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A New Spectrum Sensing Method for Cognitive Radio Networks Based On Fuzzy Neural Network and Improved Histogram

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Abstract

Cognitive Radio (CR) can effectively cope with the mounting requirement and insufficiency of the wireless spectrum. With the intention of exploiting limited spectrum resourcefully, CR technology permits unlicensed clients to access licensed spectrum bands. In view of the fact that the licensed clients have priorities to utilize the bands, the unlicensed users required to constantly observe the licensed users' behavior to avoid interference and collisions. The major complicated task in spectrum sensing is to acquire consistent results of the licensed users' behavior. In accordance with the sensing outcome, the unlicensed clients are supposed to adjust their transmit powers and access policies to safeguard the licensed communications. Conventional spectrum sensing approaches like waveform based sensing algorithm, matched filter algorithm and energy detection algorithm are employed for recognizing the spectrums holes in the band. Even though it recognizes the spectrum holes competently, it has certain complications like error sensing is extremely poorer in conventional approaches, spectrum sensing accuracy is not adequate and collision among secondary user and primary user are extremely high. In order to overcome these complications, a novel spectrum sensing method is proposed in this paper. The proposed spectrum sensing method includes spectrum segmentation based on the improved histogram which is primarily employed to identify the boarders of the subband and assists in increasing the spectrum sensing efficiency. Fuzzy neural network is employed for sensing the spectrum successfully and sensing error at some stage in the process spectrum sensing is also employed. The parameters like power spectral density, bandwidth efficiency, SNR and channel capacity is exploited for assessing the status of the spectrum. The experimental results shows that the sensing the spectrum by means of the proposed method is extremely better than the other methods.

Keywords: Hyper Primary User, Secondary User, Fuzzy neural network, Spectrum sensing and linear minimum mean square error.

1 Introduction

The Radio Frequency (RF) spectrum is an expensive however strongly controlled resource because of its exceptional and imperative responsibility in wireless communications. Due to the continuous increase of wireless services, the requirements for the RF spectrum are persistently developing, leading to inadequate spectrum resources. In contrast, it has been found that localized temporal and geographic spectrum exploitation is enormously small [1, 2]. In actual fact, the unlicensed clients, also regarded as Secondary Users (SUs), required to constantly observe the behavior of the licensed users, also called Primary Users (PUs), to discover the Spectrum Holes (SHs), which is characterized as the spectrum bands that can be exploited by the SUs without obstructing with the PUs. This practice is called spectrum sensing [3]. At present, new spectrum strategies are being formulated by the Federal Communications Commission (FCC) that will permit SUs to opportunistically access a licensed band, when the PU is not present [4].

In several frequency bands and at several positions across time, the prime occupancy of the spectrum is sparse, i.e., only a little portion of the spectrum is exploited by the PUs. As a result, the SUs typically required to be able to sense multiple frequency bands simultaneously. Following Shannon’s renowned sampling theorem, wideband spectrum sensing conventionally necessitates extremely high sampling rates, which possibly be basically difficult. In order to decide the existence or nonexistence of the PU transmission, several spectrum sensing methods have been employed, like matched feature detection, filtering detection and energy detection [5]. On the other hand, the performance of wideband spectrum sensing is restricted by noise ambiguity, shadowing and multipath fading, which are the elementary features of wireless channels.

Cognitive Radio (CR) has turned out to be a potential solution to resolve the spectrum insufficiency complication in the next generation cellular networks by making use of opportunities in time, space domains and frequency [6]. Since CR are regarded as SUs for utilizing the licensed spectrum, an essential constraint of CR networks is that they must competently make use of under-utilized spectrum (indicated as spectral opportunities) without causing destructive interference to the PUs. In addition, PUs has no compulsion to share and transform their operating parameters for sharing spectrum with CR networks. Consequently, CR is supposed to be capable of independently detecting spectral opportunities without any support from PU, which is regarded as one of the most significant factors in CR networks.

