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Enhanced Beamforming Techniques in Intelligent Antenna Systems

Rupesh Kumar Mishra*[1], Pavan Mankal[2], Suhasini Vijayakumar[3], Padmavathi Vurubindi[4], N. Nagalakshmi[5]

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Abstract: This research paper presents the development and optimization of a Smart Antenna system for advanced communications using the Signum Data Least Mean Squares (LMS) beamformer with Signum Double application. The mathematical model begins with defining the problem statement and system architecture, followed by a detailed signal model considering received signals, noise, and interference sources. Exploiting the LMS algorithm, the mathematical model describes the iterative weight adjustment process of the antenna array to optimize signal reception. Furthermore, to enhance system performance, the Kaiser Bessel window is applied to reduce peak side lobes, thereby improving the overall antenna array response. The effectiveness of the proposed approach SSDLMS-KW is evaluated through simulations under various communication scenarios, considering metrics such as signal-to-interference-plus-noise ratio (SINR). Results demonstrate the efficacy of the Smart Antenna system in achieving superior communication performance, making it a promising solution for next-generation wireless communication networks.

Keywords: *Smart Antenna, Signum Data LMS Beamformer, Advanced Communications, Kaiser Bessel Window, Peak Side Lobe Reduction, Signal Processing, Wireless Communication, Antenna Array Optimization.*

1. Introduction

The demand for efficient and reliable communication systems has led to the development of advanced Smart Antenna technologies. These systems utilize sophisticated signal processing techniques to enhance signal reception, mitigate interference, and improve overall communication performance. In this context, the Signum Data Least Mean Squares (LMS) beamformer, augmented with Signum Double application, emerges as a promising solution for optimizing Smart Antenna systems. By leveraging adaptive algorithms, such as the LMS algorithm, Smart Antennas can dynamically adjust the weights of antenna arrays to adapt to changing communication environments. Additionally, the integration of the Kaiser Bessel window further enhances system performance by reducing peak side lobes and improving the antenna array's response characteristics. As seen in Fig. 1, a smart antenna system's transmission and reception components are conceptually comparable. This paper focuses on the development and optimization of a Smart Antenna system for advanced communications, employing the Signum Data LMS beamformer with Signum Double application.

[1]*Associate Professor, Department of CS&AI, SR University Warangal*
[2]*Department of E&CE, Guru Nanak Dev Engineering College, Bidar, Karnataka.*
[3]*Professor Bharati Vidyapeeth's Institute of Management and Information Technology*
[4]*Associate Professor Department of Computer Science and Engineering Chaitanya Bharathi Institute of Technology (CBIT(A)) Hyderabad, Telangana*
[5]*Assistant Professor, Department of Information Technology, Anurag University*
** Corresponding Author Email: rupeshmishra80@gmai1.com*

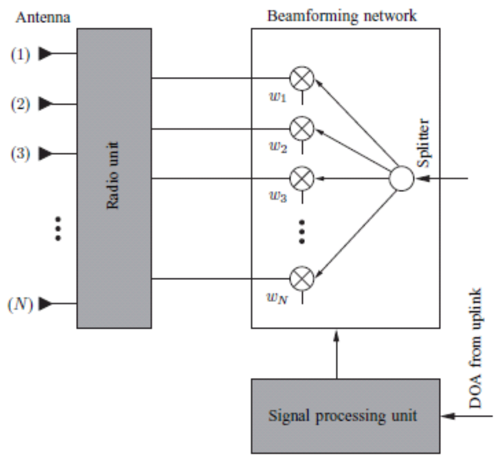

Fig 1: A smart antenna's transmission component.

We begin by outlining the system architecture and signal model, considering various factors such as received signals, noise sources, and interference sources. Subsequently, we describe the mathematical model governing the iterative weight adjustment process of the antenna array, facilitated by the LMS algorithm.

Furthermore, we discuss the application of the Kaiser Bessel window to mitigate side lobes, thereby enhancing system performance. Through simulations and analysis, we evaluate the effectiveness of the proposed approach in achieving superior communication performance, thereby demonstrating its potential for next-generation wireless communication networks.

