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A Low Complex Spectrum Sensing Technique for Medical Telemetry System

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Wearable wireless sensors play a vital role in healthcare applications to connect remote patients with the hospital. Generally, wearable devices are used for monitoring, diagnosing, and treating various medical conditions. In this paper authors propose a novel energy detection scheme for spectrum allotment to a medical telemetry network. By using medical body area networks, we can improve remote patient monitoring as well as facilitating immediate response from the service provider. Further, we also outline the challenges of implementing spectrum sensing for body sensor networks. In this work, spectrum sensing using energy detection is used for developing medical telemetry networks. The proposed Normalized Median Least Mean Square (NMLMS) algorithm with sign regressor operation also solves the problem of complexity of circuit in basic spectrum sensing using energy detection phenomenon. In practical communication networks, the computational complexity for implementing the proposed technique on chip is a key parameter for developing lab on chip or system on chip. The experimental results show that performance of NMLMS gives better performance in terms of convergence. The probability of detection of a spectrum are demonstrated at various false alarm rates as 0.025, 0.05, and 0.1 and signal to noise ratio from −10 dB to 0 dB.

Keywords: Cognitive radios, Energy detection, Health care monitor, Spectrum sensing, Threshold Point

Introduction

World Health Organization (WHO) reported that throughout the globe the major mortality is due to cardiovascular diseases.[1] It is also reported that the increase in this mortality is mainly due to the fact that the patient is not treated timely. American heart association[2] reports also state that deaths are due to cardiovascular diseases, so WHO decided to decrease death rate to 25% by 2025. In such a scenario remote healthcare monitoring and medical telemetry are considered as the key phenomenon that need develop in the contest of health care industry. To process information and communication strategies medical telemetry method is used for health care services. Wireless communication plays a vital role for healthcare services like monitoring patients who are far away from hospitals, in smart hospitals, etc. Wireless medical telemetry services are used in developed countries like the USA, for a specific frequency band[3] and it is recognized by federal communication commission (FCC). But there are interferences due to these wireless medical telemetry services because of installation problems in adjacent channels of digital television and non uniform access priorities.[4]

To avoid these interference problems, here is a need to develop cognitive radio-based algorithms. For serving remote located and elder patients, cognitive radio method is used along with medical body area networks[5], then by proposed frequency spectrum allocations, patients can be treated in time. In wireless communication techniques, cognitive radio method[6] is a method and it is based on software defined radio (SDR), spectrum utilization can be known easily by using this method. By adopting high bandwidth services, cognitive radios provide frequency reuse with characteristics of a better channel. Then from the possibilities of claiming of licensed users to provide sources to secondary users, then spectrum allocation[7] method is used for secondary users with different quality of service requirements with applications like in the area of medical telemetry presented. Cognitive radio systems are continuously monitored for avoiding interferences and to share a frequency, then absence or presence of licensed spectrum users is identified. If the allocated frequency is still vacant, then it is used by a secondary user to utilize free

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frequency, it is also known as a cognitive user. Various wireless signal processing techniques have been studied by various researchers.[8–12] So Wireless technologies like Bluetooth and Zigbee are used to know about patient's conditions using body area sensor networks with a frequency band of 2.4 GHz.