When a channel is sensed free, the SU tries to approximate its Signal to- Noise Ratio (SNR) and potentially utilizes this sensed-free channel for communication. The cognitive user required to equal the constraints of operational consistency and throughput maximization. Certainly, when the time allotted to sensing and SNR probing is raised, the cognitive terminal obtains a more consistent sensing result and an enhanced SNR estimate. On the other hand, this diminishes the time accessible for real data transmission. As a result, a key question happens concerning the optimal sequence in which the channels are supposed to be sensed, the optimal sensing constraints, and the optimal SNR probing constraints. At present, researchers introduced a numerous approaches for sensing the spectrum and transmitting the data once the channel is free.

Even though the spectrum is sensed in enhanced way, the present spectrum sensing approaches have certain complications like the majority of authors not concentrated on the impact of sensing errors, the collision probability with the PU is unconstrained and channel SNR probing is considered to be ideal and instant as mentioned in [4]. In order to overcome these complications in the existing approaches, the author in [4] introduced sensing errors and channel probabing by means of the SNR estimation together with the time for sensing and channel probabing is also taken into account. The major concern is that the sensing time taken to accomplish a specified probability of detection might be high and detection performance is depending on the ambiguity of noise power.

The wideband spectrum sensing can be categorized into two stages. During the initial stage, called spectrum segmentation, the observed wide band is examined to discover the boundaries of the various subband. In a second stage, called wideband detection, the subbands are examined (one by one or mutually, based on the approach) to efficiently make a decision which subbands are engaged. In any scenario, the spectrum sensing tool must comprise: 1) an RF front end capable of down converting the spectrum segment under investigation to a predetermined wideband filter; 2) a quick sampling rate high-resolution acquisition section; and 3) a baseband signal processor, with the task of investigating the incoming signals.

In this paper, a new technique for detecting the spectrum based on artificial intelligence is formulated and estimating the errors and collision probability with primary networks for sensed channel is also employed in the proposed algorithm. The proposed technique overcomes the above mentioned complications faced by the conventional spectrum sensing algorithms.

2 Related Work

2.1 Energy Detection Based Spectrum Sensing

In recent Owing to its small complexity and computational cost, energy detection based spectrum sensing is the most familiar spectrum sensing technique. It is carried out by evaluating the received energy of the signal in opposition to a predetermined energy detection threshold to decide the existence or nonexistence of the user in the frequency band of attention [7]. The energy of the received signal is concluded by squaring and integrating the Received Signal Strength (RSS) over the observation time interval [7]. The energy detection threshold is determined by means of the noise variance of the atmosphere [8]. Consequently, minute errors in the noise variance estimation can cause considerable performance deprivation [8]. Energy detection based spectrum sensing is the best possible detection technique for zero-mean constellation signals when no information is recognized in advance regarding the user occupying the channel [7, 8]. On the other hand, energy detection based spectrum sensing cannot differentiate the kind of user occupying the frequency band [7, 8]. Additionally, in low SNR circumstances, energy detection executes inadequately [7, 8].

Energy detector has a band-pass filter which restricts the bandwidth of the received signal to the frequency band of interest, a square law device which squares each term of the received signal and a summation device which sums the entire squared values to figure out the energy.

The energy is computed as follows:

$$E = \sum_{n=0} |x(n)|^2 \tag{1}$$

The energy is now compared against a threshold for inspecting which hypothesis becomes true.

$$E < \lambda \Rightarrow H_0 \tag{2}$$

$$E > \lambda \Rightarrow H_1 \tag{3}$$

The probability of detection (P_d) and probability of false alarm (P_{fa}) can be provided as follows:

$$P_d = Q_m(\sqrt{2\gamma, \sqrt{\lambda}}) \tag{4}$$

Where $Q_m(a,b)$ is generalized Marcum Q-function.

$$P_f = \frac{\Gamma(m, \lambda/2)}{\Gamma(m)} \tag{5}$$

Where $\Gamma(a)$ represents the complete gamma function and $\Gamma(a,b)$ indicates the incomplete gamma function. γ and λ indicates SNR and detection threshold correspondingly. The performance of energy detector dependent sensing is restricted in case of when two common assumptions do not hold [9]. The noise possibly will not be stationary and its variance might not be recognized. Other complications with the energy detector comprise baseband filter effects and spurious tones [10].

