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Beamforming in cognitive radio networks using partial update adaptive learning algorithm

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ABSTRACT
Cognitive radio technology is a promising way to improve bandwidth efficiency. Frequency which is not used in any aspect will be utilized by using some of the most powerful resources in this cognitive radio. One of the main advantages of cognitive radio signal is to detect the different channels which are there in the spectrum and it can modify the frequencies which is utilized frequently. It allows the licensed users to gain the licensed bandwidth under the condition to protect the licensed users from harmful interference i.e., from secondary users. In this paper, we would like to implement cognitive radio using the beamforming technique, by using power allocation as a strategy for the unlicensed transmitter which is purely form on the result of sensing. It is on the state of the primary user in a various cognitive radio network whereas the unlicensed transmitter gives a single antenna and it modify its power transmission. For the cognitive radio setup, we have used normalized adaptive learning algorithms. This application would be very useful in medical telemetry applications. Nowadays wireless communication plays a vital role in healthcare applications for that we have to build a separate base. It reduces the effort of the building of separate infrastructure for medical telemetry applications.

Section: RESEARCH PAPER

Keywords: Adaptive learning, bandwidth, cognitive radio, frequency, power transmission

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1. INTRODUCTION

In medical telemetry wireless communication techniques are used widely in the present generation. Generally, these types are used to monitor the condition of a person via pulse, respiration, etc., This wireless medical telemetry service was first established by the federal communications commission by allocating some of the frequency bands separately for this wireless purpose so that it will not have any discrepancies while allocating frequency bands while cross-checking the patient's condition [1]. Instead of that, we can use the existing spectrum for a medical telemetry application by using cognitive radio. In this cognitive radio spectrum sensing technique would be there for this spectrum sense we use the beamforming technique. The efficient utilization of spectrum is the most important thing in cognitive radio. cognitive radio offers a spectrum allocation for unlicensed users simultaneously with licensed users. So, the secondary users need to detect the spectrum availability using spectrum sensing by sensing the primary user in the same frequency [2], [3]. The main purpose to introduce beamforming technique is to remove the unwanted noise in different systems which we are using in this process like military SONAR and RADAR systems. This will be separating the sources when the overlapping frequency content which originates at different spatial locations [4]-[6]. This technique is mainly used for sensing purposes, in this phase, the licensed user transmitter will be estimated by the secondary user transmitter according to that estimation the spectrum allocation will be done [5]-[8]. This technique is used to provide an exchange of information within the cells and the remaining near cells will be in a secured manner.

The interference which is occurred in signals is mainly due to the imperfection of spectrum sensing, Due to that secondary user are freely accessing the primary user channels [9], [10]. At the same time, this technique should return to the channel before the secondary users. This beamforming would be very effective while sensing the spectrum without any interference. A cognitive radio network is one of the important systems in the broadband communication system. The beamforming technique [11], [12] which we are proposing in this paper is used to connect the information inside the cells and the outer cells which are in use from all the users. It has proved that the beamforming technique is the smooth technique for spectrum sensing analytically too. In that paper, they explained some statistical tests between Maximum-to-Minimum Eigenvalue and Maximum-to-Minimum Beam Energy algorithms based on the statistical values they conclude that beamforming is a smooth sensing technique [13].

The sensors in secondary users are used to assume their particular PU DoAs. Always the secondary users access the primary user's accounts freely and simultaneously, licensed users also intend to get back the mechanism before the unlicensed user acquire expires. At last, the binding centre collaborate with DoAs into a Primary User localization estimation. The result of our final implementation gives that to make possible to make a localization system with a poor complexity and a good primary user localization capability in this cognitive network. The capabilities which are present in PU localization are used to enhance the PU interference [14]. Generally, in services of wireless communication, it has rectifiers at every junction point to manage every event of the upcoming trending technologies which gives profit from abstraction property. It has gained from different latest antenna sets and also from algorithms that form adaptive beams [15]. The process which we have used is purely based on Least Mean Square (LMS) algorithm, which gives a brief and proper care to the signal model which we have used for the beamforming technique. To get the accuracy convergence rate more than the expected one for the LMS which we have used in the smart antenna system, we have used BBNLMS (Block-Based Normalized Least Mean Square) algorithm. The presence of this algorithm gives a lot of difference in convergence rate. Mainly this algorithm will be performed only in the existence of different effects and many users which is scanned using MATLAB simulations using different white signals. The LMS formula was used only in the sensible antenna systems in between the adjustive beam forming algorithms [16]. In place of quick exploitation, the traditional square of the error vector is used [17]. Although many methods have been implemented and implemented with the new ideas for the DOA (Direction of Arrival) of signal.

The adaptive array was first discovered by VAN Atta in the year 1959 which is defined as a self-phased array [18]. It reflects all the incident signals in the arrival direction using a clever phasing scheme. These beamforming algorithms are divided into various methods they are mainly fixed weight beamforming and adaptive beamforming algorithm. This Adaptive algorithm will update the array weights continuously which is based on optimization of changing signal environment. This section briefly discusses LMS, recursive least square, conjugate gradient algorithm, and quasi-Newton algorithm [19]. Data transmission in a communication channel with a low probability of bit error is possible up to a certain bit rate with a given SNR (signal-to-noise ratio). Therefore, in addition to the adaptive algorithm, to increase the noise immunity of the wireless system, let us consider the use of channel coding schemes. Such coding is a series of transformations of the original bit sequence, as a result of which the transmission of information flow becomes more resistant to the deterioration of the quality of the transmitted information caused by noise, interference, and signal fading. Channel coding allows reaching a compromise between bandwidth and the probability of bit error [20]. This paper gives a different aspect in the direction of arrival of signals with a different error rate and at last, in this paper, we provide the simulation results which provides better evidence for the technique which we have provided in this paper.

