ACTA IMEKO
ISSN: 2221-870X
March 2022, Volume 11, Number 1, 1 - 7

Spectrum sensing using energy measurement in wireless telemetry networks using logarithmic adaptive learning

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ABSTRACT

To identify primary user signals in cognitive radios spectrum sensing method is used. Due to statistical variances in received signal, noise is present in primary user signals, this noise powers are varied due to random nature of noise signals and leads to noise uncertainty problem in the performance of energy detection. The task of energy measurement and further detecting the unused frequency spectrum is a key task in cognitive radio applications. For avoiding these problems, least logarithmic absolute difference (LLAD) algorithm is proposed in which noise powers are adjusted at sensing point of licensed users. With help of proposed method, estimated noise signals are eliminated. Sign regressor version of LLAD algorithm is considered due to it reduces computational complexity and convergence rate is improved. Further probability of detection (P_{od}), probability of false alarm (P_{ofa}) is estimated to know threshold value. From results, it is clear that good performance in terms of P_{ofa} versus P_{od} in range of low signal to noise ratio in multiple nodes. Therefore, the proposed energy measurement-based spectrum sensing method is useful in remote health care monitoring, medical telemetry applications by sharing the un-used spectrum.

Section: RESEARCH PAPER

Keywords: Adaptive algorithm; cognitive radio; energy measurement; noise uncertainty; threshold point

Citation: Nagesh Mantravadi, Md Zia Ur Rahman, Sala Surekha, Navarun Gupta, Spectrum sensing using energy measurement in wireless telemetry networks using logarithmic adaptive learning, Acta IMEKO, vol. 11, no. 1, article 34, March 2022, identifier: IMEKO-ACTA-11 (2022)-01-34

Section Editor: Md Zia Ur Rahman, Koneru Lakshmaiah Education Foundation, Guntur, India

Received December 28, 2021; **In final form** February 18, 2022; **Published** March 2022

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1. INTRODUCTION

Radio frequencies are limited natural resources they are controlled by government authorities, in a particular band the primary users can exclusively use licensed spectrum even the secondary users are unoccupied as these unlicensed users are avoided for use. Due to the enormous growth in wireless communication applications the usage of radio frequencies is increasing rapidly. To overcome this spectrum utilization issues, cognitive radio systems are emerged with new technology [1]-[3] in wireless communications. Enormous efforts are used for enhancing the usage of efficiency of cognitive radio systems, there is huge change in the usage of frequencies, time and space domain and then secondary users are allowed without creating any interference to the primary users. To overcome these interferences [4], [5] in wireless communications and for increasing spectrum utilization IEEE 802.22 wireless frequency band can be used. With the help of these frequency bands, the data will be transmitted without causing interference in health care monitoring wireless application by using ZigBee, Wi-Fi, ad hoc networks with operating frequency less than 3 MHz. Orthogonal frequency division multiplexing (OFDM) is the eminent method used in wireless communication systems. Channel estimation issues raised in OFDM based cognitive radio system are discussed in [6]-[8], this is because of mean square error (MSE) of channel estimations. The unknown noise components effecting the spectrum sensing also studied. Performance evaluation of channel estimation techniques for imperfect channels is analysed for correlated channels of cognitive radio system, then mutual information is considered at the input and output to provide better communication sensing and channel uncertainty. The receiver's minimal mean square error is then computed to obtain the fading coefficients of the fading channel, as well as the anticipated attainable rate for Gaussian signalling and linear modulation schemes, assuming interference and channel estimation errors occur at primary users [9], [10]. Spectrum sensing is used to avoid difficulties with spectrum underutilization and interference. The most commonly used detection techniques are wavelet detection, cyclostationary detection, energy detection, and covariance detection. The first three techniques require prior information of the principal user signal, frequency components, interference, and noise variance, but the fourth approach requires no prior data and is hence the most often used spectrum sensing method. In addition, for energy sensing, circuit implementation and computing complexity are minimal. Spectrum sensing [11]-[17] performance is assessed in terms of false alarm and detection probabilities; it assumes that the primary user is idle or active during the spectrum sensing period, and then spectrum holes are detected in the spectrum frequency range based on this. There is a compromise between probability detection and false alarm, however by utilizing these factors, we can see if there was any interference among the primary and secondary users. In [18] Sensing trade-off in cognitive radios is studied when numerous primary users arrive randomly. The trade-off is also caused by the performance of cognitive radio spectrum utilization and spectrum sensing, which is based mostly on primary user activity. A numerical technique was used to investigate this trade-off utilizing cooperative spectrum sensing. The spectrum potential for successful communication between a transmitter and receiver of cognitive networks is being investigated. Also studied about when secondary user sensing time increases, false alarm probability reduced, it means there is high chances to secondary users are having to access idle channel, but less chance to transmit because of transmission time is limited. Main objective is efficiently use spectrum utilization with optimum sensing for improving spectrum opportunities of cognitive radio networks. Practically cognitive radios are having channel sensing errors because of miss detection and false alarms these problems will affect channel estimation [19] design also quality channel estimation error problems, receiver operating characteristics are also analysed for these parameters. Further cooperative cognitive radio is considered for analysis of fading scenarios occurred with improved energy detection method. For this Nakagami multipath fading is considered with power 2 based energy detection spectrum sensing [20], [21], then performance is improved in cognitive radio networks in terms of detection probability parameters and their operating curves also analysed. In spectrum sensing, there after spectrum allocation one of the promising methods is energy detection. In this work a new energy measurement methodology is proposed based on least logarithmic absolute difference algorithm. This methodology of energy detection and measurement is a key task in measurement technology as well as in cognitive radio-based communication systems. To overcome noise uncertainty problems double threshold-based spectrum sensing is studied for improving energy detection. This cognitive radio concept is widely used in health care applications, but interferences occurred due to wireless devices will affect the performance. To avoid these interferences occurred with health care, novel cognitive radio method is used by proposing modified normalized least mean square algorithm (MNLMS) for hospital environment applications so that errors/interferences occurred with medical devices are removed and their performance is evaluated using MATLAB simulations.