2.2 Cyclostationary-Based Spectrum Sensing

Provided the disadvantages of energy detection based spectrum sensing, cyclostationary-based spectrum sensing provides a smart substitute [11]. By making use of the cyclostationary characteristics of the received signal [11], cyclostationary-dependent spectrum sensing is able to differentiate which category of user is exist [11] and discovering the occurrence of a user under low SNR circumstances [7]. These advantages come at the cost of supplementary hardware complication and a lengthier discovery procedure when compared against energy detection based spectrum sensing [7]. Cyclostationary characteristics are the consequence of periodicity in the received signal or its statistical features [11]. As such, discovery is realized by finding the unique cyclic frequency of the spectral correlation function of the received signal [7], [11]. The spectral correlation task is decided by considering the Fourier transform of the cyclic autocorrelation function and spectrum sensing.

It is found in literature that cyclostationary-based techniques carry out worse than energy detector based sensing techniques when the noise is stationary. Alternatively, cyclostationary characteristics might be fully lost because of channel fading [12], [13]. It is found in [13] that model uncertainties generate an SNR wall for cyclostationary dependent attribute detectors like energy detectors [14]. In addition, cyclostationarity based sensing is recognized to be susceptible to sampling clock offsets [15].

2.3 Matched Filter Detection

The Matched Filter is employed to increase the SNR. This technique integrates a filter matched to the PUs signal at the CR receiver. Clearly, this technique is optimal in the sense that it increases the SNR, reducing the decision faults. On the other hand, this technique is not sensible, in view of the fact that it necessitates the cognitive user to recognize the PUs signalling category [16]. It is a linear filter and previous knowledge of the PU signal is extremely indispensable for its operation. The operation carried out is correspondent to a correlation. Matched filter associates the signal with time shifted version and evaluates between the last output of matched filter and fixed threshold will decide the PU existence.

2.4 Waveform-based Sensing

Known patterns are typically employed in wireless systems to support synchronization or for other purposes. These patterns comprise preambles, midambles, commonly transmitted pilot patterns, spreading sequences etc. A preamble is a recognized sequence broadcasted before each burst and a midamble is broadcasted in the middle of a burst or slot. In the existence of a recognized pattern, sensing can be carried out by correlating the received signal with a recognized copy of itself [17]. This technique is only appropriate to systems with recognized signal patterns, and it is regarded as waveform-based sensing or coherent sensing. In [17], it is found that waveform based sensing performs better than energy detector based sensing in consistency and convergence time. In addition, it is found that the execution of the sensing algorithm raises as the length of the recognized signal pattern raises.

3 Proposed Methodology

In this paper, proposed spectrum sensing method includes spectrum segmentation, spectrum sensing with the help of FNN and at last collision probability estimation for sensed channel. The spectrum segmentation is employed for enhancing the spectrum sensing efficiency.

3.1 Spectrum Segmentation

Spectrum segmentation is the primary step to recognize the subbands that are in use at a definite time, when a broad segment of the spectrum is monitored. The monitored band is investigated to discover the boundaries of the several subbands. In this paper, improved histogram based on fuzzy is proposed for spectrum segmentation [18]. Prior to that power spectral density value is computed for signal ahead of recognizing the boundaries of the band. This FNN model calculates the channel condition as “1” for an engaged channel and “0” for empty channel.