2. METHODOLOGY

The networks that we are using in this paper are Cognitive Radio Network (CRN) and Non-Orthogonal Multiple Access (NOMA) are widely used system in the 5G broadband communication system. There is one advantage for the users who are using a cognitive radio network is to protect the information from different devices like multiple-input multiple-output-NOMA. In our paper, we are trying to implement the substitute of beam forming technique which is already available to protect the data exchange inside the cells and outer cells from different users and their system model is shown in Figure 1. The intervention was caused by a faulty signal of the unlicensed users. The unlicensed users are intended to get the availability of licensed users. Though the licensed user repays the channel before the licensed user access terminates. Adaptive antenna systems include a mixture of different antenna components with a signal-processing ability to improve its radiation or acceptance pattern instinctively in response to the signal environment. The method which we are proposing in our paper on a Partial Update Least Mean Square (PU-LMS) algorithm is an algorithm that is used to control the overload and less power consumption in the implementation of an adaptive filter. Thus, the problem of adaptive filtering algorithm improves the filter coefficients is shown in Figure 2. Hence, we provide a better result from our proposed technique.

LMS algorithm is an algorithm admired in adaptive beam formers in which we use the antenna arrays. It is also used for channel levelling to conflict the inter-symbol interference. Simultaneously, few applications of LMS can incorporate interference, echo cancellation, space-time modulation, and coding, and the signals which are in observation. Whereas, the already algorithms have high faster convergence rate like recursive least square and least mean square which is already admired because of their implementation and its computational costs. It is one of the effective methods for power consumption and for reducing the computational load in the adaptive filter implementations, which is appealing in mobile communications.

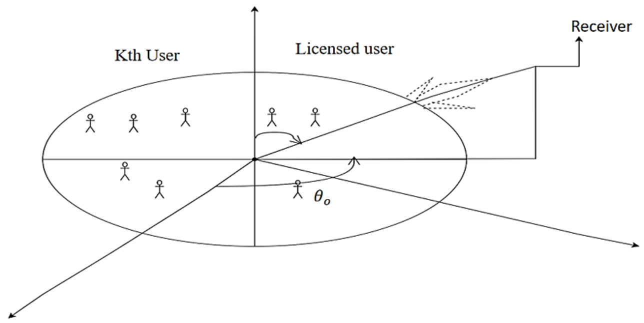

Figure 1. Cognitive system mode.

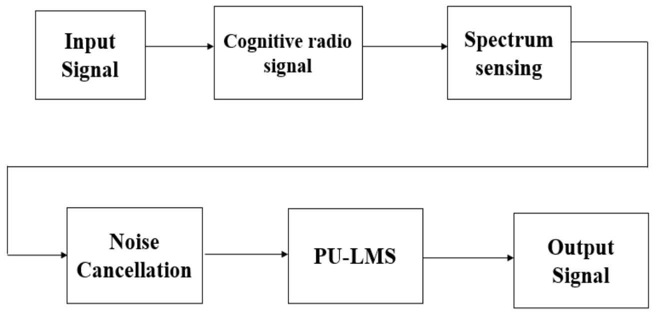

Figure 2. Overview of project implementation.

Block diagram and overview of proposed algorithm is shown in Figure 3 and Figure 4, respectively. There are many mobile communication devices and those applications like channel equalization as well as echo cancellation which requires the adaptive filter to get a high number of coefficients. To modernize the entire signal vector which is costly regarding RAM, capacity, and computation and sometimes it does not fit mobile units. Finally, in this paper, we present the analysis of the confluence of partial update adaptive learning (PUAL) algorithm lesser than different types of suppositions, and when the diversions are visible then it can be prevented by different coefficient updates accidentally, which is also known as sequential partial update adaptive learning (SPU-AL).

2.1. Cyclostationary input signals

Cyclostationary is one of the processes which is having different analytics which differ cyclically with respect to meter. It is the one that can be showed as a various interleaved stationary process. It is also having a detection method for estimating and for spectral autocorrelation function technique to analyse the spectrum sensing. It can be detected whether it is active or not and whether the signal is used by licensed users or not it can sense these easily because this technique is robust in the sense. Sequential PU-AL algorithm, shows how the coefficients are updating in simulation and associated samples of the signals which are used in every overhaul (*x* power $1/4$)(*n*) being the value of the retreat signal at the present instant and its flow chart is shown in Figure 4. It simulates as a higher bound for each step size of PU AL compatible algorithm when the signal is given as an input signal as a periodic reference which consists of many euphonious

$$\begin{aligned} E\{h(l+T)\} &= E\{h(l)E\{h(l+T)h(l+T+n)\} \\ &= E\{h(l)h(l+n)\} \end{aligned} \tag{1}$$

$$\begin{aligned} y(l) &= [y(l)y(l-1)y(l-2)\ldots.,y(l-N+1)]^{\mathrm{T}} \\ B_y(l) &= E\{y(l)y^{\mathrm{T}}(l)\} \\ &= \mathrm{diag}\left[\sigma_y^2(l),\ldots.,\sigma_y^2(l-N+1)\right] \end{aligned} \tag{2}$$

$$\sigma_y^2 = \begin{cases} M_1 \text{ for } i\,T < l \leq i\,T + \alpha\,T \\ M_2 \text{ for } i\,T + \alpha\,T \leq (i+1)\,T \end{cases} \tag{3}$$

or $0 < \alpha < 1$ and $i = \cdots, -4, -3, -2, -1, 0, 1, 2, 3, 4, \ldots$ and sinusoidal power of a variation in time.

$$\sigma_y^2 = \beta(1 + \sin(\omega_o l))\,. \tag{4}$$

Here, is larger than zero, and ω_0 falls between 0 and π, with $\omega_0/(2\,\pi)$ being a rational integer. If the sinusoidal power of a variation in time period is more than three, then $y(l)$ is not an input signal.

