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WIDEBAND SPECTRUM SENSING USING ADAPTIVE NEURO FUZZY INFERENCE SYSTEM IN COGNITIVE RADIO NETWORKS

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ABSTRACT

Radio Frequency (RF) spectrum is anexpensive and limited natural resource for wireless communication systems. In recent times, Cognitive Radio (CR)has come out as one of the most competent candidates for enhancing the spectral exploitation effectiveness. Spectrum sensing is one of the most decisive elements in a CR system facilitating CR to access the licensed spectrum when it is not exploited by Primary Users (PUs).Conventional spectrum sensing approaches such as waveform based sensing algorithm, matched filter algorithm and energy detection algorithm are employed for recognizing the spectrums holes in the band. In actual fact, existing wideband spectrum sensing approaches in a distributed CR network is complicated to recognize, owing to huge implementation/computational complication and huge economic/energy costs. In order to overcome these concerns, a novel spectrum sensing method based on the ANFIS algorithm which is principally exploited to identify the borders of the subband and recognize the spectrum holes in specified input band. ANFIS is employed for effectively sensing the spectrum and considerably reducing the sensing error throughout the process spectrum sensing. The parameters such as power spectral density, bandwidth efficiency, SNR and channel capacity is used for identifying the condition of the spectrum. The experimental results shows that the sensing the spectrum using the proposed method is better than the other techniques.

Keywords: primary users (PU), radio frequency (RF), adaptive neuro fuzzy inference system (ANFIS), cognitive radio (CR).

1. INTRODUCTION

Due to the continuous development of applications and services in wireless communications, the requirement for access to supplementary frequency spectrum has been growing considerably. Given that almost the entire frequency spectrums are allocated, reacting to the requirement has turn out to be one of the chief challenges in wireless communications. On the other hand, various spectrum occupancy measurement surveys, carried out by the Federal Communications Commission (FCC) [1] and Shared Spectrum Company (SSC) [2], have exposed that most of the allocated spectrum is either unexploited or under-utilized. As a result, spectrum insufficiency in wireless communications is believed to be owing to the inadequacy of static frequency distribution rather than the intense usage of the spectrum.

When a wide-band spectrum is allocated to a number of primary users, secondary users can look for unoccupied channels (spectrum holes) inside the wide-band spectrum and converse in that band. The conventional approach for detecting holes in a wide-band spectrum is channel-by-channel scanning. To put into practice this, an RF front-end with a collection of tunable and narrow band pass filters is required. The occupancy of each channel can be decided by measuring the energy of the signal at the output of each filter.

Spectrum sensing is the process of obtaining knowledge regarding the spectrum usage and existence of primary users in a geographical region. Given that there is no collaboration between primary users and secondary ones, spectrum accessibility for secondary users is decided with the help of spectrum sensing. As a result, the secondary user observes the spectrum and if it locates a hole then it transmits. Indeed, the initial fundamental cognitive task of a CR is to exploit spectrum sensing for determining spectral availability. The spectrum bands can be categorized into three types: [3]

- Black spaces: which are engaged by high-power local interferers
- Grey spaces: which are moderately engaged by low-power interferers
- White spaces: which are without RF interferers apart from ambient noise, which is made up of natural and artificial forms of noise

White spaces and grey spaces (with a smaller amount probability) are candidates for exploitation by secondary users.

In order to identify a primary user in addition to keep away from false alarm are of highly essential for such a system. In actual fact, it is extremely complicated for a cognitive radio to have the information of direct measurement of a channel between a primary transmitter and receiver.

The three major signal processing approaches for sensing the existence of a primary user (PU) that appear in the literature are matched filter detection, Energy Detection (ED) and cyclo stationary feature detection [4]. Matched filter detection and cyclostationary feature detection approaches necessitate the previous knowledge of the PU's signal to formulate the decision regarding the existence or nonexistence of the PU signal [5]. Even though ED technique does not necessitate any prior knowledge of PU's signal, the performance of this technique is vulnerable to noise covariance uncertainty [6]. Because both the previous knowledge regarding the PU's signal and the noise variance are indefinite to the CRs in practical circumstances, exploring well-organized and blind SS techniques for CRs has emerged as an significant research confront. Numerous blind SS techniques have been developed [7] without necessitating the previous knowledge of the PU's signal, the channel and the noise power. In addition, the performance of conventional SS techniques is inadequate by received signal strength which may be rigorously degraded in multipath fading and shadowing circumstances. Several diversity enhancing approaches such as multi-antenna, cooperative and oversampled techniques have been introduced in the literature to increase the SS efficiency in wireless fading channels. The majority of these approaches employs the properties of the Eigenvalues of the received signal's covariance matrix and employs current results from advances in Random Matrix Theory (RMT).

