data and the reference signal is computed as

$$S_{s_0q_0}=E[r_0(k)q_0^*(k)]=V_{M-1}(\theta)C_r1 \tag{9}$$

where $V_{M-1}(\theta)$ consists of the first M-1 rows of V(θ) and $(.)^*$ stands for complex conjugate. The cross-correlation can be considered as a linear composition of all the direction vectors v(θ_i) ,which implies that it contains the signal information. Also,it can be noticed that the noise term in the cross-correlation is absent, indicating that it can efficiently eliminate the additive noise. In this way, a matched filter is demonstrated by cross-correlation,thus the filter extracts the desired signals from the background noise. A normalized matched filter is defined as

$$h_1=\frac{S_{s_0q_0}}{||S_{s_0q_0}||} \tag{10}$$

Where ||.|| stands for the vector norm.

Following the procedures in theMSWF [10], we partition the observation data $p_0(k)$ with the matched filter h_1. The desired signal $q_i(k)$ and the observation data $p_i(k)$ at the i th stage can be achieved by

$$q_i(k)=h_i^H p_{i-1}(k) \tag{11}$$

and

$$s_i(k)=s_{i-1}(k)-h_iq_i(k)=F_ip_{i-1}(k) \tag{12}$$

where $B_i=I-h_ih_i^H$ is the blocking matrix.Furthermore the matched filter h_i is computed by

$$h_i=\frac{S_{s_{i-1}q_{i-1}}}{||S_{s_{i-1}q_{i-1}}||}=\frac{E[p_{i-1}(k)q_{i-1}^*(k)]}{||E[p_{i-1}(k)q_{i-1}^*(k)]||} \tag{13}$$

In a four-stage MSWF block diagram, $e_i(k)$ is the estimation errors and ω_i is the scalar k weights, stateds as

$$\omega_i=E[q_{i-1}(k)e_i^*(k)]/E[|e_i(k)|^2] \tag{14}$$

$$e_{i-1}(k)=q_{i-1}(k)-\omega_i^*e_i(k) \tag{15}$$

It can be seen that the desired signal $q_i(k)$ is obtained by filtering the observation data $p_{i-1}(k)$ with the matched filter h_i , but annihilated by the blocking matrix B_i . The observation data $p_i(k)$ is partitioned stage by stage. After performing M-1 successive recursions, we obtain M-1 desired signals as

$$q_0(k)=[q_1(k),q_2(k),q_3(k)\dots\dots q_{M-1}(k)]^T=H^Hp_0(k), \tag{16}$$

Where H=[$h_1,h_2,h_3\dots.h_{M-1}$].

4. SIMULATION RESULTS

Considering a wideband CR system with M=16 antenna arrays,PU signals are present in K=3 subbands among the total W=20 subbands. PU signals impinge upon the antenna arrays from distinct directions . In the following simulations, five hundred Monte Carlo trials have been carried out respectively,D(N) in (20) is set to be D(N)= $\frac{2.3}{\log(N)}$ as in [8] and SNR refers to the average SNR.

A cluster of simulations are run to check the performance of our proposal compared to ED. Fig. 2 depicts the detection probability as a function of SNR when N=1000. Also, P_d $versus P_f$ is illustrated in Fig. 3 .ED (x dB) represents energy detection with noise uncertainty being x dB. It is observed that of ED with noise uncertainty is far from CR's requirement.In Fig. 4, when the number of samples exceeds a certain value, P_d performance of ED with noise uncertainty is no longer enhanced due to SNR wall. We can draw the conclusion that noise uncertainty greatly deteriorates the performance of ED. Since it is inevitable in practical applications, ED is a quite unreliable detection algorithm. However,The proposed scheme,with the help of adaptive MSWF achieves a better performance than ED with noise ambiguity at less samples.As the rate of these elements increases it will surpass ED with noise uncertainty . In the meantime,for performance comparison,the maximum-minimum eigenvalue (MME) detection and energy with minimum eigenvalue (EME) detection proposed in [2] are also adopted.by utilizing the cross correlation between the observation data and reference signal which doesn't involve any noise term, our approach can efficiently eliminate the impact of additive noise.

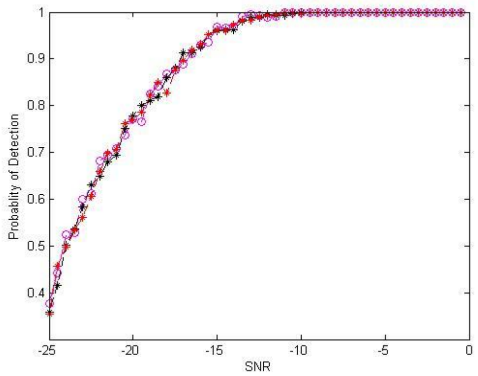

Fig 2: Performance of prototype model analytic and simulated model showing the performance in probability of detection with signal to noise ratio

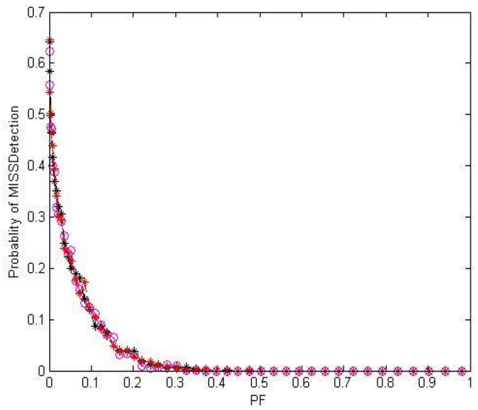

Fig 3: Performance in terms of probability of misdetection with probability of false alarm

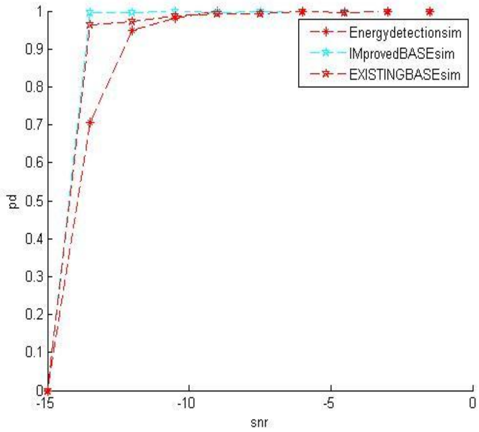

Fig 4: Probability of detection against SNR(N=1000)

5. CONCLUSIONS

In this paper, a wideband spectrum sensing scheme for CR systems with adaptive MSWF is presented. The proposed method estimates probability of detection against SNR.The probability of missdetection in contrast to the false alarm is also determined, avoiding the estimation of covariance matrix and the corresponding EVD. Thus the proposed scheme can easily achieve a low computational complexity.Besides this, the proposed method can capture the signal information and suppress the additive noise efficiently, leading to a more accurate detection performance. Additionally, the estimation of noise power or prior information of signal type is not required, making the proposal a robust and blind detection technique. Simulation results validate that our proposal is robust to noise uncertainty and outperforms existing sensing methods.Further the probability of detection can be improved using adaptive filters.

6. REFERENCES

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