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Implementation and Performance Analysis of Low Complex Beamforming Algorithms

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***Abstract*: *The work comprises of low complexity and cost effective technique referred as RAB (Robust Adaptive Beamforming) with the use of two algorithms i.e. LOSCME (Low complexity shrinkage based mismatch estimation) and OKSPME (Orthogonal krylov subspace projection mismatch estimation). The LOSCME is used to estimate the steering vector based on the correlation of the observed input data and beamformer output. This algorithm also uses OAS (oracle approximating shrinkage) in order to estimate the input data covariance matrix and INC (interference noise covariance) matrix that only requires a prior knowledge of angular sector in which the actual steering vector is located. It is not cost effective and need not to know any extra information that is related to interferers which keeps away from finding the direction of all interferers. Simulation result of LOCSME technique shows very close to optimum. The OKSPME algorithm is based on cross-correlation estimation between the observed input data array and output of the beamformer. In this technique the steering vector mismatch is estimated by considering the larger dimension linear equation and FOM (full orthogonalization method) is used to decrease the dimensional subspace. In addition to this, adaptive algorithm is implemented, which is based on the SG (stochastic gradient) & CG (conjugate gradient) searches used to update the beamforming weights, leads to low complexity of the system and avoid any costly matrix inversion. Major advantage of this mismatch estimation with low rank proposed algorithm is cost efficient when using with number of sensor arrays. The result of OKSPME technique shows excellent performance in terms of output SINR (signal to interference noise ratio), increase in the directivity and also increase in the antenna gain, when compared with other RAB algorithms.*

Index Terms*: *Beamforming, Robust adaptive beamforming

I. INTRODUCTION

The process of concentrating the array of sounds coming from only one particular direction is referred as "Beamforming". In Spatial, this look like a large dumbbell shaped lobe that is projected at the direction of our interest. Sounds from various sides are usually observed in which only one directions sound are considered thereby concentrating entire energy in this particular direction by which noise may be avoided, and the others are ignored clearly this concept is not an easy one making beamforming critical. This concept is also used for processing purpose in array signal and in many sonar systems as well.

In sensor arrays for signal transmission or reception, the signal processing technique beamforming or spatial filtering is a used. The signals at specified angles which experience interference constructively and some other signals interference destructively by combining elements in an antenna array, which is accomplished by using this technique. Both at the transmitting and receiving ends, beamforming can be used to accomplish the spatial selectivity. In radio as well as sound waves this technique is used.

Beam forming finds applications in a wide range of fields such as in RADAR systems, astronomy using radio waves, wireless communications and so on. The signal of interest can be detected and calculated by the spatial filtering method at the sensor array's output it also includes rejection of interference in adaptive beamforming.

Beamforming is also called as spatial filtering; the radio signals that come from a particular direction may be blocked at the receiver with the help of a suitable digital processing technique which may be either analog or a digital signal in the antenna array. The beamformer combines that energy over its aperture and then in the time field a filter is utilized for summing up of the energies in a specific direction as given before, in this direction antenna gain is obtained and the attenuations are also observed in the other directions.

To avoid costly inversion matrix and with low complexity the weights of the beamforming are updated the SG (stochastic-gradient) & CG (conjugate-gradient) methods are used based on adaptive algorithm. Derivation of proposed algorithm and also analysis of their complexity are easily explained. Using angular sector which is assumed, the projection of subspace is related, along with the difference of definite steering vector and steering vector estimated is done by using the MSE (mean-squared-error) is also analyzed. By mathematical analysis the steering vector which is mismatched is determined very accurately. In this approach, the upper bounds & the bounds which are lower are realized and differentiated. Simulations result shows that in order to model the mismatch effects created in coherent local scattering and incoherent local scattering. Proposed algorithms performance is determined by knowing the SINR (signal-interference-noise-ratio) output of the beamformer in accordance to snapshots & the number of antennas versus antenna gain and different input SNRs are also studied.

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II. LITERATURE REVIEW

According to Hang Ruan and Rodrigo C. de Lamare search, one of the important studies in processing of signal in the sensor arrays is "Adaptive Beamforming". This type of beamforming has spread its application in areas of audio signal processing, wireless communication, microphone and radar array processing fields.

