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LEAST SQUARED CONSTANT MODULUS FOR OPTIMIZED ERROR ESTIMATION IN BEAMFORMING UNIT

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Abstract

Radio frequency (RF) management is very important in communication system considering the limited availability of spectrum. In modern technology such as WiFi and 5G, beamforming found relevance in the management of radio frequency for optimization of signal to noise ratio thereby improving network capacity, spectral efficiency, and coverage range. In this paper, beamforming technology was studied and the results of the behavior of the error signal generating unit were observed. Blind adaptive algorithm was considered over non-blind adaptive algorithm to control the output of the combiner in the beamforming structure and also helped to focus the beam to the desired direction.Thus, utilizing the narrow lobe with maximum power and rejecting side lobes which it sees as interference, thereby supported maximum transmission. Equalizer filters which are made up of finite response filters were used to weigh the signals impinging on the elements of the receiver antenna. The output of the equalizer filters were fed directly to the combiner which used a diversity combining approach based on the principle of maximum combining ratio to combined the signal from each antenna array logically to produce improved signal strength. The output of the combiner and desired signal from the decision feedback structure were used to update the error signal in the signal processing unit for weights adaptation to changes in the radio environment based on the angle of arrival. Least Square Constant Modulus Algorithm (LSCMA) was employed for the estimation of error signal in the beamforming unit. The proposed model of the LSCMA was simulated and compared with the conventional constant modulus. From the result of the simulation models it showed that LSCMA minimized error better than the conventional Constant Modulus Algorithm (CMA). For conventional CMA, error increases with an increase in signal power received while with LSCMA, error decreases with an increase in signal power received. A suitable adaptive algorithm for the beamforming unit of the system was proposed and represented in a flow chart.

Keywords: Radio frequency, Least Square Constant Modulus Algorithm, Beamforming, Maximum combining ratio, Conventional Constant Modulus.

1. INTRODUCTION

Beamforming is used in the management of radio frequency (RF). The concept behind beamforming was invented in the early 1990s and found relevance in the latest wireless technology such as Wi-Fi and fifth-generation (5G) networks. This technology is used to direct wireless signals from multiple antennas toward a specified receiving device. Application of this technology is also relevant in radar, acoustics, and sonar. Beamforming is used to control the directionality of the transmission or reception of an antenna array. It provides a better signal-to-noise ratio (SNR) with improved network spectral efficiency, capacity, and cell range of a communications system making communications more effective, given the deployment of several nodes among mobile device users with stronger, clearer signal signals (Poor et al, 2014).

In wireless communication systems, transmission signals from base stations (BSs) with multiple antennas to one or multiple pieces of user equipment are done using transmit and receive beamforming. User's received signal power are maximized with transmit beamforming. This technology minimizes the interference signal power from the other users by concentrating different transmitters with different phases and amplitudes to transmit the same signal to a selected antenna thereby increasing capacity (Park and Lee, 2022).

Researchers having foreseen the great potential in beamforming, have carried out commendable research works on its applications in some technology and the area to carry out future research is still broad. In millimetre wave (mm-wave) communications, the evolution and advancements in antenna beamforming were studied for different settings for different requirements for indoor and outdoor communication scenarios, and beamforming techniques were introduced by stating some basic concepts of beamforming, which include typical beamforming architectures and approaches (Lee and Lee, 2023). An overview of signal processing for mm-wave wireless communication systems was done by Heath et al. (2016). They described the main mm-wave- MIMO architectures including analogue and hybrid beamforming for different types of propagation models. Also, they reviewed the algorithm for channel estimation and protocols for training beam training protocols were reviewed in detail for mm-wave communications. Ning and Tian (2023) discussed the types of beamforming techniques which can be deployed for massive MIMO systems according to 5G requirements. It focused on the classifications of beamforming techniques for wireless communication systems and investigated their effects on massive MIMO systems to determine which optimal categories can be adopted with massive MIMO system requirements. An in-depth overview of up-to-date research on classifications of beamforming techniques that can be deployed for massive MIMO systems was provided by the researchers in the work. Discussion on algorithms was done too.