2. SYSTEM MODEL

Spectrum sensing is mostly used method for detecting spectrum holes of cognitive radio network. By using this method, we can decide primary user is absent or present. Energy detection block diagram is shown in Figure 1. By using hypothesis testing, detection problem is considered as

$$\begin{aligned} T_0&: z(t) = w(t) \\ T_1&: z(t) = w(t) + s(t)\ , \end{aligned} \tag{1}$$

where $z(t)$ is received sample signal, $w(t)$ is noise effect of transmitted signal, $s(t)$ is primary transmitted signal with $t = 1, \dots, T$ length carried for identifying spectrum.

Energy detection method [22] is considered for detecting spectrum holes, energy level is measured, then estimated noise variance by placing detection threshold value. Then secondary user decides statistics of energy detection as

$$D = \sum_{t=1}^{T} [z(t)]^2\ . \tag{2}$$

Decision static have central chi square distribution with T degrees of freedom when primary user signal is absent. It is having non central chi square distribution decision statistics when primary user is present. Central limit theorem with Gaussian approximation is used if detection samples are greater than 250, then mean and variance of decision static of primary user signal given as

$$\begin{aligned} &D \sim T(T\sigma_{wt}^2, 2T\sigma_{wt}^4) \text{ for } \mathrm{H}_1 \\ &D \sim T(T((\sigma_{st}^2 + \sigma_{wt}^2, 2T((\sigma_{st+}^2\sigma_{wt}^2)^2) \text{ for } \mathrm{H}_0\ . \end{aligned} \tag{3}$$

In testing T_0 and T_1, false alarm and misdetection errors are occurred due to false identification of T_0 and T_1. Energy detector performance is measured with probability of these two errors. Probability false alarm occurred due to showing of wrong spectrum band occupancy, probability of miss detection is due to it shows as primary user absence, but actually it is present, it is also called as probability detection.

