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A Novel Blind Spectrum Sensing Algorithm for Cognitive Radio Systems Based on Algorithmic Information Theory

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Abstract—**In this paper, we propose a new algorithm of spectrum sensing based on algorithmic information theory. Since the proposed algorithm is applied in time domain, resulting in an overall reduction on the system computational complexity. In this paper, we investigate two cases of wideband and narrowband spectrum sensing problems. To sense the spectrum, we propose to use some measures based on algorithmic information theory such as Lempel-Ziv Complexity (LZC), Higuchi fractal dimension (HFD), and Algorithmic mutual information (algorithmic MI). LZC and HFD are reliable and promising measures that calculate the complexity of a time series signal in a straight forward manner. On the other hand, algorithmic MI calculates the algorithmic mutual information between two time series signals. Our proposed algorithm is blind in the sense that it requires no prior knowledge of the channel, primary users′ signals, and noise variance. In simulation section, it is shown that our proposed algorithm has better performance in contrast with the other complexity based detectors such as Shannon entropy and spectral entropy based detectors.**

***Keywords- Cognitive Radio*; *Blind Spectrum Sensing*; *Lempel-Ziv Complexity* (*LZC*); *Higuchi Fractal Dimension* (*HFD*); *Algorithmic mutual information*; *Entropy*;**

I. INTRODUCTION

According to the *Federal Communications Commission* (FCC) report published in 2002, the percentage of spectrum utilization ranges from 15% to 85% [1]. Although there is a spectrum scarcity in unlicensed spectrum, most of places in the licensed portion of the spectrum are unused. In cognitive radio systems, in order to maximize spectrum utilization, the unlicensed secondary users exploit the spectrum allocated to the licensed primary users efficiently. The secondary users transmit signal in such a way that it does not interfere with primary users′ signal. As the first major step, in cognitive radio, in order to be aware of the wireless environment, it is required to constantly sense the spectrum.

In recent years, many spectrum sensing algorithms have been proposed, including matched filter detection, energy detection, cyclostationary detection, and covariance based detection. When the secondary user has a prior knowledge of primary users′ signal,

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matched filter detection is an optimal sensing algorithm [2]. On the other hand, since the matched filter detection has to achieve to coherency with primary users′ signal, it requires less time to achieve high processing gain in comparison with other algorithms [3]. Energy detection is a very popular spectrum sensing algorithm that requires the least prior knowledge about the channel and primary users′ signal. One of the main disadvantages of energy detector is that it has low accuracy in low SNR environments. Additionally, the performance of the energy detectors degrades when there are rapid temporal changes in SNR. The imprecise estimate of noise is called noise uncertainty. Cyclostationary detection is an alternative spectrum sensing algorithm that is based on the cyclostationarity nature of the signal. This algorithm is very complex and requires a high computation time [4].

Recently, some spectrum sensing algorithms proposed that are based on information theory. Entropy is the most important concept in information theory and is a measure of randomness. Since the primary user′s signal has less entropy than the noise signal, it is possible to distinguish them from each other. In [5] and [6], some algorithms are proposed that are based on frequency or time domain entropy. In [5], entropy of frequency domain received signal provides a measure of randomness to detect the primary users. On the other hand, when the primary user′s signal exists in the spectrum, the signal at the output of matched filter becomes more regular and less complex in comparison with the case when no primary user′s signal exists in the spectrum. In [6], entropy of time domain signal at the output of a matched filter is estimated and used as a measure to distinguish between noise and primary user′s signal.

Algorithmic information theory is widely used in computer science and is a subfield of information theory. Recently, some spectrum sensing algorithm proposed that use algorithmic information theoretic measures such as Akaike information criterion (AIC), Minimum Description Length (MDL), and Lempel-Ziv complexity measure. There is a trade-off between data fitting and complexity. AIC (or MDL) provides a measure of fit and also a measure of complexity. In [7], AIC and MDL are used as model selection criteria to detect primary users.

Recently, Lempel-Ziv analysis has been applied extensively in biomedical engineering [8] and coding theory [9]. Complexity is a measure of difficulty in predicting a signal. The proposed algorithm exploits LZC as a measure of complexity of the received signal to detect primary users. LZC is defined as a complexity measure of finite sequences. This measure can be applied to non-stationary time series signals and it does not require any prior knowledge of primary users′ signals, channel, and noise. Since LZC is independent from noise variance, the performance of the proposed algorithm remains unchanged under noise uncertainty. Higuchi Fractal Dimension (HFD) is another measure of complexity that is calculated in time series. This measure is a very low computational algorithm and can be applied to short length signals.