Energy detection is one of the key methods for spectrum sensing in communication systems. For spectrum sensing, noise uncertainty is taken into consideration then parameters like probability detection, false alarm probability is calculated for certain SNR values than with predefined threshold[13] estimated target number of samples for low SNR regions. With different types of fading channels[14], spectrum sensing with improved energy detection is analyzed in cognitive radio networks, then performance is measured in terms of receiver operating characteristics, missed detection probability, and false alarm probability. For improving performance[15], in spectrum sensing formulated a multi objective function to minimize optimization problems so that performance of detection probability is maximized. For efficient use of radio spectrum sources, spectrum sensing is used in cognitive radio networks. Software defined radio (SDR) was adopted as a cognitive device[16] for accurately measuring spectrum, then performance evaluation of spectrum sensing ROC curves is obtained from SNR values. In wireless sensor networks, heterogeneous based energy efficient cognitive sensor network is proposed. Using this method channel is assigned for every spectrum. Then channel is detected in available time for channel maximization[17]and further it also allocates channel availabilities to data sensors. Over *F* fading channels, [18]spectrum sensing using energy detection is performed. Then analytical expression is derived for average number of detection probabilities after ROC curves are performed for various SNR values. An improved energy detector performance is studied by Ye *et al.*[19] to remove Laplacian noise form cognitive radio networks. A novel method is explained in Tlebaldiyeva *et al.*[20] for evaluating energy detector performance using a Nakagami-m fading channel and additive white gaussian noise channels. A combination of energy harvesting[21] and spectrum sensing increases communication level[22] and also increases throughput with improved sensing accuracy at fusion center. Test statistics and power estimation are calculated using energy detection.

The main objective of this paper is to avoid interferences that occurs in medical telemetry networks by the methodology of energy detection for spectrum allocation. In this contest we proposed methodology of energy detection using Normalized Median adaptive learning algorithm. By using this adaptive learning algorithm, the convergence, probability of energy detection, accuracy of the medical telemetry system can be improved. Also, by applying the operation of sign regressor the computational complexity of learning algorithm could be minimized by an amount equal to one less than the filter length and also the computational complexity is independent of weight coefficients length. In the next section, the adaptive learning algorithm for energy detection-based spectrum sensing is explained and demonstrated.

Energy Detection in Medical Telemetry Networks using Low Computational Complex Algorithm

Spectrum sensing intended for continuously searching for unused frequency bands and shares this vacancy bands to free users without causing interference to primary users. Depending on situation, vacancy band is used by both unlicensed users and licensed users. In literature various methods[23] like Cyclostationary detection, energy detection, and matched filter detection are reported. Among these, energy detection is a dominant technique, as it does not require any prior knowledge of primary user signal, it is easy to implement and it takes very less time to sense. Power spectral density of received signal is compared with threshold value (fixed) by using an energy detector. In this process, the input signal is passed through a bandpass filter to select frequency band and is passed through a squaring device for measuring received energy then it undergoes integration operation to determine the integration interval, later it compares with threshold point to check the primary user is absent or present. The phenomenon is illustrated in Fig. 1.

For spectrum sensing, test statistics of energy detector[24] is given as

$$S = \sum_{t=1}^{T} |I(t)|^2 \quad \ldots (1)$$

Then by using hypothesis testing, with fixed threshold energy detected is compared and is written as

$$H_1 : S > \boldsymbol{\lambda} \quad \ldots (2)$$

$$H_0 : S < \boldsymbol{\lambda} \quad \ldots (3)$$

Here H_0 and H_1 are represented as

H_0 = when primary user is in absence

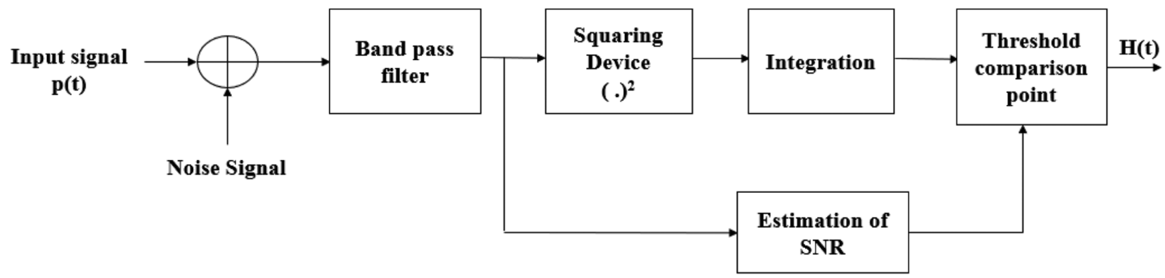

Fig. 1 — Block diagram for spectrum sensing using energy detection

H_1= when a primary user is in availability

Signals at hypothesis testing of energy detector are given as

$$H_0: I(t) = n(t) \quad \dots (4)$$

$$H_1: I(t) = p(t) + n(t) \quad \dots (5)$$

where p(t), n(t), I(t) representations are given as p(t) is a primary signal, n(t) is a noisy signal and I(t) is a received signal.

