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Spectrum Sensing for Cognitive Radio using Hilbert-Huang Transform Average Ratio Detector

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Abstract

Cognitive Radio (CR) is an unprecedented concept in wireless communication and it is a technical solution to perfect utilization of spectrum. CR sense the presence of licensed primary users through measuring parameters related to channel characteristics. The power spectrum gives vital information with regard to the presence of a user at every frequency. In this paper we analyzed different spectrum sensing techniques like energy detection, Fast Fourier Transform Averaging Ratio (FAR) whose performance is low in non-stationary environment. In this paper we proposed Hilbert Huang Transform detector (HHT) to detect presence of primary user. In practical scenario, non-stationary and non-linear processes can be efficiently detected by this HHT. It is evident from the results that the HHT transform average ratio detector outperformed the FFT average ratio detection.

Keywords: Cognitive Radio, Hilbert- Huang Transform, Intrinsic Mode Functions (IMF), Non- Stationary, Spectrum Sensing

1. Introduction

Cognitive Radio is advancement to the software defined radio platform: a dynamical transceiver system which automatically reconfigures its communication parameters of the network to that of the user requirements. Conventional analog designs are not optimized by cognitive radio[1]. The main factor for the insufficient usage of the spectrum is because of Static Spectrum Allocation[2]. The static spectrum allocation restricts the usage of unused frequencies from being utilized, even though the unlicensed user does not cause any noticeable interference in the spectrum[3]. Cognitive radio explores this concept of reusing the unused frequencies by the primary user and allocates these frequencies to the secondary user[1].

2. Spectrum Sensing for Cognitive Radio

2.1 Cyclostationary Feature Detection

The transmitted signal from the primary users should have a periodic pattern[6]. This periodic arrangement is known as cyclostationarity and this technique is used to detect the presence of primary users. The mean and the covariance of the signal are in periodic fashion. The disadvantage of this technique is that, it requires high computation complexity, long sensing time and partial information of the primary user signal[6]. Cyclostationary feature detection uses a threshold value to distinguish the availability of the primary user and unoccupied bands.

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The cyclic frequencies in the spectrum are periodically scanned continuously and at every cyclic frequency if the cyclo autocorrelation function is below a threshold value, then that frequencies is said to be unoccupied. Similarly if the function is above the threshold, then that frequency is said to be occupied.

2.2 Energy Detection

Energy detection is the most popular sensing technique due to its less implementation complexity and it can be implemented in both frequency and time domain[6]. Energy detection doesn't need any preliminary knowledge of primary user signals. Energy detection technique is much more superior to matched filter detection and cyclostationary feature detection because this technique requires a prior knowledge of the primary user signals to utilize efficiently which is practically cumbersome to realize because primary user information is differ in different case. Energy detection method also uses the threshold computation, where at every frequency in the spectrum the energy is calculated and is then compared with that of the threshold value[1,2]. The energy which is beyond the threshold is favored as the primary user and the other case: below which is consider to be unused frequency bands.

2.3 Hilbert-Huang Transform (HHT)

The conventional transforms like: wavelet transform and Fourier transform are applied only on linear/stationary signals. In real time applications the signal will be non-linear/non-stationary. HHT explores this non-linearity and can be applied to both linear as well as non-linear signals. HHT uses the Empirical model to analyze the power of the signal; it is classified into two categories: Empirical Mode Decomposition (EMD)[1,5] and Ensemble Empirical Mode Decomposition (EEMD)[1,5].

2.4 Empirical Mode Decomposition

EMD decomposes the original signal into individual frequency components known as Intrinsic Mode Functions (IMFs). These IMFs are then fed as input to the Hilbert Spectrum Analysis (HSA)[1] where the power at individual frequency is calculated over entire bandwidth. These powers are compared with the threshold and the used and unused frequencies are classified accordingly.

2.5 Ensemble Empirical Moe Decomposition

EEMD is introduced to overcome the drawbacks of the EMD where EEMD users Noise Assisted Analysis Method (NADA)[1] . EMD cannot deal the signal in the noisy environment effectively; this is known as Mode mixing. This results in aliasing in time frequency domain. In EEMD, noise is intentionally added to the original signal so as to reduce the aliasing effect by nullifying the collection of white noise in time-space ensemble mean, resulting in the survival of the original signal. To set the meaning of IMF clearly, finite amplitude of white noise is required to force the ensemble to drain all the possible solutions.