Consider $[f_0, f_N]$ represent the monitored frequency range of the radio spectrum. The segmentation procedure has to approximate $f_0, f_1, f_2, \dots, f_N$ the boundaries of the N frequency intervals.
Step 1: Compute the power spectral density value for the entire signal by means of periodogram function.
Step 2: The histogram of the smoothed PSD value $(F(i)\ \text{values})$ is computed initially. The local maxima of the histogram, whose values go beyond a certain threshold m, are explored. As a result, the threshold on the maxima detection, m, based on the minimum bandwidth considered for the sub-bands. Consider these maxima be represented as $M_1, \dots, M_k$. Every interval is the distance among two consecutive local maxima. Subsequently fuzzifies a newly-generated factor from the multiplication of two factors, the interval and the frequency of signals in the interval. The values are relative to the sub-band widths.
Step 3: Called f_i the PSD level in proportion to the center of the histogram bin, whose incidence is M_i, the PSD segments whose values exist within a range of $[f_i - \delta, f_i + \delta]$ are recognized, and a new version of the PSD is produced in which these segments are corrected to the value f_i. The tolerance δ depends on the variance of the PSD estimate.
Step 4: The slope of the rectified version of the PSD among two segments is investigated to identify a boundary. Particularly, the boundary is positioned where a smallest amount of the PSD among two segments is found. A subband is found only when the resultant bandwidth is higher than l. The value of l indicates the minimum sub-band width. As a result, it should be selected beginning from the knowledge of the minimum bandwidth of PUs in the observed frequency spectrum.

3.2 Spectrum Sensing With Errors

In this paper, an attempt is made to propose a new scheme to recognize spectrum holes. An Adaptive Neuro Fuzzy Inference System (ANFIS) model which can predict the channel status whether engaged or emty is intended for spectrum sensing. The power spectral density, capacity over subband, bandwidth efficiency is specified as an input to the FNN to forecast the condition of the subband. Spectrum sensing implies the recognition of white spaces in the band [19, 20].

The power of the signal is computed as a SNR, capacity, bandwidth efficiency, power spectral density is computed for subbands recognized from the spectrum segmentation. Subsequently, it is specified as an input to the FNN for recognizing the state depending on the input and its threshold value. SNR estimation: SNR is computed individually over several 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 computed for the entire subband is P_i where i indicates the amount 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 computed as follows,

$$SNR = P_i(d) / N_i B \tag{6}$$

Channel capacity estimation: The channel capacity C is an extremely significant constraint to investigate the channel condition. The channel capacity here can be presumed as the transmission rate over the channel.

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

$$C = B\log_2(1 + SNR) \tag{7}$$

The channel capacity diminishes as SNR lessens. When the channel is empty subsequently the noise power is more and the capacity will diminish. A low channel capacity signifies that the channel is empty.

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

$$\eta = R / B bps / Hz \tag{8}$$

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

The bandwidth efficiency is computed as

$$C / B = \log_2(1 + SNR) \tag{9}$$

where C specifies channel capacity and B represents bandwidth. It is an index to state the condition of a channel. A typical FNN model is recommended for sensing the spectrum in this paper. The FNN model fundamentally includes fuzzification, fuzzy reasoning and defuzzification functional modules. The recognized subband is provided as an input to the FNN together with the input parameters such as bandwidth efficiency, power spectral density, channel capacity and SNR. The input value specified to the FNN is transformed into the fuzzy set, in the hidden layers the input fuzzy set is investigated depending on the predefined threshold value. For instance, when the channel capacity for the subband is lower than the threshold value or almost equals to zero, in that case the subband is empty. The spectrum condition is recognized in the hidden layers and in defuzzification layer fuzzy value is transformed into the standard value. The predicted values from the entire neurons are summaries into output value in the final layer.

3.3 Sensing errors

In view of the fact that errors are feasible in channel sensing, the true condition of the channel (active or inactive) and accordingly the statistics of the additive disturbance are not completely known by the cognitive receiver. Consequently, channel estimation requires to be carried out in the existence of such sensing errors and uncertainties. Even though the proposed FNN is employed for spectrum sensing in CN, it is estimated by means of the error sensing techniques. In spectrum sensing, it is preferred to diminish spectrum sensing error (i.e., total of false alarm and miss detection probabilities) because reducing spectrum sensing error both decreases collision probability with PU and improves usage level of empty spectrum. With the intention of providing consistent spectrum sensing performance (i.e., lessen spectrum sensing error), one of the huge challenges is determining threshold value, because spectrum sensing performance completely based on the threshold level. When concluding threshold level, moreover spectrum sensing error, spectrum sensing constraint which needs false alarm and miss detection probabilities to be lower target level should also be taken into account because it promises minimum required protection level of PU and usage level of empty spectrum.