Furthermore, beamforming system is made up of the following units; input from the antenna, filters, flow lines, combiner, decision feedback system, and the signal processor (Vouyioukas, 2013). The input for the beamforming processing unit was gotten from the antenna designed. Equalizer filters were considered for this work. These filters are made up of a finite response filter design. The coefficients were gotten by sampling a known pulse shape and using the sampling in reverse order as the filter coefficients. It was used to correct losses in the transmission of the signal using its capability in making the output to be equal to the input and making inconsistence frequency response flat thereby giving all frequencies equal energy. This was achieved by weighing the input of each element with the inverse of the transmission coefficient. Combining units was based on a diversity combining approach which logically combines the signals from each antenna array to produce gain. It used a maximal ratio combining scheme to combine the outputs of all the weighted signal (output of the equalizer filters) antenna arrays to maximize the ratio of combined received signal power to noise and antenna power gain. Diversity combining does not guarantee maximizing the gain for any particular node.

However, to determine the combining strategy to maximize the total signal power received rather than that of a particular node, the effective antenna pattern provides peak gain to radiators of the desired node regarding other co-channel nodes as interference. The combiner adds the signal weighed by the equalizer filters and output to compare with the desired signal to generate an error signal. The objective of this work is to provide the best tool for estimating the error signal to help get the desired outcome from the beamforming system, hence least square constant modulus algorithm (LSCMA) was proposed for use. In this work, an adaptive blind algorithm used for signal processing was proposed for study. The adaptive algorithm was used by the processor to control the adaptation of the weights to changes in the environment based on angle of arrival. It updates the equalizer tap weights using an adaptive blind algorithm based on least square constant modulus algorithm (LSCMA).

2. LITERATURE REVIEW

2.1 THEORY OF THE WORK

Beamforming techniques include the following;

i. Analog beamforming

ii. Digital beamforming

iii. Hybrid beamforming

iv. Massive MIMO

Analog Beamforming: This type of beamforming sends the same signal from multiple antennas using phase-shifters (Rozé et al, 2016). The phases of the signal are set to be different, resulting in an antenna pattern that points in a specific direction. The signal phases of antenna signals are adjusted in an RF domain, thereby improving radio coverage.

Digital Beamforming: In this type of beamforming, each antenna has different signals in a digital baseband. Following the law of reciprocity, digital receivers are placed at the radiating elements of each antenna. For more flexibility digital beamforming, different phases are applied to different frequency bands. Numerous independent beams are steered by a digital beamforming processor in any direction as desired. This is technology is relevant in spatial multiplexing technology (Venkatesham, 2013).

Hybrid Beamforming: This technique involves the combination of analogue and digital beamforming (Han et al, 2015). This can be used in 5G base stations. The hybrid approach combines analogue beamforming alongside with digital precoding, for multi-stream transmission, forming radiating beam patterns transmitted from an antenna array.

Massive MIMO (Multiple Input and Multiple Output):- this is an antenna technology used in wireless communication networks designed with multiple antennas (Swindlehurst, 2014). Application of Massive MIMO is in technology such as wireless communication systems, Wi-Fi, and 5G technology. In steering the antenna in Massive MIMO to desired direction, a common frequency is applied. This technology uses digital signal processors and its application is robust in combating multipath interferences. Path redundancy is provided by the multiple time-division duplexing channels formed by the arrival times of the different signals.

Beam Steering: - this type of beamforming involves changes in the phase of input signals on each radiating antenna element. In this technology, the receiving device is tracked by steering a signal to it. It uses a common frequency to steer a signal beam in the desired direction.