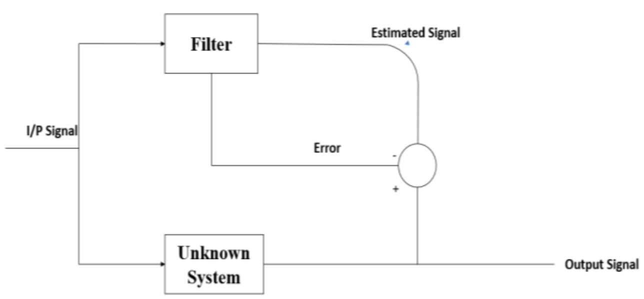

Figure 3. Overview of partial update algorithm.

2.2. Sequential Partial Update Adaptive Learning Algorithm

The needed signal is denoted by $d(l)$, the desirable weight vectors are denoted by ω_0, and the noise measurement is denoted by $v(l)$

$$d(l) = y^{\mathrm{T}}(l)\omega_0 + v(l) \tag{5}$$

$$e(l) = e(l) - y^{\mathrm{T}}(l)\,u(l) \tag{6}$$

$$u(l+1) = u(l) + \mu_e(l)I_K(l)y(l)\,. \tag{7}$$

Here $u(l)$ is the weight vector (adjustable filter coefficient vector), $d(l) = y^{\mathrm{T}}(l)\,u(l)$ indicates fallacy of method (whatever algorithm we have taken) and I coefficient preference matrix is:

$$I_{\mathrm{k}}(l)\ \mathrm{diag}[i_1(l), i_2(l), \ldots\ldots, i_N(l) \tag{8}$$

with $A = N/K$. Here, A is taken as integer $\%(l, A)$ represents the '%' operation which results the remainder after making division l by A.

$$\sum_{i=1}^{N} i_j(l) = K, i_j \in \{0,1\}$$

The coefficient subsets E_{i} are different up to they reach the following requirements:

1. $U_{\mathrm{i}=1}^{\mathrm{A}} E_{\mathrm{i}} = Z$ where $Z = \{1,2,\ldots,N\}$
2. $E_i \cap E_j = \emptyset, \forall_j, j \in \{1,2,3,\ldots,A\}$ and $i \neq j$.

2.3. Performance analysis for the input signal

$$\breve{u}(l+1) = \breve{u}(l) - \mu_e(l)I_K(l)y(l) \tag{9}$$

Here is

$$\tilde{u}(l) = \omega_0 - u(l). \tag{10}$$

Using (11),

$$g(l) = y^{\mathrm{T}}\tilde{u}(l) + v(l) \tag{11}$$

is obtained. Putting (11) into (9), then

$$\begin{aligned} &\tilde{u}(l+1) \\ &\quad = 1 - \mu\, I_k(l)\, y(l)\, y^{\mathrm{T}}(l)\, \tilde{u}(l) \\ &\quad - \mu\, v(l)\, I_K(l)\, y(l) \end{aligned} \tag{12}$$

Taking the exception on both sides of (12), we get

$$E\{\tilde{u}(l+1)\} = (I - \mu\, E\{I_K(l)\, y(l)\, y^{\mathrm{T}}(l)\})\, E\{\tilde{u}(l)\} \tag{13}$$

Time varying variance model

$$\sigma_y^2 = \begin{cases} M_1 \ \text{ if } \mathrm{mod}(1,T) = 1 \\ \quad\ldots \\ M_{T-1} \ \text{ if } \mathrm{mod}(1,T) = T-1 \\ M_T \ \text{ if } \mathrm{mod}(1,T) = 0 \end{cases}. \tag{14}$$

We took the set M_1, M_2, …, M_T, which has one large value (like 1) and one tiny value (like 0.001). It's to make sure that (3) and (4) are both true (14). Between the SU-partial update parameter A and the input signal period T, the six instances reflect all potential scenarios.

2.3.1. Case Study 1

$T \leq A$ and $\%(1,T) = 0$. In case of (13) can be rework as

$$E\{\tilde{u}(l+1)\} = 1 - \mu i_j(l)\sigma_y^2(l-j+1)E\{\widetilde{u_j}(l)\} \tag{15}$$