In earlier case, if there is any slight variation in the environment then the changes will directly affect the adaptive beamforming because they are very sensitive in nature and in highly active environment the steering system require large amount of elements that are sensors, making use of such elements will result in decrease in the rate of convergence and also computational complexity is also increased these are the parameters used for calculating the beamformer[1]. The effects on adaptive beamforming can be diminished by developing the technique called RAB (robust adaptive beamforming). According to S. A. Vorobyov et.al they depicted a known approaches such as diagonal loading, optimizing worst case [2], techniques for projection and Eigen subspace [3]. Considering the large number of sensor arrays there are some restrictions for this techniques, that leads to low signal to noise ratio (SINR) and computational cost is very high for calculating the parameters of beamformer. Therefore, according to R. C. de Lamare et.al the complexity of the system can be reduced by reducing the subspace dimension and to enhance the convergence rate [4-5] other two algorithms are developed i.e. LOSCME (low complexity shrinkage based mismatch estimation) and OKSPME (orthogonal kyrlov subspace projection mismatch estimation).

L. Landau et.al have derived to estimate the mismatched steering vector the LOCSME algorithm is used which is a low complexity shrinkage method that is based on mismatch estimation[6]. Y. Chen et.al stated that the computational complexity of this algorithm is usually less, for the data provided through input two matrices are computed namely the covariance matrix and the other is the covariance with the noise interruption i.e. INC (interference noise covariance) matrix using OAS method that stands for oracle approximating shrinkage[7]. According to A.Khabbazibasmenj et.al LOCSME algorithm only needs the previous value of the angular sector in which the desired signal is steered or located in that angle that leads to less costlier than the existing methods[8]. The subspace projection matrix for any given sector can be easily calculated in very easy steps. Firstly, the OAS method's extension is used in order to execute the calculation of shrinkage, the shrinkage is estimated with the two conditions, the one in which a cross correlation vector is to be formed among the information got at the receiver and the yield of the beamformer, the other one is covariance matrix for information at the receiver. Further the estimation of the data received is done by using the steering of vector that contains the signal needed and also the power in this signal is calculated simultaneously. In final step, the interference with noise covariance that is the INC matrix is obtained by taking the difference between the two vectors namely the covariance matrix of a signal needed and the calculated covariance matrix i.e. output of OAS method. Simulation output shows that the LOCSME performs local scattering in both the cases coherent and incoherent.

Another OKSPME algorithm is proposed which is established related to utilization of cross correlation between array input information and the result of beamformer that avoids costly optimization process. At first, a linear system with high dimension is constructed involving the statistics of the sampled data and mismatched steering vector. Later, according to A. Filimon the computation of a subspace that contains orthogonal Krylov, a recursive method FOM (stands for full orthogonalization method)[9] is considered using both the less sufficient rank the model order is determined that ensure there is no information is lost while determining the signal that is of interest, having additional interferences along with the condition of execution and stopping of the FOM that by itself will ignore the over-steering many of the fundamentals of the sub space that being calculated. After estimation the vector contains the output of the cross correlation which is then projected on to the subspace of the krylov for purpose to upgrade the vector of steering.

To avoid matrix inversion and to reduce the complexity, this method introduces adaptive algorithm. RAB technique is proposed using the Oracle approximating shrinkage OAS method covariance obtained at the input will be estimated in the form of a matrix and also the matrix of covariance that contains both noise and interference is also depicted here. According to L. Wang et.al two major gradient techniques namely stochastic and conjugate searches [10] can be used, so that the weights used in beamforming will have less complexity and the matrix inversion will also be of less cost and this technique is based on adaptive algorithm. The proposed algorithms derivations are very easily explained along with an analysis of their additional complexity. Main advantages of this proposed mismatch estimation techniques and low-rank are their cost-effectiveness, when working with larger sensor arrays of high dimension subspaces. Result of the simulations output shows a very good concert when the signal to noise ratio factor and increase in the gain is the scenario for the beamformer, in comparison with different RAB techniques. Hence, the method increases the directivity up to 2%.