Probability false alarm, probability detection evaluated as

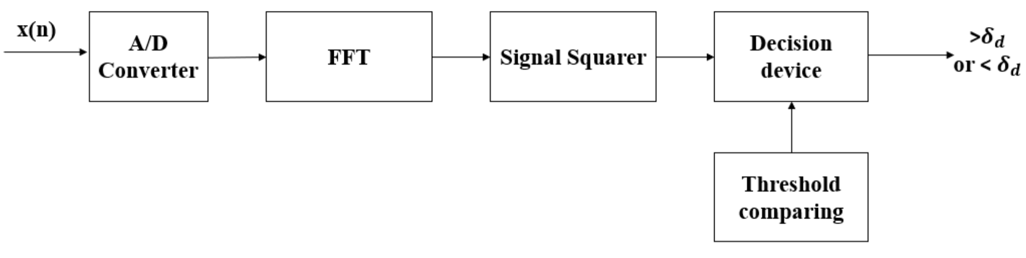

Figure 1. Energy detector block diagram.

$$P_{\text{ofa}} = Q\left(\frac{\delta_d - T\sigma_{wt}^2}{\sqrt{2\,T\,\sigma_{wt}^4}}\right) \tag{4}$$

$$P_{\text{od}} = Q\left(\frac{\delta_d - T(\sigma_{st}^2 + \sigma_{wt}^2)}{\sqrt{2\,T(\sigma_{st+}^2\sigma_{wt}^2)^2}}\right), \tag{5}$$

where $\delta_d = \sigma_{wt}^2\left(Q^{-1}(P_{\text{ofa}})\sqrt{2T} + T\right)$ is the threshold.

2.1. Least Logarithmic Absolute Difference Algorithm

Least logarithmic absolute difference (LLAD) technique elegantly and gradually adapts conventional cost function depends on amount of error in its implementation.

In impulse-free noise environments, LMS and LLAD algorithm exhibits likely convergence behaviour, while LLAD algorithm is robust against impulsive interference and exceeds sign algorithm [23], [24]. Flowchart for LLAD algorithm is as shown in Figure 2.

Mathematical Modeling

T is filter length, μ is step size parameter is considered.

Let the tap input be $\mathrm{x}(n)$ and filter length T is moderate to large, $\mathrm{w}(0) = 0$ is considered as initial condition, $\mathrm{x}(n)$ is T -by-1 tap input vector to filter n_2 at time n as

$$[\mathrm{x}(n), \mathrm{x}(n-1), \ldots, \mathrm{x}(n-T+1)]^{\mathrm{T}} \tag{6}$$

$\mathrm{w}(n)$ is tap weight vector, $\mathrm{d}(n)$ is desired response at time n, ω_{o} is an unknown vector, $(.)^{\mathrm{T}}$ is the transpose of $(.)$.

To be computed:
$\mathrm{w}(n+1)$ is to be computed tap-weight vector at time $n+1$.

Computation

An unknown vector ω_{o} is represented with linear model as

$$\mathrm{d}(n) = \omega_{\mathrm{o}}{}^{\mathrm{T}}\,\mathrm{x}(n) + \mathrm{n}_t \tag{7}$$

The instantaneous estimate of gradient vector J is written as:

$$\nabla'\mathrm{J}(\mathrm{n}) = -\,2\,\mathrm{x}(n)\,\mathrm{d}^*(n) + 2\,\mathrm{d}(n)\,\mathrm{x}^{\mathrm{T}}(n)\,\mathrm{w}(n) \tag{8}$$

where $\mathrm{x}(n)$ is the input tap vector, $\mathrm{w}(n)$ is tap weight vector. $\mathrm{w}(n)$ is random vector depends on $\mathrm{x}(n)$ with its taps stored in a row vector given by

$$[w(n), \mathrm{w}(n-1), \ldots, \mathrm{w}(n-T+1)]^{\mathrm{T}} \tag{9}$$

Output of the filter

$$\begin{aligned} \mathrm{y}(n) &= [\mathrm{w}_0(n)\,\mathrm{x}(n) + \cdots + \mathrm{w}_{L-1}(n)\,\mathrm{x}(n-M+1)] \\ &= \mathrm{w}^{\mathrm{T}}(n)\,\mathrm{x}(n). \end{aligned} \tag{10}$$

Expression for estimation error is given by

$$\mathrm{e}(n) = \mathrm{d}(n) - \mathrm{w}^{\mathrm{T}}(n)\,\mathrm{x}(n). \tag{11}$$

where the term $\mathrm{w}^{\mathrm{T}}(n)\,\mathrm{x}(n)$ is inner product of $\mathrm{w}(n)$ and $\mathrm{x}(n)$.