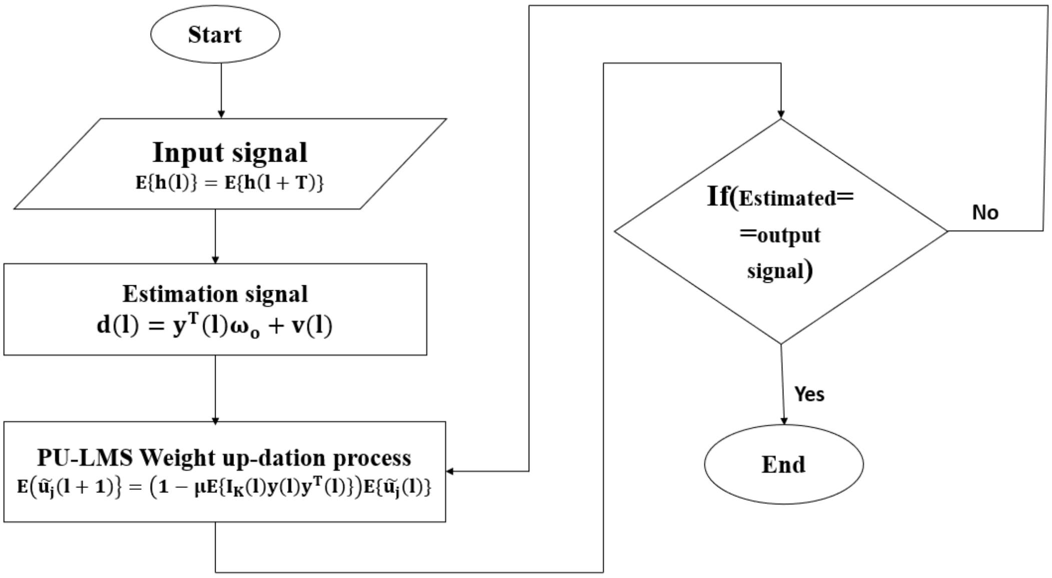

Figure 4. Flow Chart of a partial update adaptive learning algorithm.

Here $\widetilde{u_j}(l)$ is the j th entry of $\tilde{u}_j(l)$. By verifying (7), the rechecking (15) is changed for every A iteration. By adding the A iterations of (15)

$$E\{\widetilde{u_j}(l+B)\} = \left(1 - \mu\sigma_y^2\left(l_j - j + 1\right)\right)E\{\widetilde{u_j}(l)\} \tag{16}$$

Here l is taking as integer satisfying l where $l_j < l + A$. Let declare the parameter $d_j = l_j - \left[l_j/A\right]A$ to indicate which entry of $E\{\widetilde{u_j}(l)\}$ where l_j is satisfies $l_j < l + A$. Let declare the parameter like $d_j = l_j - \left[l_j/A\right]A$, to represents the coming of $E\{\widetilde{u_j}(l)\}$ is upgraded. The function $[y]$ converts y to largest integer $\leq y$. By giving the sequential PU variable A, d_j only depends on j value.

Here $\%(A,T) = 0$, we have the equation $\sigma_y^2\left(l_j - j + 1\right) = M_{t_j}$ here $\widetilde{t_j} = c(\widetilde{t_j})$ and $d_j + N - j + 1 - [d_j + N - j + \frac{1}{T}]$ and $c(y) = y - T|\mathrm{sign}(y)| + T$. By putting this $\sigma_y^2\left(l_j - j + 1\right) = M_{t_j}$ in to (16), we get

$$E\{\widetilde{u_j}(l+B)\} = \left(1 - \mu\sigma_y^2 M_{t_j}\right)E\{\widetilde{u_j}(l)\} \tag{17}$$

Here $\%(A,T) = 0$ and t_j is like take as an integer, by looping (17), we get

$$E\{\widetilde{u_j}(l+b+1)A\} = \left(1 - \mu M_{t_j}\right)E\{\widetilde{u_j}(l+bA)\}\,. \tag{18}$$

In this instance, $\boldsymbol{b}$ is a positive integer. It would be the combination of (17) and (18), according to (18). $\boldsymbol{E\{(\widetilde{u_j}(l + (b+1)A\}}$ depends on $\boldsymbol{M_{t_j}}$. If $\boldsymbol{M_{t_j}}$ in the input signal which is cyclostationary is very small, is explained in [11]. Input signal will change partially for every iteration, it effects the $\boldsymbol{\widetilde{u_j}(l)}$to converge and moving towards update. Hence, in this sequential PU-AL will certainly met with those tough conditions.

2.3.2. Case Study 2

$T \leq A$ and $\%(A,T) \neq 0$ and Greatest Common Divisor (GCD) (A,T) is equal to 1. Here $\mathrm{GCD}(A,T)$ represents the GCD of A by $\sigma_y^2\left(l_j - j + 1\right) = M_{t_j(l)}$ here $t_j(l)$ is taken like an integer declared as $T_j(l) = c(\widetilde{t_j}(l))$ and $\widetilde{t_j}(l) = l_j - \left[l_j/T\right]T$. Then, $T_j(l)$ is depends on the values of both j and l. Hence, (17) becomes

$$\begin{aligned} &E\{\widetilde{u_j}(l+B)\} \\ &\quad = \left(1 - \mu M_{T_j(l)}\right)E\left\{1 - \mu M_{T_j(l)}\right)E\{\widetilde{u_j}(l)\} \end{aligned} \tag{19}$$

Looping the equation (19) for A number of times, we get

$$E\{\widetilde{u_j}(l+2B)\} = \left(1 - \mu M_{f\left(T_j(l)\right)}\right)E\{\widetilde{u_j}(l+A)\} \tag{20}$$

$$\begin{aligned} &f\left(T_j(l)\right) \\ &= \begin{cases} T_j(l) + \left(\%(A,T)\right), & T_j(l) + (\%(A,T) \leq T \\ T_j(l) + (\%(A,T) - T, & \text{otherwise}\,. \end{cases} \end{aligned} \tag{21}$$

Since $T \leq A$, $\%(A,T)$ is not equal to 0 and $\mathrm{GCD}(A,T)$ is equal to 1, looping (21) for T times, we get

$$\begin{aligned} &E\{\widetilde{u_j}(l+TB)\} \\ &\quad = \left[\!\left[1 - \mu M_{f\ldots f\left(T_j(l)\right)}\right]\!\right]E\{\widetilde{u_j}(l+(T-1)A\} \\ &\quad = (1 - \mu M_1)\ldots(1 - \mu M_T)E\{\widetilde{u_j}(l)\} \end{aligned} \tag{22}$$

where $f \ldots f\left(T_j(l)\right)$ represents the configuration of $f(.)$ in T times. In (22), here we can observe the updates the process of input signal is declared by T variances $\{M_1,\ M_2, \ldots M_T\}$. As a consequence, the strategy (serial PU-AL) will not interfere with toughness in this scenario. If the step-size meets the requirements, the PU-LMS is stable.