In order to sense the spectrum, LZC (or HFD) is calculated in each subchannel individually. By comparing the calculated LZC (or HFD) with a predefined threshold, the primary users′ signal is detected in each subchannel. For wideband primary users′ communication systems, neighboring subchannels occupancies may be correlated with each other. In this case, by considering subchannels individually, we will lose the mutual information between the subchannels. In other words, in this case, the sensing decision should take the neighboring subchannels into account. This case was previously investigated in [10]-[12]. In [10], [11], the spectrum sensing problem is solved by maximizing the aggregated opportunistic throughput. In [12], the occupied subchannels are detected via maximum a posteriori (MAP) estimation and minimum mean-square error (MMSE) criterion based algorithms. In this paper, we propose an algorithm to sense the spectrum based on algorithmic mutual information. Algorithmic mutual information measures the increase in the complexity of the subchannels′ signals from one to another.

The rest of this paper is organized as follows. Section II describes system model. Section III introduces some algorithmic information theoretic measures such as Lempel-Ziv complexity, Higuchi Fractal Dimension analysis, and Algorithmic mutual information. Section IV discusses how to use the algorithmic information theoretic measures to sense the spectrum. Section V analyzes the performance of our proposed algorithm, and compares its performance with those of others through simulation results. Section VI presents the conclusions.

The notations used in this paper are as follows. Bold upper- and lower-case symbols will be used to denote matrices and vectors, respectively; Lower case symbols are used to represent scalars.

II. System Model

In this section, we describe the system model that is depicted in Figure 1. We consider a slow fading channel and N primary users. The key question is that is there any active primary user in the system. The received signal is expressed as

$$y_i(t) = a_i s_i(t) + w_i(t), \quad i = 1, 2, \ldots, I . \tag{1}$$

where $y_i(t)$, $s_i(t)$, and $w_i(t)$ denote received signal, primary user′s received signal, and additive white Gaussian noise (AWGN) in the i′th subchannel, respectively. $a_i \in \{0,1\}$ determines whether the i′th subchannel is occupied by primary users or not. We define $\mathbf{y}_i = [y_i(1), y_i(2), \ldots, y_i(K)]$, $\mathbf{s}_i = [s_i(1), s_i(2), \ldots, s_i(K)]$, and $\mathbf{w}_i = [w_i(1), w_i(2), \ldots, w_i(K)]$, respectively as the vectors of received signal, primary user′s received signal, and noise in the i′th subchannel which are constructed by sampling uniformly from $y_i(t)$, $s_i(t)$ and $w_i(t)$, respectively. We can rewrite (1) as

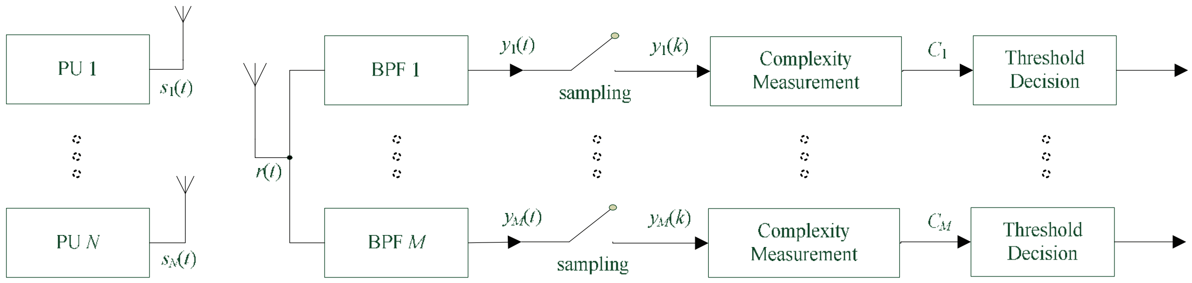

Fig 1. The block diagram of the proposed detector.

$$\mathbf{y}_i = a_i\,\mathbf{s}_i + \mathbf{w}_i \,. \tag{2}$$

Spectrum sensing problem in the i'th subchannel can be formulated as a binary hypothesis test between two hypotheses ($\mathrm{H}_{0,i}$ and $\mathrm{H}_{1,i}$). $\mathrm{H}_{0,i}$ and $\mathrm{H}_{1,i}$ indicate whether active primary users exist or not in the i'th subchannel. We can write the binary hypothesis for the i'th subchannel as

$$\begin{cases} \mathrm{H}_{0,i}: & \mathbf{y}_i = \mathbf{w}_i, \\ \mathrm{H}_{1,i}: & \mathbf{y}_i = \mathbf{s}_i + \mathbf{w}_i. \end{cases} \tag{3}$$

In the above equations, $\mathbf{y}_i$ in H_0 is a Gaussian noise has higher degrees of randomness in contrast with $\mathbf{y}_i$ in H_1. So, using a randomness (or complexity) measure, we can distinguish these two hypotheses from each other.