The linear MMSE estimator is employed for recognizing the errors in proposed spectrum sensing technique. At this point, four circumstances are taken into account subsequent to sensing the spectrum by means of the FNN. 1) When channel is busy, and is identified as busy 2) When channel is busy, however it is identified as inactive, 3) When channel is busy, however it is identified as inactive, 4) When channel is inactive, and is identified as inactive, the overall sensing threshold is considered as a λ, the LMMSE estimation of the channel fading coefficient is found by using the following equation,

$$\min_{h} E\left|h-\hat{h}\right|^2 \quad (10)$$

h indicates the fading coefficient in the channel among the secondary transmitter and receiver, and it is considered to be a zero-mean circularly-symmetric complex random variable with variance σ_h^2. $\hat{h}$ represents any estimate that is a function of the observation y. In specified the observation y, the linear MMSE estimate under sensing decision $\hat{H}_0$ (i.e., if the channel is sensed as inactive) i.e, the false alarm probability for $\hat{H}_0$ can be given as

$$p_f(\lambda) = \Pr(y > \lambda | \hat{H}_0) \quad (11)$$

$$= Q((\frac{\lambda}{\sigma_u^2} - 1)\sqrt{N} \quad (12)$$

Where

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x \exp(-\frac{z^2}{2}) dz \quad (13)$$

Where σ_u^2 is monitored value from the spectrum sensing. In the same way, the linear MMSE estimate when the channel is identified as busy is,

$$p_d(\lambda) = \Pr(y > \lambda | \hat{H}_1) \quad (14)$$

$$= Q\left\{(\frac{\lambda}{\sigma_u^2} - \gamma - 1)\sqrt{\frac{N}{2\gamma+1}}\right\} \quad (15)$$

As a result, the miss detection probability can be indicated as follows,

$$p_m(\lambda) = 1 - p_d(\lambda) \quad (16)$$

4 Experimental Results

In this section, numerical results are provided to assess the performance accomplished by the proposed spectrum sensing technique, in comparison against few conventional techniques. The parameters employed to assess the performance of the proposed technique are linear MMSE value. Here presumed that the channel among secondary and primary user is Rayleigh faded. It should be observed that the simulation is not performed over a physical network model, since this work does not depend on any physical layer setting. In a CR system, each SU has a detection probability P_d and a false alarm probability P_f on a primary channel.