In order to overcome these issues in existing spectrum sensing techniques, a novel artificial intelligence algorithm is proposed for predicting the state of the spectrum.

2. RELATED WORKS

Arroyo *et al.* 2014 [8] established distributed wideband spectrum sensing practice over adaptive diffusion networks. The author principally consider unidentified and different channels between the primary and the cognitive users, an averaged received power spectrum across all the cognitive users is estimated by every user by means of diffusion adaptation approaches. This averaged power spectrum estimate is consistent enough for the users to carry outspectrum sensing and make a decision concerning the existence or the nonexistence of the primary user.

Feng & Zongben (2014) [9] developed a new method for cooperative spectrum sensing by utilizing sparsity. This method uses the concept of Bayesian hierarchical prior modeling in the framework of sparse Bayesian learning. This model has sparsity-inducing penalization terms leading to sparser solutions evaluated against typically l1 norm dependent ones. Depending on the factor graph that indicates the signal model of the hierarchical prior models, the Variational Message Passing (VMP) algorithm is employed to approximate the Power Spectral Density (PSD) map.

Shahrasbi & Rahnavard (2013) [10] formulated an efficient coordinated spectrum sensing algorithm for wideband large-scale cognitive radio networks. This scheme depends on clustering secondary users in accordance with their spectrum sensing results and carrying out the spectrum sensing tasks collaboratively inside each cluster. Additionally, the clusters can work together with each other to accomplish an optimal distributed spectrum sensing across the network. The author set up a cognitive radio framework and estimates this approach using numerical simulations.

Liu *et al.* 2013 [11] examined node allocation schemes to make the most of the minimum sensing performance between the sub-bands. The author introduced Iterative Hierarchical Hungarian Allocation (IHHA), Bow-Shaped Allocation (BSA), Class Division Allocation (CDA) to recognize the Max-Min objective. In addition, on the basis of PU priority level and anti-interference capability, the frequency Band Property Parameter (BPP) is characterized. By enhancing the minimum sensing performance with BPP, modified equality that suits for the actual scene is obtained.

Zhenghao *et al.* 2011 [12] formulated a probabilistic graphical model to signify and fuse multi-prior information from one hop neighboring secondary users. Belief Propagation (BP) is exploited for the statistical inference of the spectrum occupancy.

Hongjian *et al.* 2011 [13] developed a novel Multi-rate sub-Nyquist Spectrum Detection (MSSD) system for cooperative wideband spectrum sensing in a distributed CR network. By means of only aa small number of sub-Nyquist samples, MSSD is capable of sensing the wideband spectrum without complete spectrum recovery. In particular, given the low spectral occupancy, sub-Nyquist sampling is carried out in each sampling channel and an assessment statistic is formed by exploiting sub-Nyquist samples from multiple sampling channels. Moreover, the exploitation of different sub-Nyquist sampling rates is developed to enhance the system detection performance, and the performance of MSSD over both non-fading and Rayleigh fading channels is analyzed.

Chin-Liang *et al.* 2011 [14] created an optimization problem to stabilize the sensing-throughput tradeoff for a CR network with wideband spectrum sensing, at the same time the combined aggregate throughput for all the two potential scenarios of the CR network is maximized under a specified interference imposed on the primary network. In order to reduce the computational complexity, the author further presented a two-stage iterative approach to solve the optimization problem.

Mahram *et al.* 2012 [15] considered the wideband spectrum sensing setback in cognitive radio networks. The author offered a new approach to sense the spectrum depending on DOA (Direction of Arrival) estimation model. With the intention of sensing the spectrum, the author inspected the MUSIC-like algorithm by means of fourth-order cumulants matrix of the received signals. Wideband spectrum is presumed to be linear and consistently spaced among subchannels. In order to approximate the number of occupied subchannels, singular value decomposition of the fourth-order cumulants matrix is exploited and to approximate the position of occupied subchannels, the author examined optimizing a cost function that is obtained from MUSIC-like algorithm.