Benefits of Beamforming:

i. Directs more power to the beam's specified direction.

ii. Improves the signal quality that reaches the receiving device, thereby increasing the coverage capacity of the cell tower or base station.

iii. Reduced error and latency.

iv. Enhances Signal interference avoidance.

v. Analog beamforming is relatively simple to implement and has lower power requirements.

Current Challenges of Beamforming:

i. More computing resources and power for beamforming calculations are required sometimes.

ii. Digital and massive MIMO beamforming systems may be more complex, especially considering more antennas and other hardware used.

iii. High cost than traditional systems.

2.2 REVIEW OF RELATED WORKS

Several researches have been carried out in this area of study. According to (Bassoy et al, 2017 and Iwamura et al, 2010), the achievable data rate on each link of the node of the beam former will be significantly reduced as the number of connected users and/or devices increases. This is despite the fact that some advanced methods, such as multiple-input multiple-output (MIMO) technologies, coordinated multi-point (CoMP) technologies, and carrier aggregation (CA) technologies may boost the data rate reaching several Gbps in mmWave communications. Similarly, a significant number of low-power tiny cells would be deployed, giving rise to heterogeneous networks (Het- Nets), according to academic and industrial research, to further increase throughput, improve spectral efficiency, and increase connections as opined by the researches carried out by Zhang (2015) and Jianping (2017). Meanwhile, various multiple access technologies have been explored to satisfy the aforementioned requirements, including orthogonal time-frequency space (OTFS), according to the results of the work of Hadani et al (2018), rate-splitting, resulting from the research work of Dai (2015) and non-orthogonal multiple access (NOMA) which are results from Kabir (2010) and Ding (2017). These reviews deepened the interest and quest for further study and increased research in this field.

3. METHODOLOGY

3.1 Estimation of the Direction of Arrival (θ) of Wave Signal at the Receiver Antenna

For the receiver, the same antenna designed for transmitting was used for receiving purposes based on reciprocity. All the parameters are the same except that in the receiver, signal power received was weighted and combined while in the transmitting mode, the signal from the single source is fed equally to the elements. It was assumed to combine the signals impinging on the arrays of the antenna using an adaptive equalizer-combiner. The result was used to maximize the gain hereby increasing the directivity of the antenna and reduced interference when compared with the switched beam antenna system. This was done to concentrate RF power toward each node of a radio channel when required, therefore limiting the interference to other nodes in adjacent cells. To actualize the beam steering capability, phased array technology was used. It uses the angle of arrival to control the radiation pattern of the antenna focusing on the desired receiver node while treating others as interference.

Non-parametric technique was used to estimate the direction of arrival of the received signal (θ) and the desired area was scanned using Beamscan algorithm. This was done by changing the angle of elevation and angle of azimuth in Matlab platform. From the result of the observation shown in figure4.1, the azimuth angle was seen to be equal to the broadside angle. The direction of arrival of the signal was measured in a clockwise direction from the broad side of the array. The algorithm showed the power output of each beam scan angle and the one with maximum power was assumed to be the direction of the arrival signal (θ).

In modelling a uniform linear array signal, the number of elements of the antenna array (N) was chosen to be equal to 5, the antenna equal spacing (d) to be 1/2wavelength and two narrowband signals impinged on the array. This was done with MATHLAB tools. The first signal arrives from 40 degrees in azimuth and 0 degrees in elevation, while the second signal arrives from 20 degrees in azimuth and 0 degrees in elevation. The operating frequency of the system is 2.4GH z and 5.0GHz. To determine the direction of arrival of the two signals, estimated from the broadside angle which is measured from the broadside of the uniform linear array since the angle of elevation and azimuth cannot be obtained at the same time. From the observation, it showed that the broadside angles are the same as the azimuth angles. Whenever elevation is zero, the azimuth will be within [-90,90]. This covers the 180-degree scanning region.

Let signal transmitted = s(t) and signal impinged on receiver antenna element = s(t) using a uniform linear array as proposed in this work.