$$0 < \mu \leq 2/\max\left(M_1, M_2, \ldots, M_T\right) \tag{23}$$

2.3.3. Case Study 3

$T \leq A, \%(A,T) \neq 0$ and $\mathrm{GCD}(A,T)$ is greater than one. The Least Common Multiple (LCM) of T and A is represented by $\mathrm{LCM}(A,T)$. Clearly $\mathrm{LCM}(A,T) < A, T$. Here, the variance would become, $\sigma_y^2\left(l_j - j + 1\right)$ is given that $\sigma_y^2\left(l_j - j + 1\right) = M_{\xi_j(l)}$, where $\xi_j(l) = c\left(\widetilde{\xi_j}(l)\right)$ and $\widetilde{\xi_j}(l) = l_j - \left[\frac{k_j}{T}\right]T$. Then, (17) becomes

$$E\{\widetilde{u_j}(l+B)\} = \left(1-\mu\, M_{\xi_j(l)}\right) E\{\widetilde{u_j}(l)\} \quad (24)$$

Looping equation (24), then we get

$$E\{\widetilde{u_j}(l+2B)\} = \left(1-\mu\, M_{f\left(\xi_j(l)\right)}\right) E\{\widetilde{u_j}(l)\} \quad (25)$$

Though, $T \leq A$ and $\%(A,T)$ is not equal to zero and $\mathrm{GCD}(A,T)$ is greater than one, looping the equation (25) $\mathrm{LCM}(A,T)$ times, then

$$\begin{aligned} E\{\widetilde{u_j}(l+\mathrm{LCM}(A,T))\} \\ &= \left(1-\mu\, M_{f\ldots\ldots f\left(\xi_j(l)\right)}\right) \times \ldots \\ &\times \left(1-\mu\, M_{\xi_j(l)}\right) E\{\widetilde{u_j}(l)\}, \end{aligned} \quad (26)$$

where $\mathrm{LCM}(A,T)/A$ is less than T, there is a one or more than one parameter in the set $\{M_1, M_2, \ldots\ldots, M_T\}$ that is not matched to input signal i.e., $E\{\widetilde{u_j}(l)\}$. The parameters is with the input signal i.e., $E\{\widetilde{u_j}(l)\}$ all are tiny values, the up-dation purpose of the input signal of $E\{\widetilde{u_j}(l)\}$ will be very slow, while resulting the interference.

2.3.4. Case Study 4

$T > A$ and $\%(A,T) = 0$

In this case the divergence would become $\sigma_y^2(l_j - j + 1) = M_{\xi_j(l)}$ in this equation $\xi_j(l)$ would be taken as positive integer and having an equal probability for taking on those values of $[\widetilde{s_j}, \widetilde{s_j}+A, \ldots, \widetilde{s_j}+T-A]$ where $0 < \widetilde{d_j} < A$ is related to d_j through $\widetilde{d_j} - d_j = z$, where z=0, 1, 2,…. Then we get

$$E\{\widetilde{u_j}(l+B)\} = \left(1-\mu M_{\left(\xi_j(l)\right)}\right) E\{\widetilde{u_j}(l)\} \quad (27)$$

Looping equation (27), we get

$$E\{\widetilde{u_j}(l+2B)\} = \left(1-\mu M_{q\left(\xi_j(l)\right)}\right) E\{\widetilde{u_j}(l)\} \quad (28)$$

$$q\left(\xi_j(l)\right) = \begin{cases} \xi_j(l) + A & \xi_j(l) + A \leq T \\ \xi_j(l) + A - T & \text{otherwise}\,. \end{cases}$$

Here T is greater than A and $\%(A,T)$ is equal to zero, looping equation (28) T/A number of times, we get

$$\begin{aligned} E\{\widetilde{u_j}(l+B)\} \\ &= \left(1-\mu M_{q\ldots\ldots q\left(\xi_j(l)\right)}\right) E\{\widetilde{u_j}(l+T-A)\} \\ &= \left(1-\mu M_{g\ldots\ldots g\left(\xi_j(l)\right)}\right) E\{\widetilde{u_j}(l+T-A)\} \end{aligned} \quad (29)$$

If all values in the taken set $\{M_{q(\xi_j(l),\ldots}, M_{g\ldots g\left(\xi_j(l)\right)}\}$ have very tiny values, up-dation for input signal i.e., $E\{\widetilde{u_j}(l)\}$ might be slightly slow, sequential PU-LMS might show very low interference.

2.3.5. Case Study 5

$T > A,\ \%(A,T) \neq 0$ and $\mathrm{GCD}(A,T)$ is equal to one. Likewise coming to case 2, the Sequential PU-LMS is stable if equation-24 obeys the step-size. $T > A,\ \%(A,T) \neq 0$ and $\mathrm{GCD}(A,T)$ is greater than one. Likewise looking to case-3, the sequential PU-LMS faces the low interference. Note: We learned from this that for input signals with regularly time-varying variance (observe equations-2, 3, 4, and 15), the sequential Partial Update-LMS method would not confront the low intersection challenging condition in case-2 or case-5. A and T become co-prime integers in just two situations, with the $\mathrm{GCD}(A,T)$ equal to 1. A and T are not co-primes, and the sequential Partial Update-LMS algorithm may demonstrate a very sluggish intersection, depending on how the repeating power levels were balanced.