In this paper, for correlated subchannel occupancy, we consider the occupancy of all the subchannels as a whole. In this case, we will have 2^I hypotheses ($\mathrm{H}_0, \mathrm{H}_1, \ldots \mathrm{H}_{2^I}$). It is notable that by increasing the number of subchannels, the number of hypotheses will increase exponentially. If we define $\mathbf{A} = \mathrm{diag}([a_1, a_2, \ldots, a_I])$ as the diagonal occupancy matrix, (1) can be rewritten as

$$\mathbf{Y} = \mathbf{A}\,\mathbf{S} + \mathbf{W}\,, \tag{4}$$

where $\mathbf{Y} = [\mathbf{y}_1; \mathbf{y}_2; \ldots; \mathbf{y}_I]$, $\mathbf{S} = [\mathbf{s}_1; \mathbf{s}_2; \ldots; \mathbf{s}_I]$, and $\mathbf{W} = [\mathbf{w}_1; \mathbf{w}_2; \ldots; \mathbf{w}_I]$. The resultant spectrum sensing problem is to estimate the diagonal elements of $\mathbf{A}$ (i.e. $a_1, a_2, \ldots, a_I$). As was mentioned earlier, the unoccupied subchannels have higher complexity in comparison with the occupied ones. So, there are changes in the complexity of columns of $\mathbf{Y}$ corresponding to the occupied and unoccupied subchannels. By calculating these changes, we can sense the spectrum.

To investigate the performance of the proposed algorithm false alarm probability (P_{fa}) and detection probability (P_d) are calculated. P_{fa} is defined as the probability of presence of the primary user' signal (H_1) under the absence of the primary user' signal (H_0). P_D is defined as the probability of presence of the primary user' signal (H_1) under the presence of the primary user' signal (H_1). These probabilities are shown in the following.

$$P_{fa} = P(\mathrm{H}_1 \mid \mathrm{H}_0)\,, \tag{5}$$

$$P_D = P(\mathrm{H}_1 \mid \mathrm{H}_1)\,. \tag{6}$$

III. Algorithmic Information Theoretic Measures

In this section, we study some measures to calculate the absolute and relative complexity which are based on algorithmic information theory. These measures are used frequently to analyze the time series and are suitable to be applied in different situations.

A. *Lempel-Ziv Compelxity*

Lempel-Ziv Complexity (LZC) is a measure of the complexity of the time series signal. The first step in the (LZC) analysis is to obtain a finite binary sequence from comparing the signal with a threshold. The aim of the analysis is to find the rate of recurrence of patterns in this sequence. The resultant binary sequence is given by:

$$P = \{p_1, p_2, \cdots, p_K\}\,, \tag{7}$$

where K is the data length. Each elements of P in i'th subchannel is obtained from:

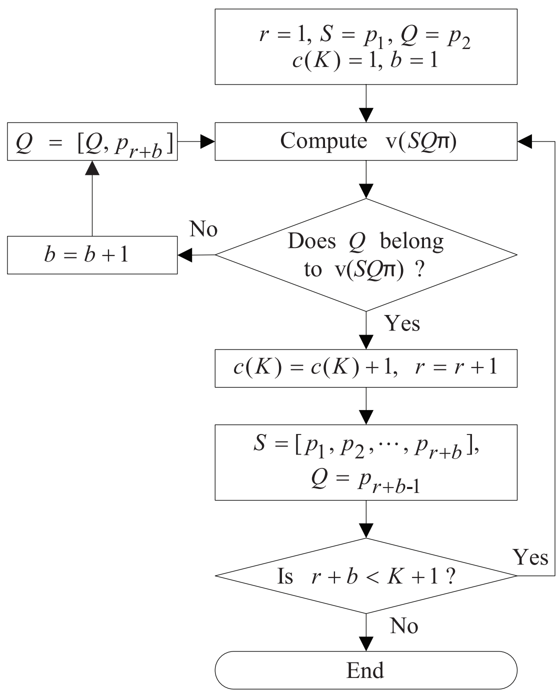

Fig 2. The flowchart of Limpel-Ziv Complexity analysis.

$$p_k = \begin{cases} 0, & \text{if } y_i(k) \le T_d, \quad k = 1,\ldots,K, \\ 1, & \text{if } y_i(k) > T_d, \quad k = 1,\ldots,K. \end{cases} \tag{8}$$

In (8), T_d is a threshold and is chosen as the median of P. We perform a self-eliminating learning algorithm. First of all, we define $c(K)$ as the complexity counter and set its initial value to 1. We investigate P from left to right to find new subsequences that was not previously appeared. Each time we find new subsequence, $c(K)$ is increased by one. By normalizing $c(K)$, we can obtain LZC. Figure 2 shows the flowchart of this algorithm.