Srinu *et al.* 2011 [16]discussed regarding spectrum sensing which necessary conception in Cognitive Radio (CR) systems and the author formulated energy measurement algorithm for measuring the energy consumption in each sub band at some stage in the spectrum sensing. It utilizes the ineffective utilization of radio frequency spectrum without generating destructive interference to the licensed/primary user communication. In recent years, several investigations on spectrum sensing are concentrated on cooperative/multinode detection approaches. On the other hand, they are confined to the recognition of signals in a single frequency band or narrow band. With the intention of improving the opportunistic throughput, the CR must sense the signals in multiple bands or wideband.

Dan *et al*. 2010 [17] developed a novel signal separation approach for spectrum sensing and signal separation, which places and divides signals occupying the wideband frequency spectrum. This approach includes two phases: 1) wavelet edge detection algorithm is employed to trace the signal spectrum edge; 2) wideband signal separation scheme takes care of signal separation and recovery.

3. PROPOSED METHODOLOGY

In this research work, a new technique is attempted to recognize spectrum holes. An adaptive neuro fuzzy inference system model which can predict the channel status whether occupied or un- occupied is intended for spectrum sensing. The power spectral density, capacity over subband, bandwidth effectiveness is provided as an input to the ANFIS to predict the condition of the subband. Spectrum sensing involves the discovery of white spaces in the band.

The power of the signal is computed with the help of the parameters such as SNR, Power spectral density, capacity, bandwidth efficiency is computed for subbands recognized from the spectrum segmentation. Subsequently it is given as an input to the ANFIS for identifying the state depending on the input and its threshold value.

SNR estimation: SNR is computed individually over different subbands and is characterized as the ratio of the signal power in each subband to the noise power in that subband.

Consider that the power calculated for each and every subband is P_i where i represents the number of subbands. The noise of the subband is indicated as N_i and bandwidth for overall signal is indicated as a B. The SNR is calculated as given below,

$$SNR = P_i(d)/N_i B \tag{1}$$

Channel capacity estimation: The channel capacity C is an extremely vital parameter to examine the channel condition. The channel capacity here can be assumed as the transmission rate over the channel.

The channel capacity of a channel with bandwidth B and SNR is given as follows

$$C = B\log_2(1 + SNR) \tag{2}$$

The channel capacity decreases as SNR decreases. When the channel is unoccupied then the noise power is elevated and the capacity will diminish. A low channel capacity points out that the channel is empty.

Bandwidth efficiency: The bandwidth efficiency reflects how competently the allocated bandwidth is exploited. It is the throughput data rate per hertz in a specified bandwidth.

$$\eta = R/B \text{ bps/Hz} \tag{3}$$

Where R represents the data rate in bit/sec and B represents the bandwidth allocated for the signal. At this point R represents the channel capacity C, i.e. the transmission rate over the channel.

The bandwidth efficiency is computed as follows,

$$C/B = \log_2(1 + SNR) \tag{4}$$

Where C represents channel capacity and B represents bandwidth. It is an index to declare the condition of a channel.

Noise uncertainty

The detection sensitivity can be characterized as the minimum SNR at which the primary signal can be precisely (e.g. with a probability of 0.99) identified by the cognitive radio and is given as,

$$\gamma_{min} = \frac{P_p L(D + R)}{N} \tag{5}$$

Where N represents the noise power, P_p is transmitted power of the primary user, D represents the interference range of the secondary user, and R indicates the maximum distance between primary transmitter and its matching receiver.

The last equation recommends that in order to compute the required detection sensitivity, the noise power has to be identified, which is not available in reality, and needs to be estimated by the receiver. On the other hand, the noise power estimation is limited by calibration errors in addition to changes in thermal noise generated by temperature variations. Since a cognitive radio possibly will not meet the sensitivity requirement owing to an underestimate of N, min should be calculated with the worst case noise assumption, by this means necessitating a more sensitive detector [18].

a) Aggregate interference uncertainty

In future, owing to the widespread exploitation of secondary systems, there will be increased prospect of multiple cognitive radio networks operating over the same licensed band. Consequently, spectrum sensing will be influenced by uncertainty in aggregate interference (e.g. owing to the unknown number of secondary systems and their positions). Despite the fact that, a primary system is out of interference range of a secondary system, the aggregate interference possibly will lead to incorrect detection. This uncertainty generates a requirement for supplementary sensitive detector, as a secondary system may destructively interfere with primary system positioned beyond its interference range, and consequently it should be capable of detecting them.

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b) Spectrum sensing

A comprehensive coverage of ANFIS can be seen in [19]. The ANFIS network is a neurofuzzy network that was developed by Jang in 1993 [20]. In view of the fact that the ANFIS is an adaptive network, fractions of its nodes are adaptive, which indicates that their outputs is in accordance with the parameters such as SNR, noise uncertainty and aggregate interference. The structural design of ANFIS is illustrated in Figure-2, and the node function in each layer is depicted below.