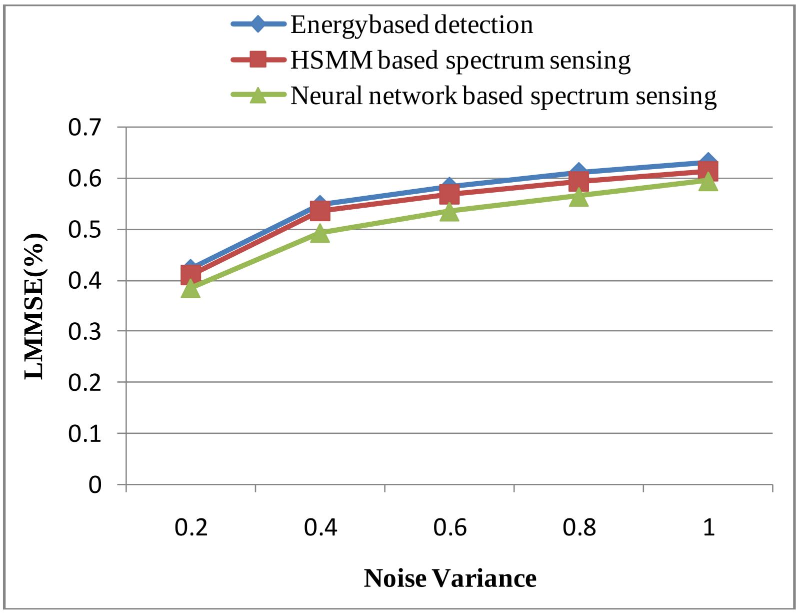

Figure 1: Comparison of LMMSE vs noise power

In Figure. 1, the Linear Minimum Mean-Square Errors (LMMSEs) of the proposed spectrum sensing algorithm is compared against the existing approaches like energy detection and spectrum sensing based on HSMM are plotted against 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 detected that the proposed approach attains the lowest LMMSEs at the same time other approaches had the worst performance. Additionally, as the noise variance increases, the LMMSEs increase and the performance of the estimators get nearer to each other. The Table 1 shows that the values of the comparison of LMMSE vs noise power for proposed and existing algorithms.

Table 1 Comparison of LMMSE vs noise power

noise power	Energy based detection	HSMM based spectrum sensing	FNN based spectrum sensing
0.2	0.423	0.41	0.385
0.4	0.548	0.536	0.4932
0.6	0.5836	0.568	0.5351
0.8	0.6123	0.593	0.5638
1	0.6318	0.613	0.5943

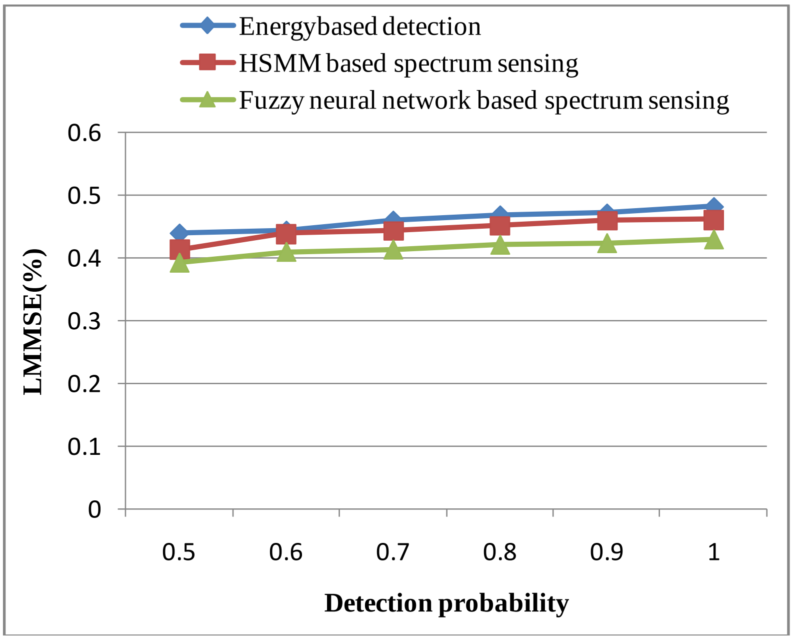

Figure 2: Comparison of LMMSE vs detection probability

In Figure 2, the LMMSEs of the proposed spectrum sensing algorithm is compared against the existing approaches such as energy detection and spectrum sensing based on HSMM are plotted versus detection probability. It is found that the proposed algorithm achieves the lowest LMMSEs while other approaches had the worst performance. Also, as the noise variance increases, the LMMSEs increase and the performance of the estimators get nearer to each other. Table 2 shows that the values of the comparison of LMMSE vs. detection probability for proposed and existing algorithms.