Then, the signal incident on the element in the figure 3.1 expressed as

$$X_1(t) = s(t)\exp\left(j\frac{2\pi}{\lambda}(i-1)dcos\theta\right) + n(t)\,, i = 1,2,3\ldots \quad 3.1$$

Assuming the signal arriving on the element i are of same frequency (fc) with incident angle θ, I = 1, 2, 3… N, signal transmitted be s_1 (t), s2 (t)…s_N (t) and the received signal X_N(t) being equal to the sum of the incident signal and noise.

Then the total signal incident on the receiver is represented as;

$$\therefore X(t) = \sum_{i=1}^{n} h(\theta_i)\, s_i(t) + n(t) \quad 3.2$$

Where n(t) is considered as a matrix N X 1 vector of the noise at array elements.

$$h(\theta_i) = \begin{bmatrix} 1 \\ e - jkr1 \\ e^{-jkr_2} \\ \cdot \\ \cdot \\ \cdot \\ e^{-jkr_N} \end{bmatrix} \qquad 3.3$$

$$h(\theta_i) = \begin{bmatrix} 1 \\ e^{-\frac{j2\pi \ \ dcos\theta_i}{\lambda}} \\ \vdots \\ e^{-\frac{j2\pi\,(i-1)dcos\theta_i}{\lambda}} \end{bmatrix} \qquad 3.4$$

Where $h(\theta_i)$ *is the steering vector.*

Representing equation 3.2 in matrix form, X(t) = $h(\theta_i$ x(t) +n(t)

∴ h is MxN matrix of the steering vectors.

$$h(\theta_i = [h\theta_1 \quad h\theta_2 \qquad --- \quad h\theta_N] \qquad 3.5$$

$$s(t) = \begin{bmatrix} s_1 & (t) \\ s_2 & (t) \\ \cdot & \\ \cdot & \\ \cdot & \cdot \\ s_N & (t) \end{bmatrix} \qquad 3.6$$

Expressing equation in vector form, we have;

$$\text{Xi(t)} = [h\theta_1 \quad h\theta_2 \quad -- \quad h\theta_N]\, X \begin{bmatrix} s_1 & (t) \\ s_2 & (t) \\ \cdot & \\ \cdot & \\ \cdot & \cdot \\ s_N & (t) \end{bmatrix} \qquad 3.7$$

$X_i(t) = h\,(\theta)x_i(t)$ 3.8

s_i(t) = input of the data vector.

The result of the observation done on Matlab platform using equation 3.8 was analysed using Figure 4.1.

3.2 Estimation of Error and Weights

Blind algorithm was chosen based on its ability to make weight adapt to change without training because, during training, the channel will be idle, that is, no transmission will be allowed to take place. Also, it does not require an additional component to update the weight, it uses the error signal to make the weights adapt to changes in the environment. Least square modulus was chosen over the conventional CMA because it has the capability of converging faster when compared with the conventional CMA.

In determining the error signal, the output of the combiner and the desired output from the decision feedback unit were used. The difference between the output from the combiner and the desired output is the error.

The weights are determined using the current weights, a signal input from the antenna, step function, and the error signal. To determine the weights, let the received signal be equal to Xi and the transmitted signal be equal to S(t).

Then,

$$X_i = hS_i + n_i(with\ interference\ inclusive) \qquad 3.9$$

With$|S_i| = 1_i$

constant modulus for all i and the source being unknown. To determine the weight vector of the receiver (W), At the initial stage, the weight vector is defined such that the output of the beamformer is represented as;

$$y_i = W^H X_i \qquad 3.10$$

The system is desired in such a way that the desired output from the feedback unit will be;