As can be seen from the flowchart, at the first step (b = 1, r = 1), S and Q are chosen as the first and second elements of P. We define SQ as a sequence that is made from combining S and Q, i.e.

$$S = p_1, Q = p_2, \tag{9}$$

$$SQ \quad [S, Q]. \tag{10}$$

The vector $SQ\pi$ is constructed by eliminating the last element of SQ. In other words, π is an operator that eliminates the last element of its operand vector. v($SQ\pi$) is a vector that consist of all the different subsequences of $SQ\pi$. In each step, if Q does not belong to v($SQ\pi$), it means that we find a new different subsequence. Each time we find a new different subsequence, we increase $c(K)$ by one. But, if Q belongs to v($SQ\pi$), we repeat the p evious steps by increasing i by one and renewing Q to be Q = [Q, p_{r+b}]. When we find a new different subsequence, we will increase r by one and renew S and Q as follows:

$$S = [p_1, p_2, \cdots, p_{r+b}], \tag{11}$$

$$Q = p_{r+b-1}. \tag{12}$$

Using new S and Q, we construct a new SQ and repeat the p ocedure. We will repeat this procedure, until Q be the last element of P [13].

Finally, To make the complexity counter independent of K, $c(K)$ must be normalized. It is shown in [4], that the maximum value of $c(K)$ equals with:

$$c(K) \le \frac{K}{(1+\varepsilon_K)\log_2(K)}. \tag{13}$$

In the above equation, ε_K is a function of K. For sufficiently large values of K, ε_K has a very small value and can be neglected. It is notable that when data length (K) is less than about 10000, we can apply an alternative imp oved Lempel-Ziv that is defined in [14]. Finally, the normalized $c(K)$ is given by:

$$C = \frac{c(K)}{K/\log_2(K)}. \tag{14}$$

In the above equation, C is the Lempel-Ziv complexity measure.

B. Higuchi Fractal Dimension Analysis

Fractal dimension (FD) was first introduced by Mandelbrot. We can derive FD from generalizing Euclidean distance. FD can be used as a measure of the complexity of time series. Higuchi Fractal Dimension (HFD) is a low computational algorithm that asses FD using only few samples [15].

To calculate HFD for the received signal from each subchannel, we first construct d time series. For the i'th subchannel's signal with K samples, the constructed time series can be expressed as:

$$x_{i,m}^{d} = \left\{ y_i(m), y_i(m+d), \ldots, y_i\left(m + \left\lfloor \frac{K-m}{d} \right\rfloor d\right)\right\}, \quad m = 1 \sim d, \tag{15}$$

where d is an integer that is called scale size and $\lfloor \cdot \rfloor$ denotes the rounding down operation. The length of time series can be defined as:

$$L_{i,m}(d) = \frac{(K-1)\sum_{j=1}^{\left\lfloor \frac{(K-m)}{d} \right\rfloor} |x(m+jd) - x(m+(j-1)d)|}{k\lfloor (K-m)/d \rfloor}, \quad m = 1 \sim d. \tag{16}$$

Then, we average $L_{i,m}(d)$ over m to obtain $L_i(d)$ and calculate logarithm of $L_i(d)$ for $1 < d < d_{max}$. The logarithm of $L_i(d)$ will depend on d in the following form.

$$\log(L_i(d)) = C\log(1/d), \tag{17}$$

where C is an estimation of FD. This measure is used as a measure of time series complexity. In Section IV, we will use LZC and HFD as complexity measures to sense the spectrum.

C. Algorithmic Mutual Information Analysis

In previous subsections, we study the Kolmogorov complexity of a single time series signal. In this subsection, we study the algorithmic mutual information (algorithmic MI) of two time series signal. Here, algorithmic MI calculates the information one subchannels' signal contains about its neighboring subchannels' signal. Algorithmic MI is the counterpart of Shannon's mutual information (Shannon's MI) in Shannon's theory. The Shannon's MI between the sampled received signals in the i'th and $(i-1)$'th subchannels ($\mathbf{y}_i$ and $\mathbf{y}_{i-1}$) is defined by [16]

$$\begin{aligned} I(Y_i;Y_{i-1}) &= H(\mathbf{y}_{i-1}) - H(\mathbf{y}_{i-1} \mid \mathbf{y}_i) \\ &= H(\mathbf{y}_{i-1}) + H(\mathbf{y}_i) - H(\mathbf{y}_{i-1}, \mathbf{y}_i) \end{aligned}, \tag{18}$$

where $H(\mathbf{y}_i)$, $H(\mathbf{y}_{i-1})$, and $H(\mathbf{y}_i, \mathbf{y}_{i-1})$ are defined, respectively, as the marginal entropy of $\mathbf{y}_i$, $\mathbf{y}_{i-1}$ and their joint entropy and are given by