Sunghyun Cho and Ji-Woong Choi's research, presented on downlink soft handover using multi-cell MIMO for 4G-LTE smartphones. Soft handover is a critical aspect of cellular communication systems, ensuring seamless transition between base stations to maintain connectivity. The authors propose leveraging multi-cell MIMO techniques to enhance downlink performance, aiming to improve data rates, coverage, and reliability for 4G-LTE smartphones [1].

In his paper presented the benefits and challenges of smart antennas for mobile communication systems. Smart antennas offer advantages such as increased coverage, capacity, and spectral efficiency. However, their deployment poses challenges related to complexity, cost, and compatibility with existing infrastructure. Tsoulos provides insights into the trade-offs involved in implementing smart antennas in mobile networks [2].

R.H. Kwong and E.W. Johnston's paper introduces the Variable Step Size VSSLMS algorithm, published in August 1990. This adaptive filtering algorithm dynamically adjusts its step size based on input signal characteristics, leading to faster convergence and improved performance compared to traditional LMS algorithms. The VSSLMS algorithm finds applications in various signal processing tasks, including noise cancellation, equalization, and system identification [3].

Molisch and M. Win's work with antenna selection. Antenna selection is a technique aimed at improving MIMO system performance while reducing complexity. By selecting a subset of antennas from a larger array based on channel conditions, antenna selection can increase capacity and reduce power consumption in MIMO systems. The authors discuss practical implementation strategies and evaluate the performance of MIMO systems with antenna selection [4].

The authors in [5] present an adaptive beamsteering algorithm designed to achieve beamforming with linear complexity, making it suitable for real-time implementation in CDMA systems. Through simulations, they validate the algorithm's effectiveness and compare its performance with existing beamforming techniques, demonstrating its advantages in mitigating multipath fading effects and enhancing signal reception in CDMA channels.

The authors in [6] proposed method utilizes directive elements on a conformal surface to estimate DOA accurately. This research contributes to improving the accuracy and reliability of DOA estimation techniques, enhancing the performance of wireless communication systems [6].

Antenna arrays offer significant advantages in mobile communication systems, including improved coverage, capacity, and interference rejection. Godara provides insights into beamforming techniques and their application in mobile communication scenarios, laying the groundwork for the development of smart antenna systems in wireless networks [7].

Hayes' work serves as a foundational resource for understanding the statistical principles underlying digital signal processing techniques, facilitating their application in various signal processing tasks and systems [8].

In [9], proposed utilizing neural networks to solve the MVDR beamforming problem, a technique widely used in array signal processing for steering the beam towards a desired direction while minimizing interference and noise. This research contributes to the advancement of beamforming algorithms by leveraging the capabilities of neural networks for adaptive signal processing [10].

Smart antennas offer benefits such as increased coverage, capacity, and interference rejection in wireless communication systems. This paper serves as a comprehensive resource for understanding the design and implementation of smart antenna systems in mobile networks [11][12].

Haykin's work serves as a foundational resource for understanding adaptive filter theory and its practical applications in signal processing systems [13]. Bernard Widrow and Samuel D. Stearns topics such as adaptive filters, gradient-based algorithms, and applications in noise cancellation and equalization. Widrow and Stearns provide insights into the theory and practice of adaptive signal processing, making it an essential resource for researchers and practitioners in the field [14]. The paper discusses the algorithm's theoretical foundation and its application in signal processing tasks such as equalization and demodulation [15].

The algorithm aims to improve the tracking performance of smart antennas in mobile communication systems by dynamically adjusting the weights of transmit antennas. This adaptive approach enhances the accuracy of signal reception and tracking in varying propagation environments, contributing to the overall performance of smart antenna systems [15].

The adaptive beamforming technique improves signal reception quality and enhances the system's ability to discriminate between desired signals and interference, leading to improved communication performance [16].