The normalized error cost function introduced using logarithmic function is given by

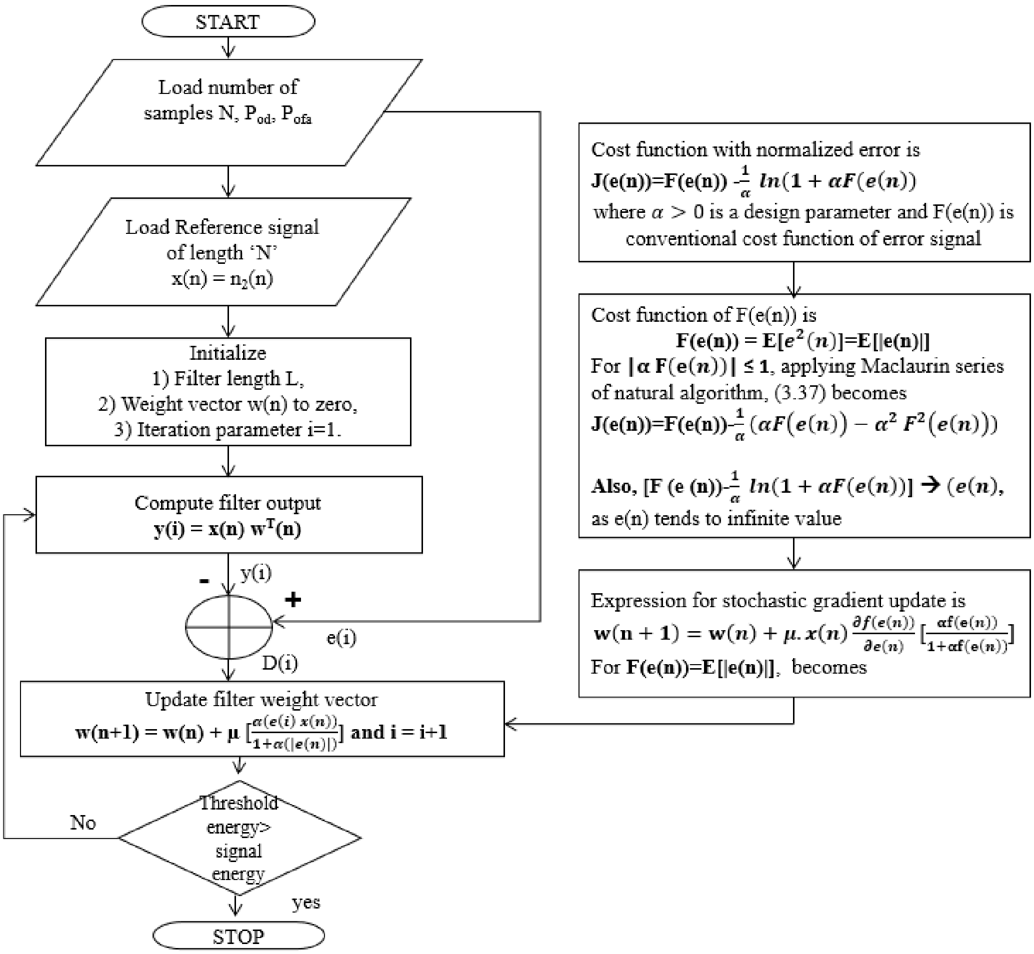

Figure 2. Spectrum sensing using LLAD.

$$\mathrm{J}(\mathrm{e}(n)) = \mathrm{F}(\mathrm{e}(n)) - \frac{1}{\alpha}\ln\left(1 + \alpha\,\mathrm{F}(\mathrm{e}(n))\right) \tag{12}$$