3. SIMULATION RESULTS

In this simulation part, the response of a signal with one DOA comes at the base station with an angle of 60 degrees. Threshold values of 0.1, 0.5 and 1 simulation results are conducted. For each threshold point interference rate is considered in terms of the samples which we have used to reach the steady state. From the simulation results clearly, we can know that the received signal converges at a mean square error of 0.0007. Generally, if we observe the simulation results for α = 0.5 and 1, steady state converged faster when compared to the conventional LMS algorithm and also, we can clearly observe the delay period for these threshold points. This delay corresponds to the samples which are observed before the adaptive antenna is ready to adapt. The improvement in interference rate purely depends on the number of taps adapted.

3.1. One white signal three DOAs

In this module effects of multipath in antenna systems are studied for various threshold conditions. Three multipaths with the three different directions of arrivals of 60, 30 and -20 degrees are transmitted to a base station with the different sampling periods. Hence, three signals are arrived with time differences of $t,\ t-1$, and $t-2$ each with amplitudes of 0.6, 0.75 and 1.0. Using the PU-AL algorithm three different weight updating equations are used for processing each multipath signal. These

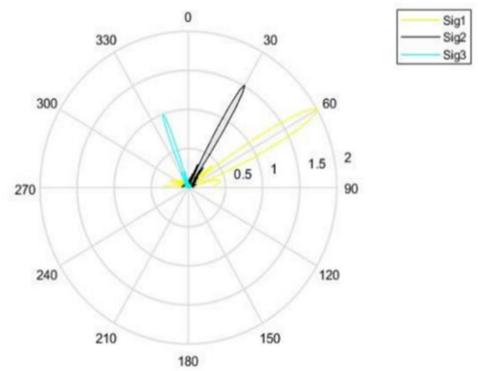

Figure 5. Beam Pattern of one white signal with 3 DOAs using PU-AL for α = 0.1.

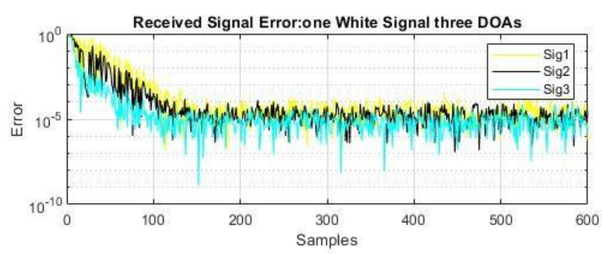

Figure 6. Received Error Signal of one white signal with three DOAs using PU-AL for α = 0.1.

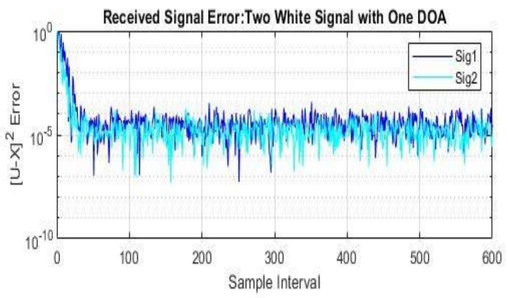

Figure 7. Received Error Signal of two white signal with one DOA using PU-AL for α = 0.1.

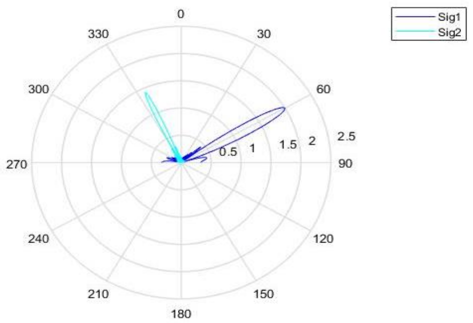

Figure 8. Beam pattern of two white signals with one DOA using PU-AL for α = 0.1.

simulation results are conducted at threshold values of 0.1, 0.2 and 1. Interference tables are for each multipath signal is shown in terms of samples to reach the steady state. For each multipath signal, the mean square error is approximately lies between 0.006, 0.0014 and 0.00036 respectively and their simulation output is shown in Figure 5. Beam patterns of the proposed PU-AL algorithm are shown in Figure 6. From that, we can clearly say that the proposed algorithm is having a better ability to steer the beams in different directions, and nulls are placed in the place of interferences. Gain of the beam is obtained corresponding to gain introduced by each multipath signal.

3.2. Two white signals with one DOA each

Transmitting of one signal with two multipath signals and two white signals with one DOA effect which is similar. In those cases, two signals are uncorrelated to each other, and it is divided by one sample period. Firstly, the signal with an amplitude of 0.5 and the second signal with an amplitude of 1.0 is considered. The interference table of each signal in terms of the number of samples is shown. From this, we can know that smaller gain amplitudes lead to longer responses to adapt taps and for estimated signals. For $\alpha = 0.1$ value, it will converge faster when compared to 0.2 and 1. From this delay is created for these values so it takes a longer time to the response before adaption of taps. These threshold points can adapt to the limited number of taps and it affects the system performance and its simulation output in Figure 7. The beam pattern is shown in Figure 8 with two beams corresponding to the DOAs at 60 and -25 degrees. This demonstrates a smart antenna system with desired signals and interfering ones.