$$\hat{S_\iota} = y_i * \frac{\overline{y_\iota}}{|y_i|}$$

Identifying w for$\overline{y_\iota} = 1 \quad for\ all\ i$

For optimization using CMA,

$$\min_w J(w) = E[(|y_i|^2 - 1)^2] \qquad 3.11$$

To determine the current weight, update the weight using stochastic gradient,

⇨ $Wnew = Wcurrent + \Delta Wcurrent$

$\because Wnew = Wcurrent + (StepSize)\, ue*$

$$W_{i+1} = W_i + \mu X_i(|y_i|^2 - 1)\overline{y_i}^* \quad 3.12$$

Where w is a vector of all weights W_i, X is a vector of all inputs X_i and the * operator denotes the complex conjugate

$$W_{i+1} = W_i - \mu\nabla J(w_i), \quad 3.13$$
$$where\ \mu = step\ size.$$

To compute for gradient;

$$|y_i|^2 = y_i\overline{y_i} \quad 3.14$$

$$|y_i|^2 = W^H X_i X^H W \quad 3.15$$

Then,

$$\nabla J(w) = 2E[(|y_i|^2 - 1) - \nabla(W^H X_i X^H W)] \quad 3.16$$
$$= 2E[(|y_i|^2 - 1) - X_i X^H]$$

$$= 2E[(|y_i|^2 - 1)\overline{y_i}\ X_i] \quad 3.17$$

Implementing the conventional CMA in weight update,

$$J(w) = E[(|y_i|^2 - 1)^2] \quad 3.18$$

$$J(w) = E[(|W^H X_i|^2 - 1)^2]$$

$$y_i = W^{(i)H} X_i$$

$$W^{(i+1)} = W^{(i)} - \mu X_i(|y_i|^2 - 1) \quad 3.19$$

Estimating error using the least square constant modulus algorithm,

$$y_i = W^{(i)H} X_i \quad 3.20$$

$$\therefore Error\ update(e) = \widehat{S_i} - W^H X \quad 3.21$$

And the estimated desired output will be;

$$\widehat{S_i}^{(k)} := \frac{\overline{y_1}}{|y_1|}, \quad \frac{\overline{y_2}}{|y_2|}, \quad \frac{\overline{y_3}}{|y_3|}, \dots, \frac{\overline{y_N}}{|y_N|} \quad 3.22$$

$$W^{(i+1)} = W_{i-}\mu\left(\widehat{S_i}^{(i)} - y(i)\right)x(i) \quad 3.23$$

Note: The step size used by the adaptive algorithm is specified as a positive scalar. Increasing the step size reduces the equalizer convergence time. The result of the error estimation of Equation 3.21 was analyzed using Figure 4.2.

3.3 Development of an Adaptive Algorithm Suitable for the Beamforming Unit of the System Considered.

Blind algorithm was chosen in this work for the adaptive algorithm based on the fact that it does not require a sequence of training and no additional component is needed for training. It used the properties of the desired signal received to adjust to changes in the radio environment under study. Also during training, the channel will be idle i.e. no transmission is permitted to take place and data cannot be sent over the radio channel. This affects the network spectral efficiency negatively. Blind algorithm adopted was based on DOA (blind algorithm) and used for the control of the system. Considering the fact that channel and DOA are time-varying factors, constant weights used in beam forming cannot track these varying factors, therefore, the adaptive algorithm used in the beamforming system causes the antenna to change its response dynamically to the changes in the signal environment. The signal processor modified its parameter with the error signal resulting from the differences in the output signal from the combiner and internal feedback control as the antenna operates. The combiner was designed to add the signal weighed by the equalizer filters and output was used to compare the desired signal from the decision feedback to generate an error signal using least square constant modulus algorithm (LSCMA). In this work, an adaptive algorithm used for signal processing was proposed and discussed in this section. The processor uses the adaptive algorithm to control the adaptation of the weights to changes in the environment based on angle of arrival as shown in Figure 3.3 below. It updates the equalizer tap weights using an adaptive blind algorithm based on least square constant modulus algorithm (LSCMA). This was chosen over non-blind algorithm based on the fact that during training in non-blind algorithm, no transmission is done and it requires additional components. But blind algorithm uses the available resources that is, the difference between the desired signal and the output of the combiner to control the weights.