Based on steepest descent method, general weight update recursion is given by

$$\mathrm{w}(n+1) = \mathrm{w}(n) - \mu\,\nabla \mathrm{J}(n) \tag{13}$$

New recursive relation for $\nabla \mathrm{J}(n)$ is written as

$$\begin{aligned}\nabla \mathrm{J}(n) &= E\{\nabla|\mathrm{e}(n)|^2\} = E\{\mathrm{e}(n)\nabla \mathrm{e}^*(n)\}\\ \nabla \mathrm{e}^*(n) &= -\mathrm{x}^*(n)\end{aligned} \tag{14}$$

Thus, resultant expression for gradient vector is given by

$$\nabla \mathrm{J}(n) = -E\{\mathrm{e}(n)\,\mathrm{x}^*(n)\} \tag{15}$$

Also, first gradient of the relation in is given by $\Delta_{\mathrm{w}}.\,\mathrm{F}(\mathrm{e}(n))$

The signum representation is given below:

$$\mathrm{sign}\{\mathrm{x}(n)\} = \begin{Bmatrix} 1: \mathrm{x}(n) > 0 \\ 0: \mathrm{x}(n) = 0 \\ -1: \mathrm{x}(n) < 0 \end{Bmatrix} \tag{16}$$

Step size boundary for convergence of mean square for LMS algorithm is given by

$$0 < \mu < \frac{2}{\mathrm{x}^T(n)\,\mathrm{x}(n)} \tag{17}$$

By substituting estimate of $\nabla'\mathrm{J}(n)$ in steepest descent algorithm, new recursive relation for updating tap weight vector is

$$\mathrm{w}(n+1) = \mathrm{w(n)} + \mu\,\mathrm{x}(n)[\mathrm{d}^*(n) - \mathrm{x}^{\mathrm{T}}(n)\cdot \mathrm{w}(n)]. \tag{18}$$

To provide robustness against impulsive interferences, a cost function is introduced with normalized error by use of logarithmic function stated as

$$F(\mathrm{e(n)}) = E\left[(\mathrm{e}(n))^2\right] = E[|\mathrm{e}(n)|]\,. \tag{19}$$

Thus, the stochastic gradient update is given by

$$\begin{aligned}&\mathrm{w}(n+1)\\ &\quad= \mathrm{w}(n) + \mu\cdot \mathrm{x}(n)\,\frac{\partial \mathrm{f}(\mathrm{e}(n))}{\partial \mathrm{e}(n)}\left[\frac{\alpha\,\mathrm{f}(\mathrm{e}(n))}{1+\alpha\,\mathrm{f}(\mathrm{e}(n))}\right],\end{aligned} \tag{20}$$

where $\alpha > 0$ is a design parameter also $\mathrm{F}(\mathrm{e}(n))$ as the conservative cost function for error signal $\mathrm{e}(n)$.

For $|\alpha\,\mathrm{F}(\mathrm{e}(n))| \le 1$, applying MacLaurin series using natural algorithm, equation (19) gives

$$\mathrm{J}(\mathrm{e(n)}) = \mathrm{F}(\mathrm{e}(n)) - \frac{1}{\alpha}\left(\alpha\,\mathrm{F}(\mathrm{e}(n)) - \alpha^2\,\mathrm{F}^2(\mathrm{e}(n))\right). \tag{21}$$

For low values of $\mathrm{F}(\mathrm{e}(n))$, it is an infinite combination for conventional cost functions. For smaller values of error, cost function $\mathrm{J}(\mathrm{e}(n))$ resemble $\mathrm{F}(\mathrm{e}(n))$ for instance as

$$\mathrm{F}(\mathrm{e}(n)) - \frac{1}{\alpha}\ln\left(1 + \alpha\,F(e(n))\right) \rightarrow \mathrm{F}(\mathrm{e}(n)) \tag{22}$$

Thus general update expression of stochastic gradient is stated as

$$\begin{aligned}&\mathrm{w}(n+1)\\ &\quad= \mathrm{w}(n) + \mu\cdot \mathrm{x}(n)\cdot\frac{\partial \mathrm{f}(\mathrm{e}(n))}{\partial \mathrm{e}(n)}\left[\frac{\alpha\,\mathrm{f}(\mathrm{e}(n))}{1+\alpha\,\mathrm{f}(\mathrm{e}(n))}\right]\end{aligned} \tag{23}$$

Norm is power of least probable error ais at convex cost function, signed algorithm delivers slow rate of convergence.