2.6 HHT-Averaging-Ratio

The algorithm requires baseband discrete-time signal with f_s as a sampling frequency and the output observed is the series of vectors defining the availability of the channel. Windowing technique is used here to transmit the signal segmented into T-frames and the framed samples are represented as $y_t(n)$,

where n=0 to N-1, t=0 to T-1. N is the number of samples in a frame and T is number of frames[1].

Applying this windowing technique to the sampled frames we get,

$$Y_{w,t}(n) = y_t(n)*w(n) \tag{1}$$

Now, applying HHT for the above framed signal we get the frequency spectrum of:

$$Y_t(k) = \sum_{n=0}^{N-1} y_{w,t}(n)_e - j2\Pi kn/N \tag{2}$$

Power spectrum computation is carried out in order to calculate the power for each frame after performing HHT.

The Power Spectral Density is defined as: $Pt(k)=|Yt(k)|^2$ (3)

We need to set the threshold in order to distinguish primary users' frequency and holes. So, we calculate the average power of T successive frames and the mean power across all the frequencies in the spectrum.

$$Pavg(k) = 1/T\sum_{t=0}^{T-1} Pt(k) \tag{4}$$

$$Pmean = 2/N + 2\sum_{k=0}^{N/2} Pavg(k) \tag{5}$$

The ratio of the average power to that of the mean power gives the threshold value.

The power at every frequency is compared with the threshold value and the decision d(k) of classifying the primary user and unused frequency is taken as:

$$d(k) = Pavg(k)/Pmean \tag{6}$$

The combined decision for all the frequencies is made according to:

Combined decision=
used, *if ∩ k€f {d (k)>at particular frequency}*
unused, if ∩ k€f {d(k)<at particular frequency} (7)

3. Methodology

The input to the HHT is base band discrete time signal, where the signal is differentiated into individual IMFs. The average power and the mean power are calculated according to the Equation (4), (5). The threshold value is dynamically changed according to the IMFs observed and a particular IMF is then compared with the threshold value. This method of comparing IMFs directly with the threshold reduces the complexity of finding the power of each IMF using HSA, which also reduces hardware equipment and increases the computation speed.

In our work, the number of IMF's generated is 8 and any IMF is sufficient to depict the primary user. But, the first IMF yielded closer to that of the required result.

4. Results and Discussion

The input considered for our work is a discrete-time domain signal with matrix size 20*5 known signal. The range of frequencies considered is 20 MHz – 40 MHz with a sampling frequency of 128 MHz and 20 users in this spectrum. We considered 200 frames with a window size of 200*256. The bit duration is 0.4e-3 and the probability of false alarm rate as 0.001. SNR values are set as -40dB. A known signal taken as reference signal is taken and followed by the incoming random non-stationary signal to identify the primary users' status. The incoming signal is fed to the HHT with EMD mode and also EEMD mode (Figure 4, Figure 5 respectively).

Information from IMF's:

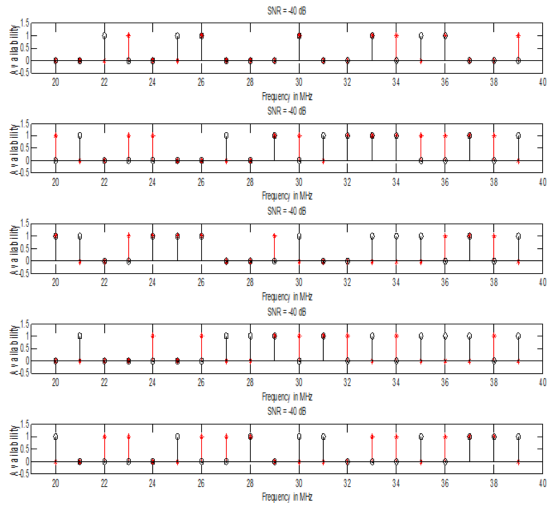

Figure 1. Sensing the user using First IMF.