Table 2: Comparison of LMMSE vs detection probability

Detection probability	Energy based detection	HSMM based spectrum sensing	FNN based spectrum sensing
0.5	0.4389	0.413	0.3932
0.6	0.4436	0.4386	0.4102
0.7	0.4598	0.4432	0.4138
0.8	0.4683	0.4516	0.4213
0.9	0.4713	0.4594	0.4238
1	0.4817	0.4612	0.4297

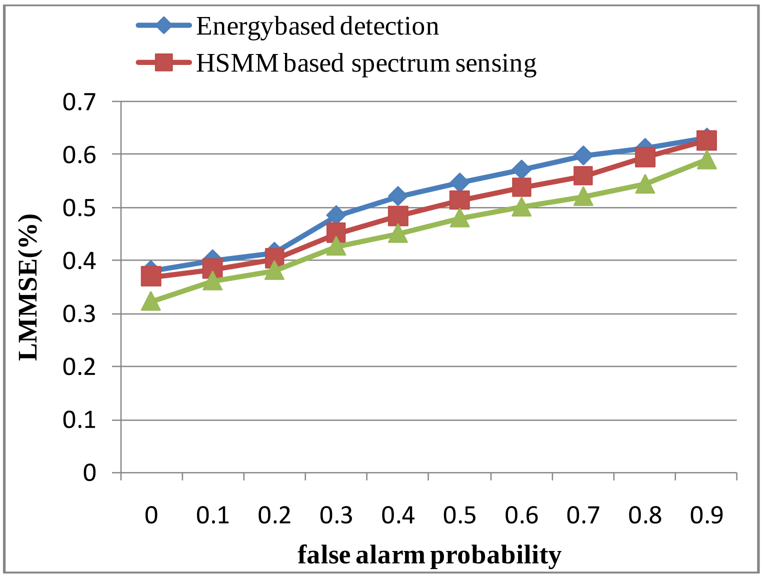

Figure 3: Comparison of LMMSE vs false alarm probability

In Figure 3, the LMMSEs values of the proposed approach is compared against the existing approaches such as energy detection and spectrum sensing based on HSMM 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 revealed that the LMMSEs increases as the false-alarm probability increases. This is principally for the reason that the power of the pilot symbol is reduced ($P_t^1 = 0.1$ is employed) in the existence of a false alarm; that is, when the channel sensing unit makes a decision that the PUs are exist in the system when actually they are not. Table 3 shows that the experimental values of the proposed algorithm and existing algorithms.

Table 3: Comparison of LMMSE vs false alarm probability

False alarm probability	Energybased detection	HSMM based spectrum sensing	FNN based spectrum sensing
0	0.3812	0.3689	0.3231
0.1	0.4016	0.3838	0.3618
0.2	0.4158	0.4037	0.3816
0.3	0.4851	0.4514	0.4276
0.4	0.5213	0.4836	0.4518
0.5	0.5467	0.5137	0.4812
0.6	0.5713	0.5376	0.5017
0.7	0.5981	0.5598	0.5218
0.8	0.6123	0.5949	0.5451
0.9	0.6318	0.6269	0.5912

5 Conclusion

A new spectrum sensing technique is proposed based on the artificial intelligence which includes spectrum segmentation, spectrum sensing and quality prediction for sensed spectrum. The spectrum segmentation technique, depending on the assessment of the improved histogram of the PSD in the observed band is formulated for recognizing the subband boundaries and it is exemplified by a low computational load. Fuzzy neural network is employed here for the purpose of identification of the spectrum hole or free subband in the spectrum that might be allocated to the aspiring SU. The occupancy is concluded by analyzing some channel parameters, e.g. channel capacity, power spectral density, SNR and BW efficiency. The proposed approach specifies channel status occupancy in a quantized index form {0,1} after proper training of the FNN engine. In this paper, error sensing is also taken into account. The estimator employed for the purpose of detecting the false alarm probability and detection probability for proposed algorithms. By considering both feature of spectrum sensing error function and inequality spectrum sensing constraint, best possible adaptive threshold level is obtained here. With the exploitation of the proposed sensing threshold, spectrum sensing error can be considerably reduced at the same time satisfying spectrum sensing requirement by comparing with existing approaches like Energy based detection and HSMM based spectrum sensing. In future several other improved techniques will be proposed to enhance the performance of the spectrum sensing techniques.

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