The complex weights are adjusted by the control using an adaptive algorithm as seen in Figure 4.2.

The signal processing unit used this adaptive algorithm developed based on least square constant modulus principles as shown in error and weights estimation above which does not require training to adapt filter coefficients (weights). The algorithm is presented as follows:

1. Initiate the process

2. Define the weight

$$W_n = \begin{bmatrix} W_n(0) \\ W_n(1) \\ W_n(2) \\ W_n(3) \\ W_n(4) \end{bmatrix}$$

3. Define the inputs

x(n) = d(n)+ I(n)

Where d(n)= desired signals, I(n)= interfering noise,

4. Convolve the inputs with weights

$X(n)= x(n)*W_n$

5. Sum the equalizer filter output

$y(n)= \sum X(n)$

6. Generate the desired signal

7. Generate Error signal

$$(e) = \hat{S_\iota} - W^H X$$

Set the index i= 0,1,2,3,4

8. Is the error minimized?

IF YES, GO TO 12

IF NO, GO TO 9

9. Optimize the step size

10. Adjust the weight

11. Is weight adjusted?

IF YES, GO TO 12

IF NO, GO TO 4

12. Any more iteration?

IF YES, GO TO 3

IF NO, GO TO 13

13. output signal

14. continue

This algorithm is represented in a flow chart of Figure 4.2

4. RESULTS AND DISCUSSION

4.1 Estimation of Direction of Arrival of Signal

The angle of arrival for signal used in this work was estimated and represented in this figure 4.1 below. Analysis was done using this figure.

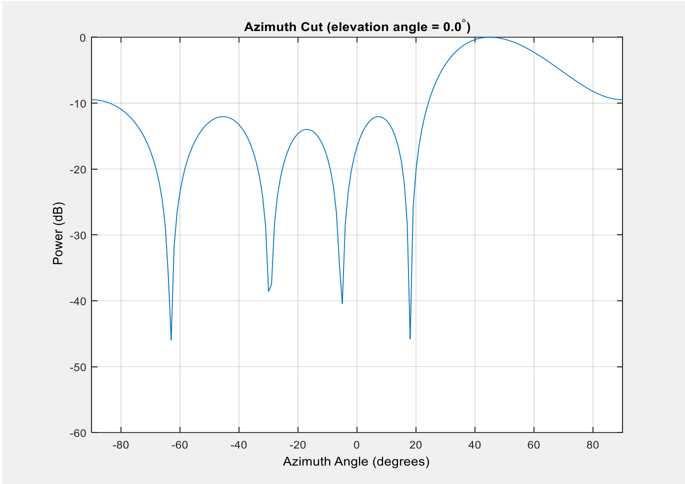

Figure 4.1: Result of Estimation of Direction of Arrival of Signal.

The angle at which the signal arrives on the elements was gotten from the broad side graph of Figure 4.1 showing that the main beam of the beamformer with maximum power. From the diagram of Figure 4.1, the largest lobe with maximum amplitude was seen around 20 degrees upward toward 80 degrees. The angle of arrival was estimated to be around 45 degrees from the broad side. It is the angle with maximum amplitude when compared with other lobes on the graph. This angle was used in estimating the weights in section 3.2 using Equations 3.21 and 3.23. It is the angle with the maximum amplitude when compared with the other lobes.

4.2 Presentation of Result from Estimation of Error and Weights signals Considered in the Development of an Algorithm used to make the Beamforming Unit Adaptive.