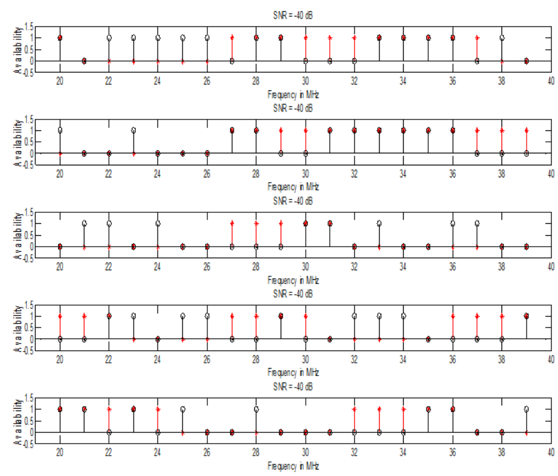

Figure 2. Sensing the user with Fourth IMF component.

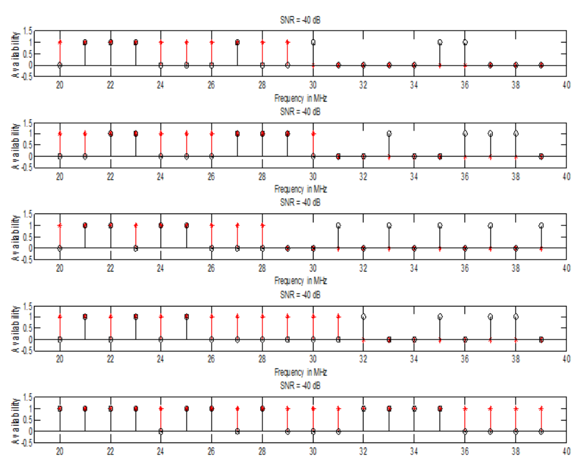

Figure 3. Sensing the user using Eight IMF.

Table 1. Comparison of simulated results (threshold= 1.0194, 20 users)

Frequency	*EFAR*	*DP*	*FAR*	*DP*	*ALL IMFs*	*DP*	*1st IMF*	*DP*	*8th IMF*	*DP*	*3rd IMF*	*DP*	*4th IMF*	*DP*
21 MHz	0.8241	0	1.0135	0	36.4344	1	-9.4519	0	1.6224	1	5.0188	1	11.5269	1
22 MHz	0.7684	0	0.9581	0	36.7754	1	69.0419	1	1.5362	1	-106.7901	0	7.1025	1
23 MHz	0.8456	0	1.1102	1	19.863	1	-33.0619	0	1.4519	1	-1.6627	0	0.7099	0
24 MHz	0.911	0	1.0503	1	40.6697	1	-20.029	0	1.3694	1	75.3518	1	-5.3677	0
25 MHz	0.9846	0	0.9406	0	-2.3624	0	-151.5442	0	1.2887	1	-11.3258	0	-9.4432	0
26 MHz	0.9448	0	1.0683	1	-18.9286	0	-113.6421	0	1.2099	1	-72.5679	0	-10.84	0
27 MHz	0.7062	0	0.9308	0	11.1541	1	45.9015	1	1.1329	1	37.9009	1	-9.0553	0
28 MHz	0.9024	0	0.9516	0	4.8895	1	80.0831	1	1.0577	1	80.9065	1	-4.6318	0
29 MHz	0.729	0	1.0599	1	27.8371	1	-61.7553	0	0.9843	0	1.4622	1	0.7357	0
30 MHz	0.9687	0	0.8804	0	-16.6421	0	53.9251	1	0.9126	0	-68.067	0	5.3005	1
31 MHz	0.9124	0	0.9889	0	46.7474	1	-74.0898	0	0.8427	0	-102.4828	0	7.632	1
32 MHz	1.059	1	0.9591	0	12.8613	1	43.01	1	0.7744	0	-107.8538	0	7.7783	1
33 MHz	1.1758	1	1.072	1	-33.2315	0	115.1585	1	0.7079	0	-90.6125	0	6.3379	1
34 MHz	0.9889	0	0.9398	0	40.0995	1	-78.2393	0	0.6431	0	-57.9544	0	3.89	1
35 MHz	0.8798	0	1.0249	1	6.3209	1	-175.7666	0	0.5799	0	-15.1091	0	1.0084	0
36 MHz	1.0503	1	1.0254	1	5.7695	1	-90.6747	0	0.5184	0	33.6698	1	-1.7335	0
37 MHz	0.981	0	0.9396	0	-17.9235	0	-121.3685	0	0.4585	0	80.5491	1	-3.7618	0
38 MHz	0.8496	0	0.96	0	-2.8199	0	49.0117	1	0.4003	0	103.2214	1	-4.503	0
39 MHz	1.3293	1	0.8779	0	18.3022	1	25.0217	1	0.3436	0	80.8938	1	-3.4409	0
40 MHz	1.2962	1	0.9048	0	0.8094	0	2.9213	1	0.2885	0	14.7819	1	-0.9394	0
Correct Detection		*11*		*13*		*9*		*9*		*12*		*8*		*9*