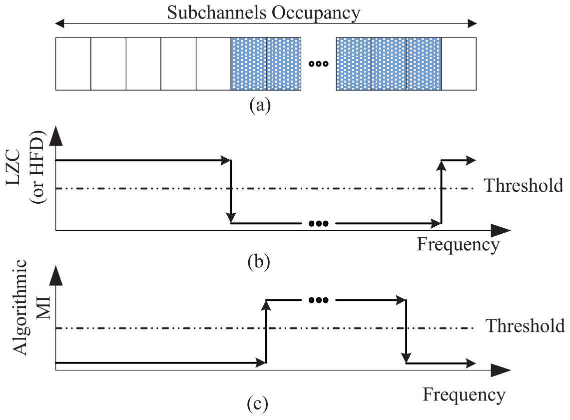

Fig 3. (a) Illusteration of the subchannels occupancy for wideband spectrum sensing problem. (b) Illusteration of the LZC (or HFD) in terms of frequency. (c) Illustration of the algorithmic Mutual Information (Algorithmic MI) in terms of frequency.

$$\begin{cases} H(\mathbf{y}_i) = -\sum_j p_j \log_2 p_j , \\ H(\mathbf{y}_{i-1}) = -\sum_j q_j \log_2 q_j , \\ H(\mathbf{y}_{i-1},\mathbf{y}_i) = -\sum_j \sum_l r_{jl} \log_2 r_{jl} . \end{cases} \quad (19)$$

where $\{p_j,\ j=1,2,\ldots J\}$, $\{q_j,\ j=1,2,\ldots J\}$, and $\{r_{jl},\ j,l=1,2,\ldots J\}$ denote, respectively, the marginal probability mass function (pmf) of $\mathbf{y}_{i-1}$, $\mathbf{y}_i$ and their joint pmf. After some manipulation, Shannon's MI is given by

$$I(Y_i;Y_{i-1}) = \sum_l \sum_j r_{jl} \log_2 \frac{r_{jl}}{p_j q_l} . \quad (20)$$

From (20), we see that for independent signals (i.e. $r_{jl} = p_j q_l$), $I(Y_i;Y_{i-1})$ equals zero. Similar to Shannon's MI, the algorithmic MI between the sampled received signals in the i 'th and $(i-1)$ 'th subchannels ($\mathbf{y}_i$ and $\mathbf{y}_{i-1}$) (i.e. the information in $\mathbf{y}_i$ about $\mathbf{y}_{i-1}$) is defined by [17]

$$\begin{aligned} I(y_i : y_{i-1}) &= K(\mathbf{y}_{i-1}) - K(\mathbf{y}_{i-1} \mid \mathbf{y}_i, K(\mathbf{y}_i)) \\ &\stackrel{+}{=} K(\mathbf{y}_{i-1}) + K(\mathbf{y}_i) - K(\mathbf{y}_{i-1},\mathbf{y}_i), \end{aligned} \quad (21)$$

where $K(\mathbf{y}_{i-1})$ and $K(\mathbf{y}_i)$ are the Kolmogorov complexity of $\mathbf{y}_{i-1}$ and $\mathbf{y}_i$ and $K(\mathbf{y}_{i-1},\mathbf{y}_i)$ is their joint Kolmogorov complexity. $K(\mathbf{y}_{i-1} \mid \mathbf{y}_i, K(\mathbf{y}_i))$ is defined as the conditional Kolmogorov complexity of $\mathbf{y}_{i-1}$ given $\mathbf{y}_i$ and $K(\mathbf{y}_i)$. If we denote the operators for inequalities with a constant term with $\stackrel{+}{>}$ and $\stackrel{+}{<}$, then $\stackrel{+}{=}$ denotes the situation when both $\stackrel{+}{>}$ and $\stackrel{+}{<}$ held. The joint Kolmogorov complexity of $\mathbf{y}_{i-1}$ and $\mathbf{y}_i$ is given by

$$K(\mathbf{y}_{i-1},\mathbf{y}_i) = K(<\mathbf{y}_{i-1},\mathbf{y}_i>) . \quad (22)$$

In (22), $<\cdot,\cdot>$ denotes the pairing function. Kolmogorov complexity is uncomputable, but is approximated with some measures such as LZC [18].

An illustration of algorithmic MI for a number subchannels is shown in Figure 3. As can be seen from Figure 3, similar to the case of Shannon's MI, when $\mathbf{y}_{i-1}$ and $\mathbf{y}_i$ are independent of each other, $I(Y_i;Y_{i-1})$ is nearly equals zero [19].