Beamforming technique as sensing technique in cognitive radio network Inside this work, we attempted to explain the beamforming approach in cognitive radio as spectrum sensing. This beamforming approach may be used in two ways:

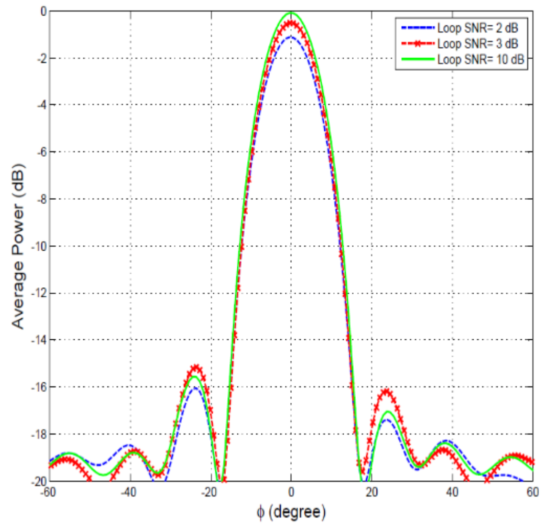

Figure 9. Average power vs. Direction of Antenna.

centralized or distributed. We've used a dispersed strategy in this case. Cognitive radio may use the beamforming approach to target a specific beam onto a specific receiver while reducing involvement in surrounding directions, improving network performance. This distributed method gives each user a separate antenna, and several of them broadcast the signal together by manipulating the transmitter's carriers. The authorized users' interference is lessened when this method is used. Cognitive radio would be able to expand the range of communication by employing this beamforming approach in the signal beam is vigorous to the appropriate direction by this spectrum. Another benefit of this beamforming technology is that it reduces delay spread, multipath fading, and radio transmission on the same frequency channel as other interferences, among other things.

The diagram depicted in the illustration is a geometrical representation of a cognitive radio network at the intended receiver location, which includes licensed users. There are *K* cognitive users who are uniformly scattered over a disc with a radius of R and a centre of P. Assume the cognitive radio users' position is (SK, $k), which is polar coordinates. Similarly, use the specified spherical coordinates to represent the receiver. We made the assumption that cognitive radio nodes are uniformly dispersed across a disc with a radius of R. A single antenna is provided for each node. Because the channel between the users and the receiver is in line of sight, there is no shadowing. The principal users, also known as licensed users, the transmitters are in the far zone of the beam pattern, while the receivers are in the near zone. The simulation depicts the statistical distribution of the radiation pattern in the lobe that includes the direction in which radiation strength is greatest (major lobe) and lobes that do not contain the main lobe (sidelobes). These are generally rays that are aimed in an unfavourable direction. It is used to examine these power levels by running 10,000 trials to create a beam pattern. The radius of the disc is *R*/(lambda) = 2, azimuth angle = 0 degrees, and elevation angle = pi/2, all of which are regularised by wavelength. These cognitive users employ uniform distribution, with numbers such as 4, 7, 16, 100, and 256 being used. The signal-to-noise ratio in the loop (SNR) of the phase loop locked output variance is expected to be 2 dB, 3 dB, and 10 dB as shown in Figure 9. At an angle of 20 degrees and 30 degrees, two licensed users or principal users are presumed to be present.

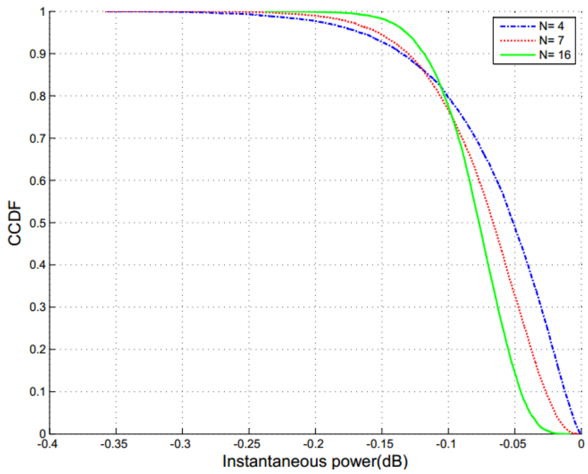

Figure 10. CCDF vs. Instantaneous Power.

The beampattern Phase-only distributed beamforming (PODB) approach does not have a perfect phase in the diagram above. In this situation, the number of users is 100. The average gain for loop SNR 10 dB is 0 dB at an angle of 0 degrees, whereas the gain marginally reduces for loop SNR 2 dB and 3 dB. Because of the incomplete phase, the main lobe is at its apex. The users are at a 20-degree and 30-degree angle, respectively, therefore the sidelobe power is about equal to -20 dB.

The cumulative complementary distribution function (CCDF) of PODB with phase offset is shown in the figure above for K values of 3, 8 and 15. The proportion of equal to or more than a certain power level beampattern is shown in Figure 10. For the CCDF computation, we ran 10,000 simulations. For a loop SNR of 10 dB, the angle would be set to 0 degrees. For values of 4, 7 and 16, the major lobe is at its highest. Finally, we employed the sequential partial update in this case. The least-square technique is used to repair errors caused by altering antenna element placements. The error between the actual and expected replies is reduced with this approach.

4. CONCLUSION

This paper has analysed the Spectrum sensing issue using the beamforming technique in that we have used an algorithm for the input signal is sequential PU-AL. Here we have taken the input signal as cyclostationary signal with white Gaussian noise and we have analysed the input signal using PU-AL in different case studies and these case studies also represent how the sequential PU-AL tolerate the convergence related issues. We have implemented many new things as a result of our project, to keep up with technological advancements. Nowadays, we rely on online sources for everything instead of utilizing the spectrum that is available not only now but also in the future to save money. By employing this approach in the future, stricter bounds on the rate of convergence can be achieved. For stationary signals, a mean update equation of PU-AL can be developed. It can also be looked at the techniques that can be used to analyse the performance of the Max PU-AL algorithm.

REFERRENCES

[1] S. Surekha, Md Zia Ur Rahman, Navarun Gupta, A Low Complex Spectrum Sensing Technique for Medical Telemetry System, Journal of Scientific & Industrial Research, Vol. 80, pp. 449-456, May 2021.