The robust Capon beamforming technique addresses the challenge of mismatch between the assumed and actual array responses in smart antenna systems. By incorporating robust optimization methods, the proposed technique improves the robustness of beamforming performance against mismatches, ensuring reliable signal reception in practical scenarios [17].

The robust presteering derivative constraints technique enhances the robustness of beamforming algorithms for broadband antenna arrays by incorporating constraints based on the derivative of the steering vector. This approach improves the resistance of beamforming algorithms to model uncertainties and environmental variations, leading to more reliable and accurate signal reception [18].

The paper investigates the impact of covariance matrix estimation errors on the performance of adaptive arrays and proposes diagonal loading as a method to mitigate estimation errors. Diagonal loading improves the robustness of adaptive arrays against estimation errors, enhancing their performance in practical applications [19].

The robust adaptive beamforming technique addresses the challenge of robustness in adaptive beamforming algorithms by incorporating constraints to minimize the effects of interference and noise. This approach improves the reliability and performance of adaptive beamforming in dynamic and noisy environments, making it suitable for practical applications [20].

The advantages of the described research paper are:

- **Development and Optimization:** The research paper focuses on the development and optimization of a Smart Antenna system, ensuring that the system is finely tuned to meet the requirements of advanced communications.
- **Utilization of Signum Data LMS Beamformer:** By employing the Signum Data Least Mean Squares (LMS) beamformer, the system benefits from efficient and effective signal processing techniques, leading to improved reception quality and overall system performance.
- **Integration of Signum Double Application:** The inclusion of Signum Double application enhances the functionality and capabilities of the Smart Antenna system, allowing for more sophisticated signal processing and adaptation strategies.
- **Comprehensive Signal Model:** The paper provides a detailed signal model that accounts for various factors such as received signals, noise, and interference sources. This comprehensive model ensures that the system design considers real-world communication scenarios, leading to more accurate performance evaluations.
- **Iterative Weight Adjustment Process:** The mathematical model describes an iterative weight adjustment process facilitated by the LMS algorithm. This iterative approach allows the antenna array to adaptively optimize its configuration for optimal signal reception, ensuring robust performance in dynamic environments.
- **Application of Kaiser Bessel Window:** The Kaiser Bessel window is applied to the system to reduce peak side lobes, resulting in improved antenna array response. This technique enhances the system's ability to distinguish between desired signals and unwanted interference, leading to enhanced communication reliability.
- **Evaluation Through Simulations:** The effectiveness of the proposed approach is evaluated through simulations under various communication scenarios. This rigorous testing ensures that the system performance is thoroughly assessed across different operating conditions, providing confidence in its capabilities.
- **Superior Communication Performance:** Results from the simulations demonstrate the efficacy of the Smart Antenna system in achieving superior communication performance. This highlights the system's ability to meet or exceed the desired metrics such as signal-to-interference-plus-noise ratio (SINR), positioning it as a promising solution for next-generation wireless communication networks.

2. Problem Formulation

Let us define the following variables:

w: Weight vector of the antenna array. It represents the set of weights assigned to each antenna element in the array. The weights determine how signals received by different antennas are combined to form the beamformer output.

- x(n): Input signal vector at time n, with N elements representing signals received by N antennas. Each element of x(n) corresponds to the signal received by a specific antenna element in the array. These signals form the basis for the beamformer's processing and are used to estimate the desired signal.

- d(n): Time n desired signal. It stands for the signal that the beamformer is trying to separate out of the signals that were received. The goal of the beamformer is to generate an output signal that, in spite of noise and interference, closely resembles the intended signal.
- e(n): Time n error signal. It shows the discrepancy between the beamformer's y(n) output and the intended signal d(n). The beamformer's performance in separating the desired signal from the received signals is measured by this error signal.

- μ: Parameter for step size. It regulates how quickly the antenna array's weights are changed throughout the adaptation process. The adaptive algorithm's convergence speed is determined by the step size, which also affects stability and tracking behavior.