IV. Spectrum Sensing Using Algorithmic Information Theory

In this section, we investigate our proposed spectrum sensing algorithm in two cases of narrowband and wideband primary users' communication systems. In the first case, there are no correlations (or mutual information) between subchannels' signals and we can investigate them individually. In the second case, one primary user can occupy more than one subchannel. So, in this case, the occupancy of subchannels can be correlated with each other. In other words, there is algorithmic mutual information between the occupied subchannels. Using the algorithmic mutual information, we can detect the primary users' signals in the subchannels. The first and second cases are investigated in Subsection IV-A and Subsection IV-B, respectively.

A. *Narrowband Spectrum Sensing Using Complexity Measures*

In Section II, we found that, in H_0 the sampled received signal is a white Gaussian noise:

$$y(k) \sim N(0,\sigma_w^2) . \quad (23)$$

In H_1, the sampled received signal is combination of primary users' signals and white Gaussian noise. In each subchannel, Probability density function (PDF) of $y(k)$ is derived from the convolution of the PDF of the primary users' signals and noise. If we assume at least one of the primary users' signals to be non-Gaussian distributed then the distribution of received signal would be non-Gaussian too. Signals with different distributions have different degrees of complexity (or randomness).

First, we investigate the case of narrowband primary users' signals. In this case we calculate the complexity of the received signal is using LZC (or HFD). By comparing this measure with a threshold (λ), we can decide whether there is any primary signal or not in the i 'th subchannel.

$$C_i \underset{H_{1,i}}{\overset{H_{0,i}}{\gtrless}} \lambda . \quad (24)$$

By applying this algorithm to all the subchannels individually, we can detect the primary users' signals in the spectrum. We determine the threshold (λ), in such a way that the false alarm probability becomes less than a predefined value. The received signal with higher LZC (or HFD) would have higher degrees of complexity and therefore higher degrees of randomness. So, when LZC (or HFD) is higher than threshold, the received signal can be considered as noise and the subchannel can be regarded as an unoccupied one.

B. Wideband Spectrum Sensing Using Complexity Measures

For the case of wideband primary users′ signals, we use (21), to calculate the algorithmic mutual information between the subchannels. As shown in Figure 3, the algorithmic mutual information is calculated for each pair of the subchannels. To detect the primary users′ signal in the i′th subchannel, we compare $I(y_i : y_{i-1})$ with a threshold (λ).

$$I(y_i : y_{i-1}) \underset{H_{0,i}}{\overset{H_{1,i}}{\gtrless}} \lambda . \qquad (25)$$

We determine the threshold (λ), in such a way that the false alarm probability becomes less than a predefined value. Although we would have performance degradation, but the algorithm of Subsection IV-A can be applied to wideband primary users. But, the algorithm of Subsection IV-B is based on the correlation between the subchannels and cannot be applied to sense an individual subchannel. From Figure 3, we can see that occupied subchannels have higher algorithmic mutual information and lower absolute complexity (LZC or HFD) in comparison with unoccupied ones.

V. Performance Analysis and Simulation Results

Simulations are performed via Monte Carlo method. We also assume to have 16 subchannels. The channels between primary users and secondary users are assumed to be Rayleigh slow-fading channels. We determine the thresholds for all the algorithms such that the false alarm probability is fixed to be 15%. Here, we assume primary users′ signals to be Laplacian distributed. We investigate two cases of narrowband and wideband primary users in Subsection V-A and Subsection V-B, respectively. In the first case, we consider 8 primary users that each occupies only one subchannel. In the second case, we consider one primary user that occupies 8 subchannels. Detection probability is compared for different algorithms and different values of SNR. Additionally, the dependency of the proposed algorithm to sampling number is investigated. We compare the performance of our proposed algorithm with ED (energy detector), SpEn (Spectral entropy) based detector [5], and En-MFD (matched filter based on Shannon Entropy) [6]. We assume 2 dB uncertainty in the variance of noise.

A. Narrowband Spectrum Sensing

In Figure 4, detection probability of the proposed algorithm using LZC and HFD measures are compared with detection probability of some other algorithms. We also consider $K = 10000$ samples. As can be seen, the proposed algorithm has better performance in contrast with energy detector and other entropy based algorithms considered here. Also, it can be seen that with equal number of samples, detector with LZC complexity measure has better performance than the one with HFD complexity measure.