Test for the presence of primary user presence is done by using different performance parameters like probability detection (PD), probability of false alarm (PF). Using these parameters, recovery of energy detection performance is done and their mathematical equations are shown below:

$$PD = Q\left(\frac{\lambda - L(1+\partial}{\sqrt{2L(1+\partial)^2}}\right) \quad \dots (6)$$

$$PF = Q\left(\frac{\lambda - L\delta_w^2}{\sqrt{2L\delta_w^4}}\right) \quad \dots (7)$$

Here $\boldsymbol{\lambda}$ is a fixed threshold point, L is number of samples, ∂ is signal to noise ratio and Q is a cumulative distributive function. Threshold point is calculated by using Eq. (7) as

$$\lambda = \delta_w^2(Q^{-1}(PF)\sqrt{2L\delta_w^4})) \quad \dots (8)$$

This threshold depends on number of samples, noise variance and false alarm probability. To set a fixed threshold value, prior knowledge of noise level in received signal is required.

The adaptive learning algorithm trains the weight coefficients to update based on the transfer function and it is controlled by variable parameters through an optimization process. Stochastic optimization uses random variables, it solves optimization problems by using objective functions like a method of gradient descent optimization. Concept of stochastic optimization and adaptive filtering are interconnected, both can start realization by considering input variables randomly and then solved problems of optimization with minimum inputs. In recent years, these adaptive filter optimization algorithms have gained interest in wireless networks like in cognitive radios. By the proposed method, we get the better convergence results when compared to the Normalized LMS discussed by Surekha *et al.*[24] Scalability, low power consumption, and robustness are desired by using adaptive filters[25,26] in the context of cognitive radio networks. Primary user signal presence or absence is identified by using threshold point and hypothesis testing considerations, but there may present a noisy signal at threshold point comparisons and may lead to instability at energy detector output. To avoid these all errors, we proposed a normalized median LMS algorithm. For basic LMS algorithms, average is considered for window size W+1, to get the error free output from the energy detector output.

Input signal is p(t) for W by 1 tap vectors a time ‘t’ with estimated window size W+1 is represented as $[\mathrm{p(t), p(t-1), ...,\ \ p(t-W+1)}]^T$

For computations, tap weight vector v is stored in a row as

$$[\mathrm{v(t)\ v\ (t-1)\ ....v\ (t-W+1)}]^{\mathrm{T}}$$

For linear estimation problems, a wiener solution is given as

$$(t) = v^T p(t) + n_0(t) \quad \dots (9)$$

FIR filter output is given as

$$(t) = v(t)p(t) = p^T(t)v(t) \quad \dots (10)$$

Estimation error n(t) is represented as

$n(t) = d(t) - v^T(t).\, p(t)$ ... (11)

Gradient vector expression is represented as follows from the steepest descent algorithm

$v(t+1) = v(t) - \mu\, \nabla J(t)$ ... (12)

Expression for LMS recursion is

$v(t+1) = v(t) + \mu\, avg_L[p(t)n(t), p(t-1)\, n(t-1) \dots \dots p(t-K)\, n(t-K)]$ ... (13)

Normalized Median LMS algorithm weight expression is given as

$v(t+1) = v(t) + \mu(t)\, avg_K[p(t)n(t), p(t-1)\, n(t-1) \dots \dots p(t-K)\, n(t-K)]$ … (14)

where step size is $\mu(t) = \frac{\mu}{||p(t)||^2}$

Normalized Median LMS resultant expression is represented as

$v(t+1) = v(t) + \frac{\mu}{p^T(t)p(t)} avg_K[p(t)n(t), p(t-$
$1nt-1 \dots pt-Knt-K$ ... (15)