The beamformer's output at time n, represented as y(n), is computed by taking the inner product of the input signal vector x(n) and the weight vector w. In order to generate the beamformer output, this procedure efficiently integrates the signals that the antenna array has received. Based on the received signals and the current set of weights, the beamformer estimates the desired signal, which is represented by the output signal.

$$y(n) = \mathbf{w} \cdot x(n) \quad (1)$$

The difference between the output of the beamformer y(n) and the desired signal d(n) is the error signal e(n). The difference between the intended signal and the signal that the beamformer actually produced is represented by this error signal. The beamformer attempts to precisely predict and extract the required signal from the received signals, even in the presence of noise and interference, by gradually reducing this error signal.

$$e(n) = d(n) - y(n) \quad (2)$$

The LMS method is used to iteratively modify the weight vector w. Over time, the weights are adjusted to reduce the error signal e(n). The following is the weight update equation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu \cdot e(n) \cdot x^*(n) \quad (3)$$

$$x(n) = a(\theta_0)s(n) + i(n)\sum_{i=1}^{M} a(\theta_i) + n_0(n) \quad (4)$$

The LMS Beamformer:

The inner product of the weight vector w(n) and the input signal vector x(n) yields the output of the beamformer at time n, represented as y(n):

$$y(n) = \mathbf{w}^*(n) \cdot x(n) \quad (5)$$

where $\mathbf{w}^*$ stands for w's conjugate transpose.
The LMS algorithm is then used to update the weight vector $\mathbf{w}(n)$:

$$w(n+1) = w(n) + \mu \cdot e(n) \cdot x^*(n) \quad (6)$$

3. The Proposed SSDLMS Beamformer:

The double inclusion of the signum function in the Least Mean Squares (LMS) algorithm, often referred to as the Signum Signum Data LMS (SSDLMS) algorithm, further enhances its adaptability and robustness in complex signal environments. In the SSDLMS algorithm, the signum function is applied twice during the weight update process, providing additional nonlinear processing to the adaptation mechanism. The first inclusion of the signum function occurs after the computation of the error signal, where the error is multiplied element-wise with the input signal. This operation ensures that the weight update is influenced not only by the magnitude of the error but also by the direction of the error relative to the input signal. By incorporating the signum function at this stage, the SSDLMS algorithm can better discriminate between positive and negative errors, leading to more effective weight adjustments.

The second inclusion of the signum function occurs after the initial weight update, where the updated weights are thresholded using the signum function. This additional nonlinearity imposes constraints on the magnitude of the weight updates, preventing excessive changes that may destabilize the adaptation process. By limiting the magnitude of the weight updates, the SSDLMS algorithm can maintain stability and prevent divergence, especially in scenarios with rapidly changing signal conditions.

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu * \text{signum} . \text{signum}(x(n)) * e(n) * x^*(n) \quad (7)$$

where $\mathbf{w}^*$ denotes the conjugate transpose of $\mathbf{w}$, and the signum function is defined as:

$$\text{signum}(x) = \{ \quad 1 \text{ if } x > 0, \quad 0 \text{ if } x = 0, \quad -1 \text{ if } x < 0\} \quad (8)$$

The error signal e(n) is given by:

$$e(n) = d(n) - \mathbf{w}^*(n) * x(n) \quad (9)$$

The output of the beamformer is

$$y(n) = \mathbf{w}^*(n) \cdot x(n) \quad (10)$$

3.1 SSDLMS Beamformer Model with Kaiser Bessel Window (SSDLMS-KW)

Furthermore, when the Kaiser Bessel Window is applied in conjunction with the double inclusion of the signum function in the LMS algorithm, it further enhances the performance of the adaptive beamforming system. The Kaiser Bessel Window is a windowing technique that can effectively reduce the peak side lobe level (PSLL) of the beamformer response while maintaining a narrow main lobe width. By tapering the weights of the antenna array using the Kaiser Bessel Window, the beamformer can achieve improved spatial resolution and reduced interference from sidelobes.