III. PROPOSED SYSTEM

M number of sensors & number of narrowband signals are k of linear antenna array which impose on the array. So, at ith snapshot the data received is represented by,

$$X(i) = A(\theta)s(i)+n(i) \quad (1)$$

Here signal source is noted as $s(i) \in C^{K\times 1}$ which is uncorrelated, the directions of arrival (DoAs) contains a vector $\theta = [\theta_1,\ldots\ldots,\theta_K]^T \in R^K$ and [.]T denotes the transpose of the vector , this matrix $A(\theta) = [a(\theta_1)+e,\ldots\ldots\ldots a(\theta_k)]=[a1,\ldots\ldots ak] \in C^{M\times K}$ contains e of the desired signal that has mismatch steering vector & also the direction of the arrival with the steering vector, circular Gaussian noise which has a complex value denoted as $n(i) \in C^{M\times 1}$ that has mean value zero & variance is denoted as σ_n^2. Beamformer output is depicted as,

$$Y(i) = w^H X(i) \quad (2)$$

Here the beamformer weight vector is represented as $w=[\omega_1 \dots \dots \omega_M]^T \in C^{M\times 1}$ and $(\cdot)^H$ denotes Hermitian transpose. By maximizing SINR the beamformer can be calculated which is optimal given as,

$$\text{SINR} = \frac{\sigma_1^2 [w^H a_1]^2}{w^H R_{I+N}\, w} \quad (10)$$

Here σ_1^2 is stated as power of the preferred signal & R_{I+N} is noted as the matrix of INC (interference-noise-covariance), by optimizing the following equation the above equation (10) SINR can be maximized,

$$\underset{w}{\text{minimize}} \quad w^H R_{I+N}\, w$$

$$\text{subject to} \quad w^H a_1 = 1$$

It is referred as beamformer of MVDR (minimum-variance-distortion-response). The vector weight optimum is stated as,

$$w_{OPT} = \frac{R_{I+N}^{-1} a_1}{a_1^H R_{I+N}^{-1} a_1}$$

Since R_{I+N} is a known value the data received at the output can be calculated with the help of the SCM (sample-covariance-matrix)

$$\hat{R}(i) = \frac{1}{i}\sum_{k=1}^{i} X(k)X^H(k) \quad (3)$$

By using the SCM (sample-covariance-matrix) the weights are calculated that results in the beamformer of SMI (sample-matrix-inversion)

$$w_{SMI} = \frac{\hat{R}^{-1} a_1}{a_1^H R^{-1} a_1}$$

However, the SMI (sample covariance matrix) beamformer is much sensitive to steering vector mismatches and requires many numbers of snapshots to converge. Earlier explained, most of existing RAB and conventional algorithms are computationally expensive, especially when large number of sensors with moving arrays.

Both the proposed LOSCME and OKSPME method is introduced. LOSCME technique is used to estimate steering

$$\hat{a}_1^H(i)x(i) = \hat{a}_1^H(i)\hat{a}_1(i)s_1(i) + \hat{a}_1^H(i)n(i)$$

vector. The shrinkage estimation is based on the vector of input data array and the output of the beamformer cross correlation that is projected onto a predefined subspace matrix. OKSPME method constructs a linear system that contains the value of estimation and also the estimated value between the vector of observed array of input data and the output of the beamformer cross correlation which is projected on a krylov subspace that is orthogonal in order for getting steering vector mismatch which reduces difficulty. SCM(sample-covariance- matrix) is utilized to calculate the data input observed array. Input data array observed and output of the beamformer cross correlation vector is determined by the equation d = E[xy*]

Here [.]* indicates the conjugation of complex value and it is represented as ,

d=E[(As+n)(As+n)H w]

By taking $|a_K^H w| << |a_1^H w|$ and k has the values from 2 to k, all signals have zero mean, the vector d cross-correlation can be rewritten as,

$$d=E[(As+n)(s_1^* a_1^* w + n^H w)] \quad (4)$$

the desired signal can be written as ,

$$d=E\,[\sigma_1^2 a_1^H w a_1 + n n^H w] \quad (5)$$

the SCV (sample cross-correlation vector) is estimated as,

$$\hat{d}(i) = \frac{1}{i}\sum_{k=1}^{i} x(k)y^*(k) \quad (6)$$

Power estimation of desired signal: (11)