Then the expression for maximum Normalized Median LMS is represented as

$v(t+1) =$
$v(t) + \frac{\mu}{\varepsilon + \max||p(t)||^2} avg_K[p(t)n(t), p(t-1)n(t-1)..p(t-K)n(t-K)]$ … (16)

For reducing computational complexity,in normalized algorithms block processing is adopted. Then we normalize recursion weight updates for large data vector values. Then modified the weight update relation for $\varepsilon = 0$ and $x_{ki} \neq 0$ is represented as

$v(t+1) = v(t) + \frac{\mu}{x_{Ki}^2} avg_L[p(t)n(t), p(t-$
$1nt-1..pt-Knt-K$ … (17)

Signum function is used for normalization then Normalized Median LMS is written as follows. Then the sign regressor version of Normalized Median LMS is given as Normalized Sign Regressor Median LMS is represented as

$v(t+1) =$
$v(t) + \frac{\mu}{x_{Ki}^2} avg_K\left[\text{sign}\left(p(t)\right)n(t), \text{sign}\left(p(t-\right.\right.$
$1nt-1..\text{sign}pt-Knt-K$ … (18)

where, $x_{Ki} = \max\left\{|x_l|, l \in Z_i'\right\}$, $Z_i' = \{iK, iK+1, \dots, iK+K-1$, $i \in Z$, and for xKi=0 and ε=0

Then the above weight recursion becomes v(t + 1) = v(t).

Now weight update relation is modified for$x_{ki} \neq 0$and $\varepsilon \neq 0$ and is represented as,

$v(t+1) =$
$v(t) +$
$\frac{\mu}{\varepsilon + \max||p(t)||^2} avg_K\left[\text{sign}\left(p(t)\right)n(t), \text{sign}\left(p(t-\right.\right.$
$1nt-1..\text{sign}pt-Knt-K$ … (19)

Signum function is applied for weight recursion equations in three ways, they are: Sign Regressor Algorithm (SRA), Sign Algorithm (SA) and Sign Sign Algorithm (SSA). Then Normalized Median LMS algorithm is named with signum functions as Normalized Sign Regressor Median LMS (NSRMLMS), Normalized Sign Median LMS (NSMLMS),and Normalized Sign Sign Median LMS (NSSMLMS) algorithms. By applying this signum function to basic weight recursion equation computational complexity is reduced. Sign regressor operation minimizes the number of multiplications by an amount equal to W-1. For earlier equations, it has high computational complexity for basic LMS equation. The overall flowchart of the proposed Normalized median LMS algorithm for spectrum sensing is shown in Fig. 2.

After initialization of number of samples, fixed threshold value, step size value, then for every iteration updating of weight update equation is done and identified the spectrum holes which are ready to be used by secondary user. In flowchart, sign regressor equation represented with S{p(t)}, S{p(t-1)} …S{p(t-K)}, in these ‘S’ is a signum function. Final equations of sign regressor based algorithms are shown in Eqs (20) to (22).

The NSRMLMS is represented as,

$v(t+1) = v(t) + \mu(t).\, \text{avgK}[n(t)\text{Sign}\{p(t)\}, n(t-1)\text{Sign}\{p(t-1)\} \dots n(t-K)\ \text{Sign}\ \{p(t-K)\}$ … (20)

The NSMLMS is given by

$v(t+1) = v(t) + \mu(t).\, \text{avgK}[\text{Sign}\{n(t)\}p(t), \text{Sign}\{n(t-1)\}p(t-1) \dots \text{Sign}\{p(t-K)\}p(t-K)]$ …(21)