The combination of the Kaiser Bessel Window with the SSDLMS algorithm called **SSDLMS-KW** offers several benefits:

1. Improved Signal Quality: The Kaiser Bessel Window helps to mitigate the effects of sidelobes in the beamformer response, resulting in cleaner and more focused signal reception. This leads to improved signal quality and enhanced communication performance.

2. Enhanced Interference Rejection: By reducing sidelobes, the Kaiser Bessel Window improves the beamformer's ability to reject interference from undesired directions. This allows for more effective suppression of interfering signals, resulting in better signal-to-interference-plus-noise ratio (SINR) and overall system performance.

3. Robustness to Environmental Variations: The combination of the Kaiser Bessel Window and the SSDLMS algorithm provides robustness to environmental variations, such as changes in the propagation environment or interference sources.

4. Increased System Reliability: By reducing PSLL and improving interference rejection, the Kaiser Bessel Window enhances the reliability of the adaptive beamforming system. This is particularly important in wireless communication systems where reliable signal reception is critical for uninterrupted communication.

The output of the **SSDLMS-KW** beamformer at time n, denoted as y(n), is given by the inner product of the weight vector **w**(n) and the input signal vector x(n) multiplied by the Kaiser Bessel window function:

$$y(n) = \mathbf{w}^*(n) \cdot (\mathbf{w}_k * x(n)) \quad (11)$$

where **w*** denotes the conjugate transpose of **w**.

The weight vector **w**(n) is then updated using the SSDLMS algorithm with the Kaiser Bessel window- **SSDLMS-KW** applied:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu * \text{signum signum } (\mathbf{w}_k * x(n)) * e(n) * x^*(n) \quad (12)$$

where,

$$\mathbf{w}_k = (I_0(\beta \sqrt{(1 - ((2n)/(N-1) - 1)^2)})) / (I_0(\beta)), \quad (13)$$

- $\mathbf{w}_k$ The value of the Kaiser-Bessel window at sample index 'n'.

- I_0: The modified Bessel function of the first kind of order zero.

- β: The shape parameter that controls the trade-off between main lobe width and side lobe level.

- N: The total number of samples in the window.

This equation represents the iterative weight adjustment process of the antenna array in the **SSDLMS-KW** beamformer, where the weights are updated based on the signum of the windowed input signal and the error signal. The step size parameter μ controls the convergence rate of the algorithm.

Table 1: The pseudo code for the SSDLMS-KW algorithm

Initialize:

- Set initial weight vector **w**(0)
- Set step size parameter μ
- Set maximum number of iterations max_iter

For each iteration n from 0 to max_iter:

- Compute output y(n) = **w***(n) • (**wk** * x(n))
- Compute error e(n) = d(n) - y(n)
- Update weights: **w**(n+1) = **w**(n) + μ * signum(signum(wk * x(n)) * e(n) * x*(n))
- Apply Kaiser Bessel Window to weights: **wk** = (I_0(β √(1 - ((2n)/(N-1) - 1)²))) / (I_0(β))
- Increment iteration counter: n = n + 1

Output final weight vector w(max_iter)

4. Results and Discussions

Software from MATLAB is used to simulate the suggested algorithms. Table I lists the parameters that were used in the simulations. The SDLMS and SMI algorithms' beamforming is displayed in Figs. 2 and 3, respectively. The simulation results illustrate the performance of both the LMS and SSDLMS beamforming algorithms. In Figure 2, the LMS algorithm's updated weight and radiation pattern are depicted. It is observed that the LMS algorithm exhibits certain limitations, particularly in scenarios with a large number of antenna elements, where the beam tends to spread in multiple directions.