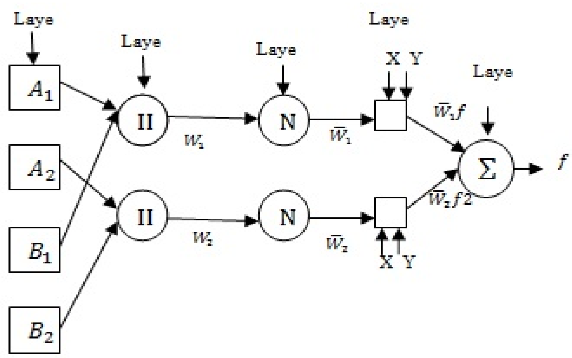

Figure-1. Equivalent ANFIS architecture.

Layer-1: The recognized subband is provided as an input to the ANFIS together with the input parameters such as channel capacity, power spectral density, bandwidth efficiency and SNR. The membership function is exploited for transforming the input to fuzzy set in the subsequent layer. Every node i in this layer is an adaptive node with a node function

$$O_{1,i} = \mu A_i(x) \quad for\ i = 1,2 \quad \text{or} \tag{6}$$

$$O_{1,i} = \mu B_{i-2}(x) \quad for\ i = 3,4 \tag{7}$$

Where $x\ (or\ y)$represents the input to the ith node and A_i (or B_{i-2}) indicates a linguistic label (such as "low" or "high") related with this node. It means, $O_{1,i}$, represents the membership grade of a fuzzy set $A\ (= A_1, A_2, B_1, or\ B_2)$ and it indicates the degree to which the given input $x\ (or\ y)$ satisfies the quantifier A. The membership functions for A and B aretypically described by generalized bell functions, e.g.:

$$\mu(x) = \frac{1}{1 + ((x - c_i)/a_i)^{2b_i}} \tag{8}$$

Layer-2: The output extracted from the first layer is provided as a input to this layer and the if component of the condition is executed for recognizing the spectrum holes in the given input. For instance,

$$O_{2,i} = w_i = \mu A_i(x)\mu B_i(y) \quad i = 1,2 \tag{9}$$

Each node output represents the firing strength of a rule.

Layer-3: The hidden layers of the input fuzzy set are examined depending on the predefined threshold value. For instance,when the channel capacity for the subband is less than the threshold value or almost equals to zero then the sub band is unoccupied.

$$O_{3,i} = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{10}$$

The outputs of this layer are called the normalized firing strengths.

Layer-4: This layer's nodes are adaptive with node function and it is exploited for the purpose of finding the condition of spectrum

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \tag{11}$$

where$\bar{w}_i$represents the output of layer 3, and $\{p_i, q_i, r_i\}$indicates the parameter set. Parameters of this layer are referred to as consequent parameters.

Layer-5: This layer's single fixed node, labeled $\sum$, calculates the final output as the summation of all the received signals

$$O_{5,i} = \sum_{i=1} \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{12}$$

Thus, an adaptive network that is functionally comparable with a Sugeno first-order fuzzy inference system is created. Defuzzification layer fuzzy value is converted into the normal value. The predicted values from all neurons are summed up into output value in the last layer.

4. EXPERIMENTAL RESULTS

In this section, the performance of the proposed spectrum sensing technique is evaluated against conventional techniques. The parameters exploited to measure the performance of the proposed technique are linear MMSE value. Consider that the channel between secondary and primary user is Rayleigh faded. It must be observed that the simulation is not carried out over a physical network model because this work does not rely on any physical layer setting. In a cognitive radio system, each SU has a detection probability P_d and a false alarm probability P_f on a primary channel.

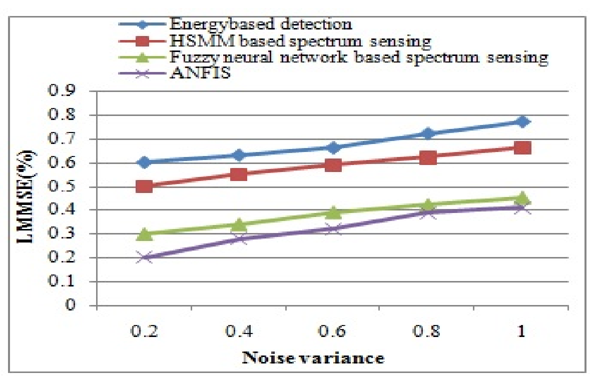

Figure-2. Comparison of LMMSE vs noise power.