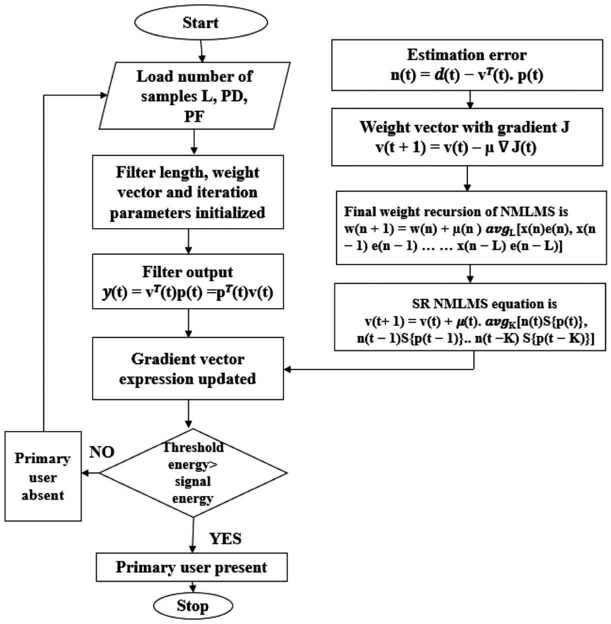

Fig. 2 — Flowchart of sign regress based low complex algorithm for energy detection

The NSSMLMS is given as,

$$v(t+1) = v(t) + \mu(t).\,\mathrm{avgL}[\mathrm{Sign}\{n(t)\}\mathrm{Sign}\{p(t)\}, \mathrm{Sign}\{n(t-1)\}\mathrm{Sign}\{p(t-1)\} \ldots \mathrm{Sign}\{n(t-K)\}\mathrm{Sign}\{p(t-K)\}] \quad \ldots (22)$$

Applying sign algorithms minimizes computational burden of the adaptation learning process. In spectrum sensing using energy detection sign algorithms are used to implement VLSI circuits.

Then the circuit complexity of VLSI circuits is decreased by using energy detection. For minimizing computational complexity, combined the normalized median LMS algorithm with sign algorithms as sign regressor algorithm, sign algorithm, sign sign algorithm. It results in by using sign regression computational complexity of circuit is decreased so that filter response is increased. Sign regressor performance is good when compared to sign LMS algorithm and sign sign LMS algorithm. Hence, here the sign regressor LMS algorithm is being used. Their Computational complexity and convergence curves will be discussed in the next section.

Experimental Results and Discussion

Primary signal is detected using energy detection by fixing a threshold value initially. By using this threshold value, we determine the probability detection (PD), false alarm probability (PF) performance parameters. The number of samples L is considered for detecting the presence or absence of user. Numbers of samples are given as a function of SNR. For every sample iteration, we are getting signal and noise variances. To get sensible curves at receiver, attenuation factor is added to probability detection equation, then calculated noise power estimation in terms of mean square error. To avoid error and unstable variances proposed an adaptive filter algorithm. By using this adaptive algorithm, we can stabilize the error variance by continuously iterating with samples. In this paper, normalized median LMS algorithm is proposed along with energy detection spectrum sensing method. By using this algorithm, we can minimize the errors occurred in detection of primary user, because weight update equation is updated for every iteration. Then we can calculate the probability detection, false alarm probability by considering parameters of threshold and for different number of SNR values and we get the simulation results in between SNR and PD. Probability detection increases if numbers of samples are increased. If numbers of samples are increased then detection of primary user is also easy. For better detection of primary user, number of samples must be high and false alarm probability value must be low.

In normalized median adaptive learning algorithm, we have to consider a small step size value and also, we have to consider network nodes for taking decision if primary user or secondary user is present. Then we calculated the probability detection and probability of false alarm and observed that for low SNR values getting better performance. Signal to noise ratio is varying from −10 dB to 0 dB. Performance analysis is compared with proposed algorithm, number of samples is taken as 1000. False alarm Probabilities considered here for simulation are 0.1, 0.05, and 0.025. From simulation results, it is clear that probability detection increases with increase of false alarm probability. But the variation is very small, so false alarm probability minorly affects the detection probability. It is shown in Table 1 and corresponding simulation result is shown in Fig. 3. Then to get a better convergence rate, computational complexity has to reduce. It was done by taking the signum function to proposed normalized median LMS algorithm. By using signum function to the basic normalized median LMS equation, reduces the computational complexity. There are three variations of signum function used in the proposed adaptive