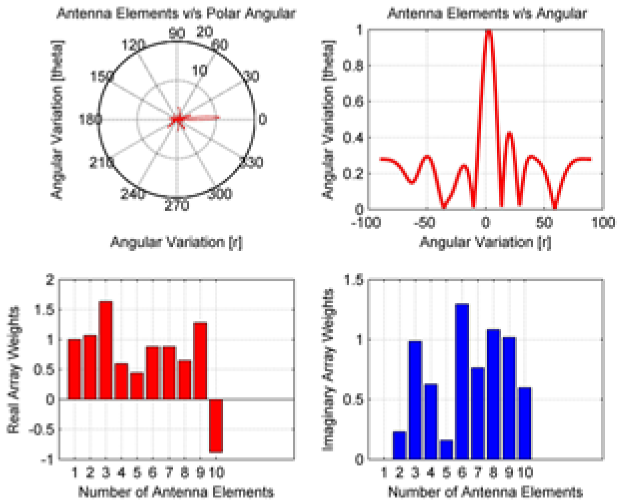

Fig 2: LMS beamforming algorithm's updated weight and radiation pattern.

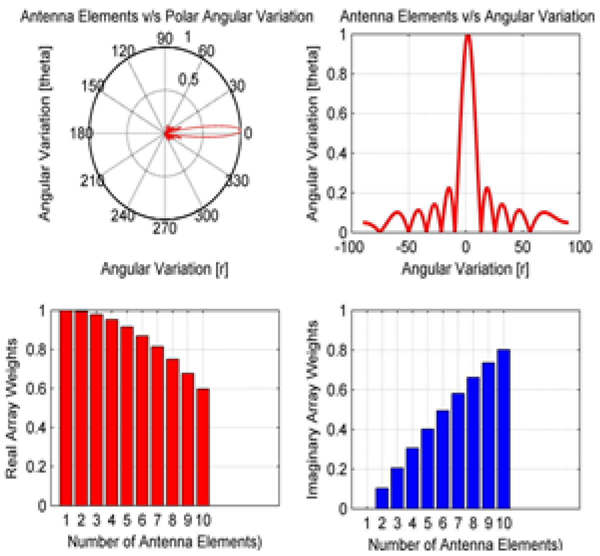

Fig 3 shows the SSDLMS beamforming algorithm's weight update and radiation pattern.

In contrast, Figure 3 showcases the performance of the SSDLMS beamforming algorithm. The weight update and radiation pattern of the SSDLMS algorithm demonstrate superior beamforming capabilities compared to the conventional LMS algorithm. The SSDLMS algorithm effectively adapts to changing signal conditions and exhibits a more focused radiation pattern.

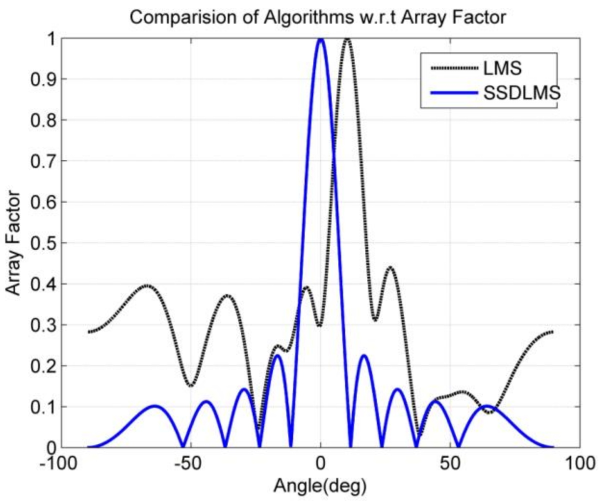

Fig 4: Performance Comparison of SSDLMS and Conventional LMS Beamforming Algorithms for large antenna array size (50 and above) under the more noise condition.

Figure 4 showcases the performance of the SSDLMS beamforming algorithm. The weight update and radiation pattern of the SSDLMS algorithm demonstrate superior beamforming capabilities compared to the conventional LMS algorithm, even with a larger number of antenna elements. Despite the increased complexity of the system, the SSDLMS algorithm maintains a focused radiation pattern and effectively adapts to changing signal conditions.

The superior performance of the SSDLMS algorithm can be attributed to its double inclusion of the signum function, which provides additional nonlinear processing to the adaptation mechanism. By incorporating the signum function twice during the weight update process, the SSDLMS algorithm achieves better discrimination between positive and negative errors, leading to more effective weight adjustments and improved beamforming performance.