In Figure-2, the linear minimum mean-square errors (LMMSEs) of the proposed spectrum sensing algorithm is

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evaluated against the existing algorithms such energy based detection, spectrum sensing based on HSMM and fuzzy neural network based spectrum sensing, are plotted versus the noise variance σ_n^2. The sensing unit is modeled to have a detection probability of $P_d = 0.6$ and a false-alarm probability of $P_f = 0.2$. It is found that the proposed approaches achieve the lowest LMMSEs while other approaches had the worst performance. Additionally, since the noise variance increases, the LMMSEs increase and the performance of the estimators get close to each other.

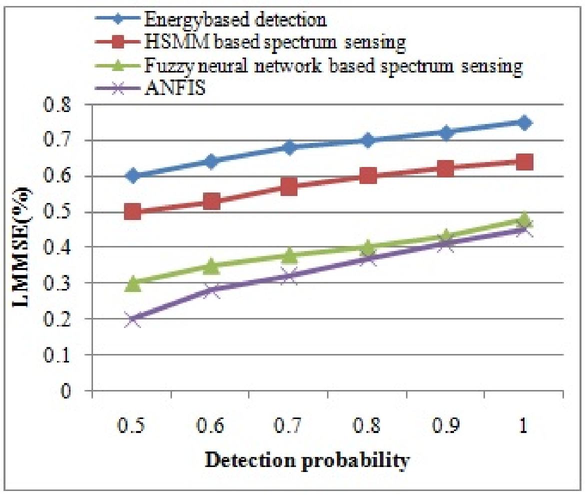

Figure-3. Comparison of LMMSE vs detection probability.

In Figure-3, the Linear Minimum Mean-Square Errors (LMMSEs) of the proposed spectrum sensing algorithm is compared against the existing algorithms such energy detection, spectrum sensing based on HSMM and fuzzy neural network based spectrum sensing are plotted versus detection probability. It is observed that the proposed algorithms achieve the lowest LMMSEs whereas other algorithms had the worst performance.

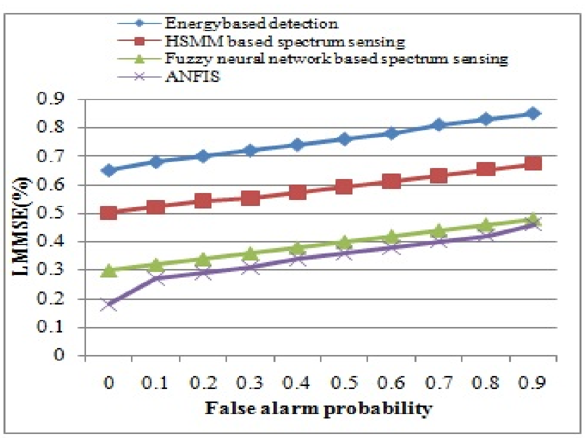

Figure-4. Comparison of LMMSE vs false alarm probability.

In Figure-4, the LMMSEs values of the proposed algorithm is compared with the existing algorithms such energy detection, spectrum sensing based on HSMM and fuzzy neural network based spectrum sensing are plotted versus the false-alarm probability for a detection probability of $P_d = 0.6$ and a noise variance of $\sigma_n^2 = 0.2$. It is observed that the LMMSEs increase as the false-alarm probability increases. This is mainly because the power of the pilot symbol is reduced ($P_{t1} = 0.1$ is employed) in the presence of a false alarm; that is, when the channel sensing unit makes a decision that the primary users are exist in the system when in fact they are not.

5. CONCLUSIONS

In this paper, a novel spectrum sensing method is proposed depending on the artificial intelligence for indentifying the spectrum. This spectrum sensing method based on the ANFIS algorithm which is principally exploited to identify the borders of the subband and recognize the spectrum holes in specified input band. In contradiction to a simple energy detector, the detector depending on the proposed ANFIS can predict the state at a future time instant. The experimental results based on real spectrum measurement data reveal that the ANFIS based detector leads to more accurate state estimation and prediction than other detectors, predominantly in circumstances with high path loss and/or strong shadowing effects. Additionally, the method was evaluated against three methods from the literature in this field, in two of the considered scenarios. This proposed approach showed success percentages comparable with those achieved by the other approaches. Further work will be directed to a statistical analysis to get an optimal setting of the three thresholds used in the method.

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