Table 1 — Detection probability (PD) for varying false alarm probability (PF)

S.No.	SNR (dB) Values	Detection Probability (PD)		
		PF=0.1	PF=0.05	PF=0.025
1	−10	0.5100	0.4571	0.3698
2	−9	0.6239	0.5123	0.4253
3	−8	0.7832	0.6250	0.5234
4	−7	0.8221	0.7259	0.6595
5	−6	0.9100	0.8459	0.7892
6	−5	0.9559	0.9123	0.8896
7	−4	0.9623	0.9356	0.9126
8	−3	0.9852	0.9621	0.9451
9	−2	0.9889	0.9896	0.9859
10	−1	0.9999	1.0000	1.0000
11	0	1.0000	1.0000	1.0000
12	1	1.0000	1.0000	1.0000

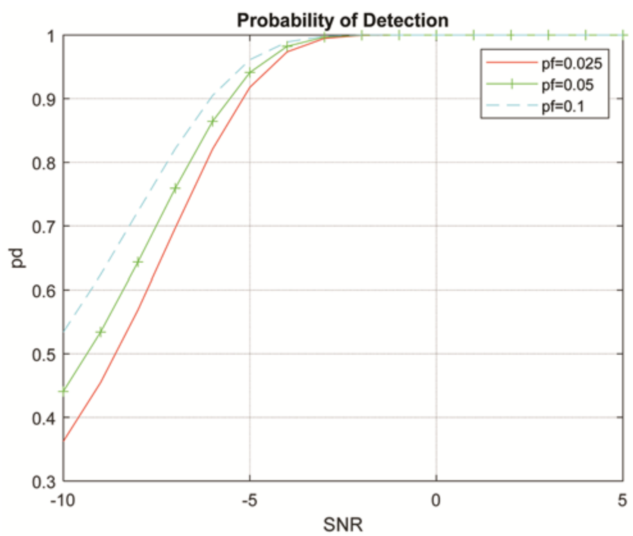

Fig. 3 — Comparison of Sign Regressor NMLMS in terms of SNR and pd

filter algorithm. By using these three versions in adaptive filter algorithm convergence rate also improved compared to normal adaptive filter algorithm. Convergence curve of normalized median LMS algorithm is shown in Fig. 3. When compared to basic LMS algorithm, using normalized median LMS algorithm convergence is better because of using signum function. Sign regressor function reduces the number of computations so that it takes less time to converge. Normalization is involved in sign regressor function for Normalized Median LMS, so convergence rate is accelerated. Normalized median LMS is inferior to normal LMS algorithm with computation complexity minimum.

Computational complexity is required to calculate adaptive filter algorithms and their sign regressor variants also. Basically, sign regressor based adaptive filter requires a smaller number of multiplications so it converges fast. Let us consider, LMS requires W+1 multiplications and additions to compute where W is the length of tap filter. Whereas in case of sign regressor adaptive filter algorithm it requires only one multiplication, the other two sign regressor algorithms do not need any multiplication when step size is considered as power of two in their equations and they are listed in Table 2. Normalized median LMS is compared with Median LMS convergence curves. Convergence curve of median LMS (MLMS) and its sign versions are shown in Fig. 4. Sign regressor version of NMLMS converged faster compared to MLMS algorithm. From the table it is clear that, sign regressor function does not need a greater number of multiplications, due to sign function is used in the data normalization input, it means all the vectors become −1,0 or 1 so that all multiplications are highly reduced. If sign function is applied to error, there is no change in multiplication, if it is applied to sign sign regressor adaptive filter algorithm, signum function is applied to both the error terms and data terms, hence there is no need of multiplications required in the weight update equation, it is only carried with addition along with sign function.