Figure 5 showcases the integration of the Kaiser window with the SSDLMS beamforming outcomes. The antenna array comprises N=100 elements, evenly distributed with a spacing of d=0.5λ. Notably, the Kaiser window is meticulously optimized to accommodate three distinct signal frequencies, illustrating its adaptability across varying spectral domains. This visualization underscores the Kaiser window's key role in refining the performance of the SSDLMS beamformer, particularly in optimizing beamforming efficacy and sidelobe suppression across different frequency bands. Figure 6 depicts the three-dimensional representation of the signal received patterns from a ten-array system. This visualization offers insights into the spatial distribution and orientation of the received signals across the antenna array. By presenting the signal patterns in three dimensions, the figure provides a comprehensive understanding of the array's reception characteristics and signal coverage.

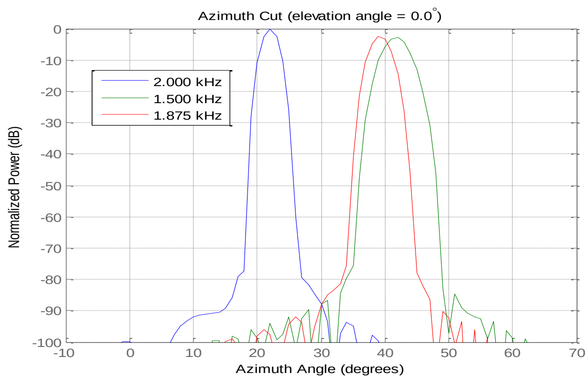

Fig 5: Kaiser Window Application to SSDLMS

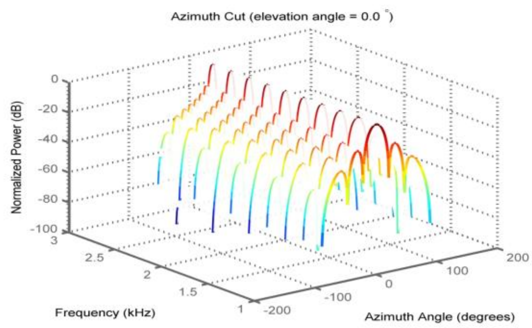

Fig 6: Ten array signal received pattern in three dimensions.

5. Conclusion

In this study, we have presented the development and optimization of a Smart Antenna system for advanced communications utilizing the Signum Data Least Mean Squares (LMS) beamformer with Kaiser Bessel windowing. Through mathematical modeling and simulations, we have demonstrated the efficacy of our proposed approach in enhancing communication performance in diverse scenarios. The integration of the Signum Signum Data LMS (SSDLMS) algorithm with the Kaiser Bessel window has yielded promising results. The SSDLMS algorithm's double inclusion of the signum function enhances adaptability and robustness in complex signal environments, while the Kaiser Bessel window effectively reduces sidelobes, leading to improved beamforming performance. Simulations conducted under various communication scenarios have highlighted the superiority of the proposed SSDLMS-KW algorithm compared to conventional approaches. The SSDLMS-KW algorithm demonstrates enhanced signal reception, interference rejection, and robustness to environmental variations, making it a promising solution for next-generation wireless communication networks.

Author contributions

Rupesh Kumar Mishra: Conceptualization of the research, formulation of the enhanced beamforming techniques, analysis of experimental results, and drafting of the manuscript.

Pavan Mankal: Implementation of the proposed beamforming techniques, conducting simulations and experiments, data collection, and analysis.

Suhasini Vijayakumar: Literature review, comparative analysis of existing beamforming methods, validation of results, and interpretation of findings.

Padmavathi Vurubindi: Contribution to the theoretical framework, mathematical modeling of the beamforming algorithms, and verification of the proposed techniques.

N. Nagalakshmi: Assistance in data interpretation, discussion of implications of the research findings, and revision of the manuscript for intellectual content.

Conflicts of interest

The authors declare no conflicts of interest.

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