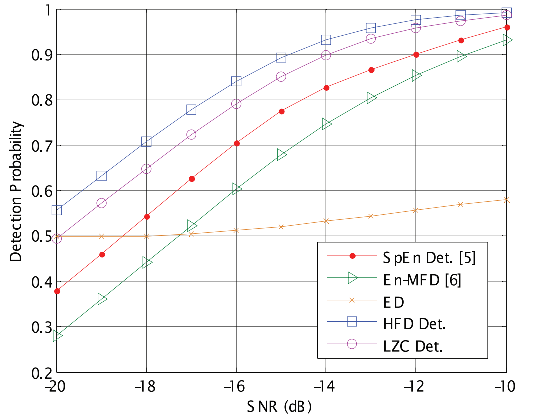

Fig 4. Detection probability vs. SNR for for the proposed algorithm using LZC, and HFD complexity meaures, energy detector (ED), spectral entropy based detector (SpEn Det.), and entropy based mathced filter (En-MFD). Here, the secondary user receives narrowband signals from the primary users.

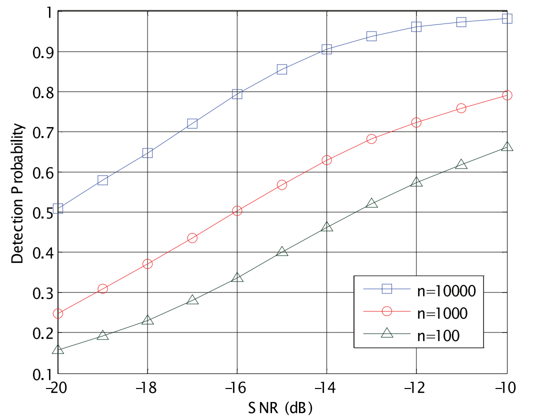

Fig 5. Detection probability vs. SNR for the proposed algorithm using LZC complexity measure, for some data lenghs. Here, the secondary user receives narrowband signals from the primary users.

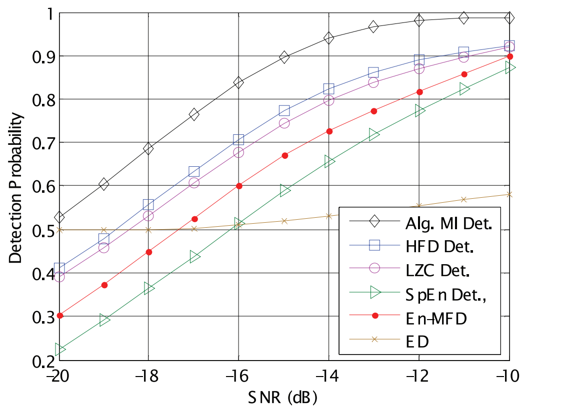

Fig 6. Detection probability vs. SNR for the proposed algorithm using Algorithmic MI (Alg. MI), LZC, and HFD complexity meaures, energy detector (ED), spectral entropy based detector (SpEn Det.), and entropy based mathced filter (En-MFD). The secondary user receives a wideband signal from the primary user.

Detection probability for the proposed algorithm in terms of SNR for some data lengths (*K*) is illustrated in Figure 5. It is perceived that, the proposed algorithm has a better performance in large data lengths. This figure shows that LZC as a complexity measure can adequately sense the spectrum, when the number of received signal samples is more than 10000.

B. Wideband Spectrum Sensing

In Figure 6, we plot detection probability of the proposed algorithm in terms of SNR for a wideband primary user's signal that occupies 8 subchannels. In this figure we detect the primary users' signal using Algorithmic MI, LZC, HFD and we compare the performance of the proposed algorithm with some other algorithms. We also consider $K = 10000$ samples. As can be seen from this figure, our proposed algorithm outperforms the other algorithms.

VI. CONCLUSION

In this paper, a new blind spectrum sensing algorithm was proposed. Our proposed algorithm use Lempel-Ziv complexity measure, Higuchi Fractal Dimension, and algorithmic mutual information as algorithmic information theoretic measures to sense the spectrum. We use Lempel-Ziv complexity measure and Higuchi Fractal dimension for the narrowband spectrum sensing problem. We also use algorithmic mutual information to the case of wideband spectrum sensing problem. Through simulation, it is shown that this algorithm has better performance than those of other entropy based algorithms.

REFERENCES

[1] FCC, "Report of the Spectrum Efficiency Working Group," Spectrum Policy Task Force, Tech. Rep, 2002. [Online]. Available: http://www.fcc.gov/sptf/reports.html

[2] I. F. Akyildiz, W.-Y. Lee, M. C. Vuran, and S. Mohanty, "A Survey on Spectrum Management In Cognitive Radio Networks," *IEEE Communications Magazine*, vol. 46, no. 4, pp. 40-48, 2008.

[3] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios," in *Signals, Systems and Computers, Conf.*, pp. 772-776, 2004.