Table 2 — Computational complexities of various Median based algorithms

S. No.	Algorithm	Multiplications	Additions	Divisions
1	LMS	W+1	W+1	NIL
2	MLMS	2W+2	W+2	NIL
3	SRMLMS	2	W+1	NIL
4	NMLMS	W+1	W+1	1
5	NMSRLMS	1	W+1	1

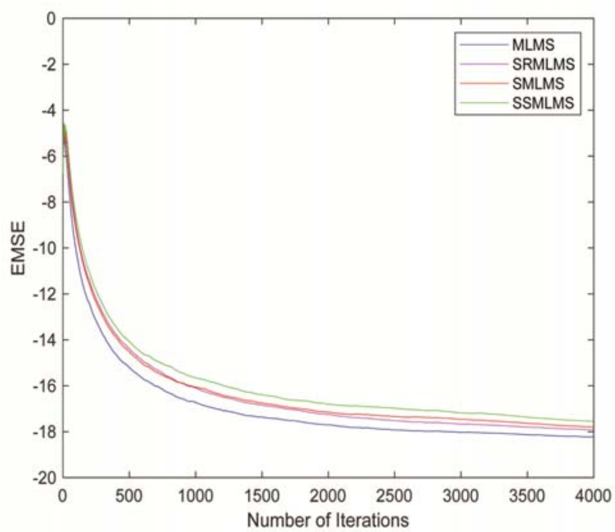

Fig. 4 — Convergence curves of sign based median algorithm in energy detection

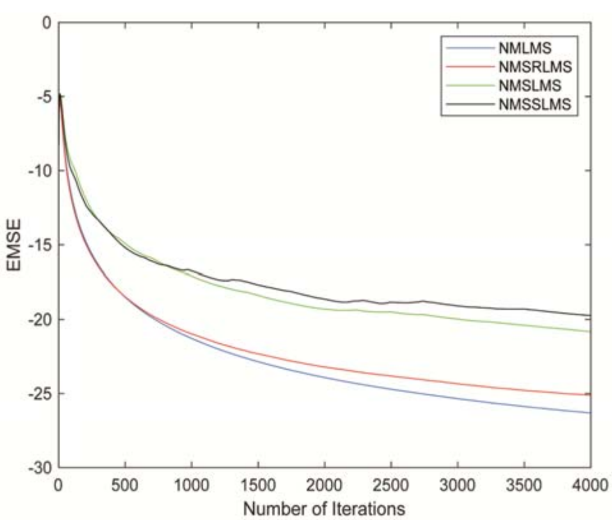

Fig. 5 — Convergence curves of Normalized sign based median algorithm in energy detection

For convergence curve as shown in Fig. 3, we are considering iterations 1000, and for each sample, a mean square error is calculated. Filter length is considered as 25, and also step size is also fixed as 0.01 and random variance is also considered as 0.01 for better convergence. Computational complexity is independent of filter length. For sign regression, multiplication length is small because it has no filter length. Signed regressor algorithms performance is always suboptimal to basic adaptive filter algorithms because of normalization factor since it rejects some information at lower complexity levels. Convergence curve is obtained by simulating in between number of iterations and mean square error for every sample and it is shown in Fig. 5. Then from the computational complexity table, convergence curves of MLMS and NMLMS, it is clear that sign regressor based NMLMS gives better results. So, for spectrum sensing using NMLMS shows better performance for removing noise interferences in medical telemetry networks in terms of probability detection improvement for low SNR values in cognitive radio networks.

Conclusions

Cognitive radio systems for healthcare applications are studied then considered the issues of interference to healthcare devices. Using cognitive radio frequencies in the field of healthcare reduces the interference also achieved required QoS requirements. Proposed a Normalized Median LMS algorithm for energy detection and applied this algorithm to the field of medical telemetry so that recovered the problems of interference. In this paper, we studied spectrum sensing using energy detection and proposed Sign regressor based Normalized Modified LMS algorithm. By proposed Normalized Median LMS we can get the accurate data of the patient when compared to the general energy detection sensing algorithm. Then the resulting detection probability performance is improved as it reached to one as a signal to noise ratio is decreasing from −10 to 0 dB for different false alarm probability values. So, we can conclude using of Normalized Median LMS algorithm in the field of medical telemetry we get output data without any noises.

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