DP- Detection Probability for 20 users.

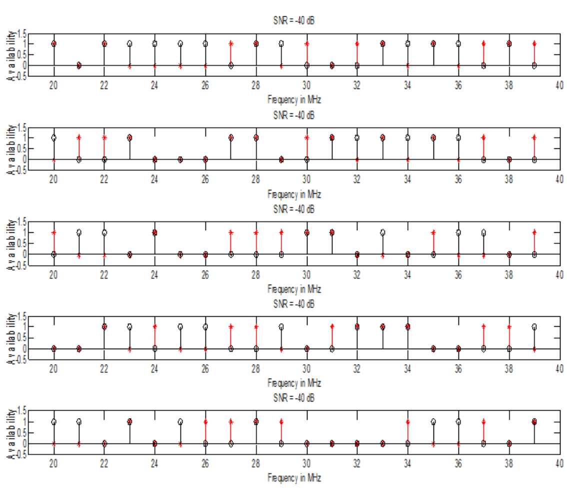

Figure 4. Sensing the users using all IMF's.

The IMFs are computed and they are enough to classify the number of primary users, which produces better results in relative to FAR, EFAR, as shown in Table 1. The threshold value generated is 1.0194 which is the ratio of average powers. Figure 4 It corresponds to the user identification (power), in which the sum of 8 IMF's generated is taken into consideration. Figure 1, Figure 2, Figure 3 reflects the individual IMF's generated for the identification of the user in comparison with the set threshold value (6). Figure 4 shows sum of all the IMF's for decision making of the user presence. It is very clear from the above observations that the first IMF produced is almost close enough to the sum of all IMF's.

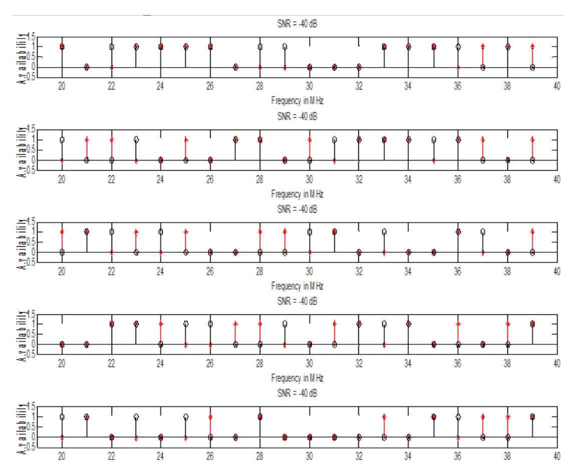

Figure 5. EEMD for user identification.

5. Conclusion

In order to differentiate the Cognitive radio users using all IMF's, a single IMF is sufficient to yield the desired identification, reducing the complexity of practical implementations. HHT in total yielded better relative detection probability because of the EMD and EEMD modes and also IMFs are utmost used to classify the detection rather that going to Hilbert-Spectrum analysis. Differentiating the users is very much closer to the realistic values in HHT-AR over FAR (Figure 4)[4]. Considering the typical frequency 27 MHz for all the methodologies, user identification using HHT produced accurate output over FAR and EFAR. The main advantage of using HHT is that it deals with the non-stationary signals and also immunized to noise. This work can be carried on for the secondary user power optimization which may cause power interference to the primary user. Also when the primary user requires a frequency slot after allocating to the secondary users, which secondary user to be evacuated is the primary question and this can be done by using the same HHT computation for every secondary user and the user with low power is replaced.

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