For $\mathrm{F}(\mathrm{e}(n)) = \mathrm{E}[|\mathrm{e}(n)|]$ in (23), then resultant expression is

$$\begin{aligned}&\mathrm{w}(n+1)\\ &\quad= \mathrm{w}(n)\\ &\quad+ \mu\,\mathrm{x}(n)\,\mathrm{sign}(\mathrm{e}(n))\left[\frac{\alpha\,(|\mathrm{e(n)}|)}{1+\alpha\,(|\mathrm{e(n)}|)}\right].\end{aligned} \tag{24}$$

Then the weight update relation of the LLAD algorithm becomes

$$\mathrm{w}(n+1) = \mathrm{w}(n) + \mu\left[\frac{\alpha\,\mathrm{x}(n)\,\mathrm{e}(n))}{1+\alpha\,(|\mathrm{e}(n)|)}\right] \tag{25}$$

To reduce computational difficulty of LMS, signed variants are preferable. Sign regressor version offers low computational complexity with a smaller number of multiplications among all signed variants. Here, sign regressor LLAD (SRLLAD) algorithm by applying sign function on each element. Is remains obtained as recursion of LMS for altering input tap vector.

2.2. Sign based Least Logarithmic Absolute Difference (LLAD) algorithms

LLAD algorithm is generalized version of higher order adaptive filter. Combination of LLAD in (25) with three types of sign variants results in SRLLAD, SLLAD and SSLLAD algorithms respectively. Hence weight update relations of signed LLAD based variants are given as follows.

$$\begin{aligned}&\mathrm{w}(n+1)\\ &\quad= \mathrm{w}(n)\\ &\quad+ \mu\,\mathrm{sign}\{\mathrm{x}(n)\}\,\mathrm{sign}\left\{\mathrm{e}(n)\left[\frac{\alpha\,(|\mathrm{e}(n)|)}{1+\alpha\,(|\mathrm{e}(n)|)}\right]\right\}\end{aligned} \tag{26}$$

$$\begin{aligned}&\mathrm{w}(n+1)\\ &\quad= \mathrm{w}(n)\\ &\quad+ \mu\,\mathrm{x}(n)\,\mathrm{sign}\left\{\mathrm{e}(n)\left[\frac{\alpha\,(|\mathrm{e}(n)|)}{1+\alpha\,(|\mathrm{e}(n)|)}\right]\right\}\end{aligned} \tag{27}$$

$$\begin{aligned}&\mathrm{w}(n+1)\\ &\quad= \mathrm{w}(n)\\ &\quad+ \mu\,\mathrm{sign}\{\mathrm{x}(n)\}\,\mathrm{sign}\left\{\mathrm{e}(n)\left[\frac{\alpha\,(|\mathrm{e}(n)|)}{1+\alpha\,(|\mathrm{e}(n)|)}\right]\right\}.\end{aligned} \tag{28}$$

3. RESULTS AND DISCUSSION

The proposed LLAD algorithm method for spectrum sensing is used to assess performance. The spectrum sensing of the transmitter of primary user and receiver of secondary user is evaluated. Spectrum sensing simulations are run for 5000 samples, T is filter length it is chosen as 10 and distinct signals are acquired for each noise sample to process. For improved results, a received signal attenuation factor was introduced, and then the performance of energy detection was evaluated under various SNR situations. Because of the noise levels in the sensing spectrum, the main goal of developing an adaptive filter is based on spectrum sensing approach. Due to incorrect detection of test

Table 1. Computational Complexities of various sign LMS based adaptive.