[4] A. V. Dandawate and G. B. Giannakis, "Statistical Tests for Presence of Cyclostationarity," , *IEEE Trans., Signal Process.*, vol. 42, no. 9, pp. 2355-2369, 1994.

[5] Y. Zhang, Q. Zhang, and S. Wu, "Entropy-Based Robust Spectrum Sensing in Cognitive Radio," *Communications, IET*, vol. 4, no. 4, pp. 428-436, 2010.

[6] X. Chen and S. Nagaraj, "Entropy Based Spectrum Sensing in Cognitive Radio," in *Wireless Telecommunications Symp., WTS*, pp. 57-61, 2008.

[7] B. Zayen, A. Hayar, and K. Kansanen, "Blind Spectrum Sensing for Cognitive Radio Based on Signal Space Dimension Estimation," in *Communications, ICC '09. IEEE International Conf.*, 2009, pp. 1-5, 2009.

[8] M. Aboy, R. Hornero, D. Abasolo, and D. Alvarez, "Interpretation of the Lempel-Ziv Complexity Measure in the Context of Biomedical Signal Analysis," *IEEE Trans., Biomedical Engineering,* vol. 53, no. 11, pp. 2282-2288, 2006.

[9] J. Ziv, "The Universal LZ77 Compression Algorithm Is Essentially Optimal for Individual Finite-Length N -Blocks," *IEEE Trans., Inform. Theory,* , vol. 55, no. 5, pp. 1941-1944, 2009.

[10] Z. Quan, S. Cui, H. V. Poor, and A. H. Sayed, "Collaborative Wideband Sensing for Cognitive Radios," *IEEE Signal Process. Magazine*, vol. 25, no. 6, pp. 60–73, 2008.

[11] Z. Quan, S. Cui, A. H. Sayed, and H. V. Poor, "Optimal Multiband Joint Detection for Spectrum Sensing in Cognitive Radio Networks," *IEEE Trans. Signal Process.*, vol. 57, no. 3, pp. 1128–1140, Mar. 2009.

[12] K. Hossain, and B. Champagne, "Wideband Spectrum Sensing for Cognitive Radios With Correlated Subband Occupancy," *IEEE Signal Process. Letters*, vol. 18, no. 1, pp. 35-38, Jan, 2011.

[13] K. Limniotis, N. Kolokotronis, and N. Kalouptsidis, "On the Nonlinear Complexity and Lempel–Ziv Complexity of Finite Length Sequences," *IEEE Trans., Inform. Theory*, vol. 53, no. 11, pp. 4293-4302, 2007.

[14] F.-t. Liu and Y. Tang, "Improved Lempel-Ziv Algorithm Based on Complexity Measurement of Short Time Series," in *Fuzzy Systems and Knowledge Discovery Conf.*, pp. 771-776, 2007.

[15] R. Esteller, G. Vachtsevanos, J. Echauz, and B. Litt, "A Comparison of Waveform Fractal Dimension Algorithms," *IEEE Trans., Circuits and Systems I: Fundamental Theory and Applications,* vol. 48, no. 2, pp. 177-183, 2001.

[16] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, 2nd ed. New York: Wiley, 2006.

[17] P. Gács, J. T. Tromp, and P. M. B. Vitányi, "Algorithmic Statistics," *IEEE Trans., Inform. Theory*, vol. 47, no. 6, pp. 2443-2463, Sep. 2001.

[18] C. H. Bennett, P. Gács, M. Li, P. M. B. Vitányi, and W. H. Zurek, "Information Distance," *IEEE Trans., Inform. Theory*, vol. 44, no. 4, pp.1407-1423, Jul. 1998.

[19] W. Lang, M. Morse, and J. M. Patel, "Dictionary-Based Compression for Long Time-Series Similarity," *IEEE Trans., Knowledge and Data Eng.*, vol. 22, no. 11, pp. 1609-1622, Nov. 2010.

[20] T. M. Cover and J. A. Thomas, *Elements of Information Theory*, 2nd ed. New York: Wiley, 2006.

[21] Z. Tian and G. B. Giannakis, "A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios," in *Proc. 1st Int. Conf. Cognitive Radio Oriented Wireless Networks Communications* (*CrownCom*), Mykonos Island, Greece, pp. 1–5, Jun. 2006.

[22] A. Goldsmith, *Wireless Communications*. Cambridge, U.K.: Cambridge Univ. Press, 2006.

[23] S. M. Kay, *Fundamentals of Statistical Signal Processing*: *Detection Theory*. Upper Saddle River, NJ: Prentice-Hall, 1998.

[24] S. B. Kordan, B. Abolhassani, "Blind Spectrum Sensing for Cognitive Radio Based on Complexity measurement," *Iranian Conf. on Electrical Engineering* (*ICEE*), pp. 1-4, 2011.

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