[2] J. Divya Lakshmi, Rangaiah. L, Cognitive Radio Principles and Spectrum Sensing, Blue Eyes Intelligence Engineering & Sciences Publication, Volume-8, August 2019, pp. 2249 – 8958.

[3] Omi Sunuvar, A study of distributed beamforming in cognitive radio networks, 2013.

[4] Numa Joy, Anu Abraham Mathew, Beamforming for Sensing Based Spectrum Sharing in Cognitive Radio Network, International Journal of Engineering Research & Technology (IJERT), 2015.

[5] Hyils Sharon Magdalene Antony, Thulasimani Lakshmanan, Secure Beamforming in 5G-Based Cognitive Radio Network, Symmetry, 2019.
DOI: 10.3990/sym11101260

[6] Kais Bouallegue, Matthieu Crussiere, Iyad Dayoub, On the impact of the covariance matrix size for spectrum sensing methods: beamforming versus Eigen values, IEEE, 2019.
DOI: 10.1109/ISCC47284.2019.8969741

[7] Aki Hakkarainen, Janis Werner, Nikhil Gulati, Damiano Patron, Doug Pfeil, Henna Paaso, Aarne Mammela, Kapil Dandekar, Mikko Valkama, Reconfigurable Antenna Based DoA Estimation and Localization in Cognitive Radios: Low Complexity Algorithms and Practical Measurements, 2014.

[8] Yu Sing Xiao, Danny H. K. Tsang, Interference Alignment Beamforming and Power Allocation for Cognitive MIMO-NOMA Downlink Networks, IEEE, 2019.
DOI: 10.1109/WCNC.2019.8885714

[9] Md. Zia Ur Rahman, V. Ajay Kumar and G V S Karthik, A Low Complex adaptive algorithm for Antenna beam steering, IEEE, 2011.
DOI: 10.1109/ICSCCN.2011.6024567

[10] Janis Werner, Jun Wang, Aki Hakkarainen, Danijela Cabric,Mikko Valkama, Performance and Cramer-Rao Bounds for DoA/RSS Estimation and Transmitter Localization Using Sectorized Antennas, IEEE Transactions on Vehicular Technology,Volume: 65, May 2016.
DOI: 10.1109/TVT.2015.2445317

[11] N. J. Bershad, E. Eweda, and J. C.M. Bermudez, Stochastic analysis of the LMS and NLMS algorithms for cyclostationary white Gaussian inputs, IEEE Trans. Signal Process., vol. 62, no. 9, pp. 2238–2249, May 2014.

[12] M. Z. U. Rahman, S. Surekha, K. P. Satamraju, S. S. Mirza, A. Lay-Ekuakille, A Collateral Sensor Data Sharing Framework for Decentralized Healthcare Systems, IEEE Sensors Journal, November 2021.
DOI: 10.1109/JSEN.2021.3125529

[13] S. Surekha, Md Zia Ur Rahman, Spectrum Sensing for Wireless Medical TelemetrySystems Using a Bias Compensated Normalized Adaptive Algorithm, International Journal of Microwave and Optical Technology, vol. 16, 2021, no.2, pp. 1-10

[14] S. Surekha, A. Lay-Ekuakille, A. Pietrosanto, M. A. Ugwiri, Energy Detection for Spectrum Sensing in Medical Telemetry Networks using Modified NLMS algorithm, 2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2020, pp. 1-5,
DOI: 10.1109/I2MTC43012.2020.9129107

[15] Shafi Shahsavar Mirza, Nagesh Mantravadi, Sala Surekha, Md Zia Ur Rahman, Adaptive Learning Based Beamforming for Spectrum Sensing in Wireless Communications, International Journal of Microwave and Optical Technology, vol. 16, 2021, no.5.

[16] Armando Coccia, Federica Amitrano, Leandro Donisi, Giuseppe Cesarelli, Gaetano Pagano, Mario Cesarelli, Giovanni D'Addio, Design and validation of an e-textile-based wearable system for remote health monitoring, ACTA IMEKO, vol.10, no.2, pp. 1-10, 2021.
DOI: 10.21014/acta_imeko.v10i2.912

[17] Ayesha Tarannum, Zia Ur Rahman, L. Koteswara Rao, T. Srinivasulu, Aimé Lay-Ekuakille, An Efficient Multi-modal Biometric Sensing and Authentication Framework for Distributed Applications, IEEE Sensor Journal, vol. 20, no. 24, 2020, pp.

15014-1515025.
DOI: 10.1109/JSEN.2020.3012536
[18] S. Y. Fathima, K. Murali Krishna, Shakira Bhanu, S. S. Mirza, Side Lobe Suppression in NC-OFDM Systems Using Variable Cancellation Basis Function, IEEE Access, Vol.5, no.1, 2017, pp. 9415-9421.
DOI: 10.1109/ACCESS.2017.2705351
[19] Imran Ahmed, Eulalia Balestrieri, Francesco Lamonaca, IoMT-based biomedical measurement systems for healthcare monitoring: a review, Acta IMEKO, vol. 10, 2021, no.2, pp. 174 - 184.
DOI: 10.21014/acta_imeko.v10i2.1080
[20] K. Murali Krishna, K. Krishna Reddy, M. Vasim Babu, S.S. Mirza, S.Y. Fathima, Ultra-wide band Band-Pass Filters Using Plasmonic MIM Wave guide Based Ring Resonators, IEEE Photonics Technology Letters, vol.30, 2018, no.9, pp. 1715-1718.
DOI: 10.48084/etasr.4194