S.NO	Algorithm	Multiplications	Additions	Divisions
1	LMS	T+1	T+1	NIL
2	LLAD	T+4	T+2	1
3	SRLLAD	4	T+2	1
4	SLLAD	T+3	T+2	1
5	SSLAD	T+2	T+2	1

data, this spectrum sensing may result in probability detection and missed detection probability mistakes. Due to incorrect detection of test data, this spectrum sensing may result in probability detection and missed detection probability errors. The proposed technique adjusts the threshold value for each sensing event and then adjusts the noise power accordingly. When the size of the receiving antenna, the averaging of eigen values rises, resulting in a reduction in estimate error. The performance of noise power estimation is measured in terms of mean square error (MSE). When the antenna size and quantity of samples are increased, the steady state error reduces. The sensitivity of adaptive filter-based energy detection is measured in terms of probability detection, which is a function of SNR and a constant false alarm probability. The proposed LLAD algorithm performs better when probability detection is used. Noise uncertainty is not a problem for this proposed strategy. This detecting capability successfully identifies spectrum gaps, allowing for prevented spectrum reuse opportunities. To accomplish probability detection (P_{od}) and false alarm probability (P_{ofa}) concurrently, SNR values are considered as minimal and number of samples, noise uncertainty relationship is adopted. To obtain greater probability detection without an adaptive method for spectrum sensing, noise uncertainty increases for minimal SNR levels. Even though there is no influence on how many received signal samples are examined for sensing spectrum, some restrictions on SNR for performance of probability detection beyond these limit false alarm values are sacrificed for values bigger than zero of noise uncertainty factor. For noise certainty levels greater than zero for every increasing SNR value, a larger number of samples are required for improved detection probability. It is obvious that raising SNR values improves detection sensitivity for noise circumstances in the proposed technique. Theoretical values for probability detection of different SNR levels for the basic energy detection technique and suggested energy detection using LLAD are determined using (4) and (5). Computational complexity of various LMS based adaptive algorithms shown in Table 1. With the suggested strategy, probability detection produces superior results, as shown in Table 2. Simulation curves for P_{ofa} versus P_{od} for various SNR values are provided in Figure 3. For low SNR levels, detection probability performance is better, as shown in Table 2 and Figure 3. Signal correlations create propagation fading in wireless communications, and their influence on the receiving antenna generates correlation losses in the received signal. The performance of the energy detector is initially unaffected by signal correlations, and noise power is evaluated using eigen values. The antenna correlation effect is avoided while calculating noise power estimate by using one primary user signal when calculating eigen values of antenna correlation effect on bigger eigen values compared to small eigen values.

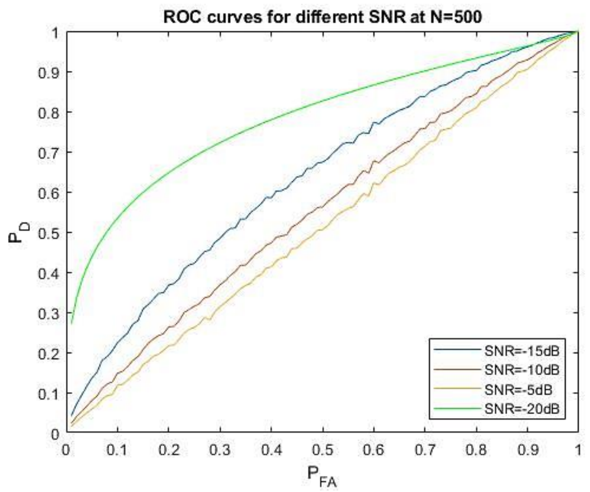

Figure 3. P_{ofa} versus P_{od} for different SNR values.

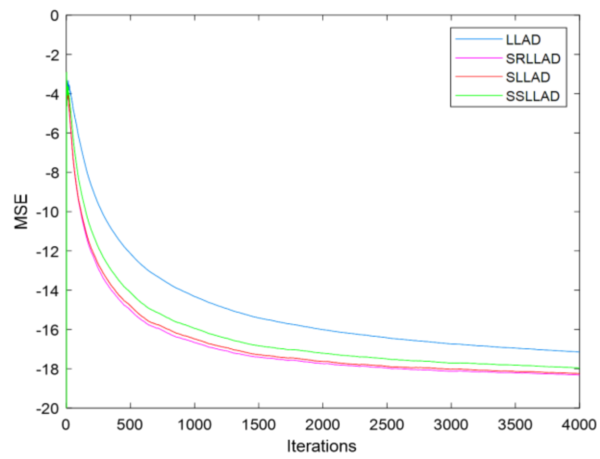

Figure 4. Convergence Curves for sign based LLAD adaptive algorithms.