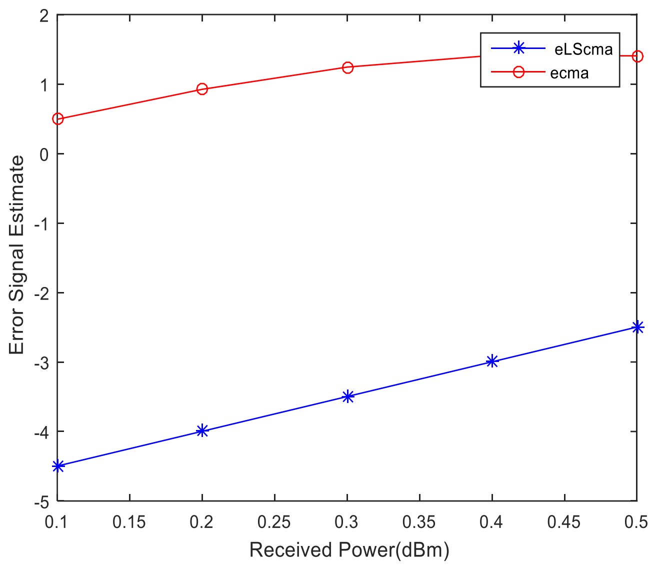

Figure 4.2: Conventional CMA versus Least Square CMA Error Estimation for Direct and Relayed Transmission Path

Figure 4.2 showed a graphical representation of the result from an estimation of error implementing conventional constant modulus and least square constant modulus. Comparing the results on the graphs. the conventional CMA error is high and it increases with an increase in input power. The high error showed that the difference between the output of the combiner and desired signal is high. This affects the signal received and the coverage range negatively. It showed that LSCMA minimized errors better than conventional CMA. Desired better performance requires minimized error signal, thus Least Square Constant Modulus was preferred to the conventional constant modulus scheme in error estimation.

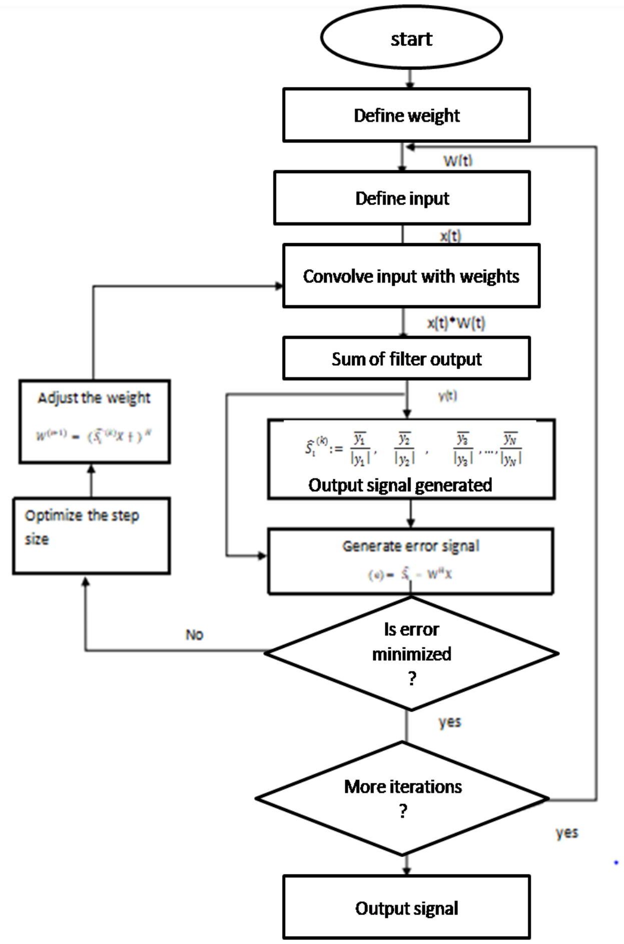

Figure 4.3: Adaptive LSCMA Algorithm for the System.

Figure 4.3 showed the flow graph of the adaptive algorithm developed based on the least square constant modules for estimating error for weight update.

5. CONCLUSION

Error estimation if properly estimated will help in actualizing the desired output. The result of the study showed that Least Square Constant Modulus Algorithm (LSCMA) had better error signal estimation with minimum error when implemented in beamformng system compared with Conventional Constant Modulus Algorithm (CMA).

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