The main goal of the proposed LLAD is to improve energy detection accuracy when used in low SNR and noise-uncertainty situations. The detection probability is then improved with constant false alarm probability and low SNR values. Threshold values are evaluated for energy detectors to perceive changes in noise power in order to minimize difficulties with noise uncertainties, therefore threshold values are adapted to compute

Table 2. Performance comparison of eigen value based spectrum sensing, proposed LLAD and its sign variants.

SNR (dB)	0		-5		-10		-15		-20	
	P_{fa}	P_d	P_{fa}	P_d	P_{fa}	P_d	P_{fa}	P_d	P_{fa}	P_d
Eigen value-based spectrum sensing	0.4	0.6789	0.3	0.6989	0.3	0.7125	0.3	0.7859	0.3	0.8752
LLAD	0.2520	0.7824	0.3	0.8997	0.3	0.9581	0.3	0.9785	0.3	0.9969
SR-LLAD	0.26	0.6241	0.2	0.6805	0.2	0.7825	0.2	0.8628	0.2	0.8853
S-LLAD	0.3821	0.5645	0.4	0.7192	0.4	0.7403	0.4	0.7893	0.4	0.7990
SS-LLAD	0.42	0.4561	0.5	0.4985	0.5	0.5782	0.5	0.5981	0.5	0.6782

noise power estimation. When compared to spectrum sensing only by using energy detection, it provides improved results for the LLAD energy detection. The proposed approach for energy detection overcomes noise uncertainty difficulties, but it is also necessary to assess the signal correlation because it is based on noise power estimations with eigen values. If signal correlation occurs, the performances of energy detection and noise power estimates have an impact on spectrum sensing.

Convergence becomes delayed by applying signum function. According to the illustrations, SRA variant is just lower than its non-signed variant. Figure 4 shows LLAD algorithm and its sign variants have a higher convergence rate than LMS. Hence SRLLAD algorithm is preferred when compared to LLAD and LMS algorithms. When the proposed LLAD algorithm exceeds the lower bound stability constraint [25], the normalized mean square deviation noise variance diverges. As a result of this equation Normalized mean square deviation provides higher stability for the proposed strategy. Normalized mean square deviation analysis yields higher convergence for modified normalized median LMS than NLMS and LMS for small step size noisy inputs. Because of instabilities, the standard modified normalized LMS method diverged at large step size values.

In health care monitoring applications for remote patients, spectrum sensing with the proposed LLAD algorithm is utilized to reduce noisy inputs and interferences caused by wireless networks. The information of the patients is transmitted to doctors through cognitive systems by arranging wearable devices to patient body. The information is transmitted and received concurrently from both channels. In this case primary user of cognitive system takes higher priority over the secondary user. The data is accessible to secondary users, but not to primary users. This proposed LLAD Algorithm eliminates interference and disturbances that arise in this situation. Medical equipment's are more sensitive than normal electric devices in health care accept. In these primary users are telemetry applications and secondary users are hospital information applications. By predicting spectrum holes the cognitive radio controller optimizes the performance of the system, cognitive radio controller regulates channel access, and probabilities are determined. For many data channels the loss and delay probabilities of cognitive radio system are enhanced.

4. CONCLUSIONS

The main objective of this paper is to reduce noise uncertainties during spectrum sensing using the proposed LLAD algorithm. Probability detection and false alarm probability are errors that arise as a result of spectrum sensing at the receiver, and their expressions are derived. After that, the impact of noise uncertainty on threshold parameter selection is investigated. The mean and mean square deviation analysis ensures stability for noisy primary user inputs. We considered Variable step size for improving the stability of the proposed spectrum sensing technique. The LLAD algorithm's performance is enhanced by a lower steady-state error rate and better convergence. In medical telemetry, this cognitive radio idea is utilized to minimize echo cancellations and signal correlations with noisy inputs at the primary user. As a consequence, we achieve improved outcomes in terms of noise uncertainty stability, convergence rate, and steady state error rate. The estimation of a false alert and the probability of detection were both computed as estimation parameters.

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