The power estimation of desired signal (σ_1^2) is calculated with the help of steering vector of the preferred signal.ML (maximum-likelihood) & MV (minimum-variance) estimator can also be employed for estimating the desired signal power. The ML and MV estimators has a higher complexity than the approach described. In this adopted method the value of the mismatch steering vector is earlier guessed and selected such that it lies inside the angular sector i.e. $\hat{a}_1(0)$ & $\hat{a}_1(1) = \hat{a}_1(0)$ are set. The array observation data with the addition of index i of snapshot can rewrite as,

$$X(i) = \hat{a}_1(i)s_1(i) + \sum_{k=2}^{k} a_k(i)s_k(i) + n(i) \quad (7)$$

Where the initial guess of the steering vectors are $\hat{a}_1(0)$ and $\hat{a}_1(i)$, i = 1,2, ….. and at the ith snapshot it has estimates, respectively.

By pre-multiplying the equation (10) by $\hat{a}_1^H(i)$ can get,

$$\hat{a}_1^H i\, x(i) = \hat{a}_1^H(i)\hat{a}_1(i)s_1(i) + \sum_{k=2}^{k} \hat{a}_1^H(i)a_k(i)s_k i) + n(i) \quad (18)$$

The desired signal assumed here is orthogonal to interferers or approximately orthogonal. Shown as, $(\hat{a}_1^H(i)a_k(i) = 0)$ here $k = 2,3, \dots \dots k$ are orthogonal of all interference of the steering vector or $\hat{a}_1^H(i)a_k(i) \ll \hat{a}_1^H(i)\hat{a}_1(i)$ approximately orthogonal of steering vector of the preferred signal (i.e., $\hat{a}_1(i)$) such that $\hat{a}_1^H(i)a_k(i)$, reaches zero and the term

$\sum_{k=2}^{k} \hat{a}_1^H(i)a_k(i)s_k(i)$ in eqn (11) is neglected, resulting in

Take the expectation to above equation $|\hat{a}_1^H(i)x(i)|_2$,

$$E[|\hat{a}_1^H(i)x(i)|_2] = E[(\hat{a}_1^H(i)\hat{a}_1(i)s_1(i) + \hat{a}_1^H(i)n(i))_*(\hat{a}_1^H(i)\hat{a}_1(i)s_1(i) + \hat{a}_1^H(i)n(i))] \quad (20)$$

By assuming that the desired signal is statistically independent to noise, then equation changes to,

$$E[|\hat{a}_1^H(i)x(i)|_2] = |\hat{a}_1^H(i)\hat{a}_1(i)|_2 E[|s_1(i)|_2] + \hat{a}_1^H(i)E[n(i)n^H(i)]\hat{a}_1(i) \quad (21)$$

Here the noise covariance matrix $Rn(i)$ is represented as $E[n(i)n^H(i)]$ which is replaced by $\hat{\sigma}_n^2 I_M$, then by a specific estimation method σ_n^2 is stated as variance of noise is calculated.. Maximum (13

Likelihood (ML) based method approach is used and E [$|s_1(i)|$2] is power used by the preferred signal and variance of noise σ_n^2 are replaced $\hat{\sigma}_1^2(i)$ & $\hat{\sigma}_n^2(i)$ estimates respectively,

$$\hat{\sigma}_1^2(i) = \frac{|\hat{a}_1^H(i)x(i)|^2 - |\hat{a}_1^H(i)\hat{a}_1(i)|\hat{a}_n^2(i)}{|\hat{a}_1^H(i)\hat{a}_1(i)|^2} \quad (22)$$

The expression in above equation shows that the steering vector of the desired signal and the level of noise are precisely determined which has low complexity and can be directly implemented.

[b]. Beamformer weight vector and INC matrix computation

Then the mismatched steering vector and power consumed by the preferred signal calculated earlier section just by taking the difference of covariance matrix of the desired signal and SCM by this the matrix INC is obtained as,

$$\hat{R}_{I+N}^{-1}(i) = \hat{R}(i) - \hat{\sigma}_1^2(i)\hat{a}_1(i)\hat{a}_1^H(i) \quad (23)$$

The weight vector of beamformer is estimated as,

$$\hat{w}(i) = \frac{\hat{R}_{I+N}^{-1}(i)\hat{a}_1(i)}{\hat{a}_1^H(i)\hat{R}_{I+N}^{-1}(i)\hat{a}_1(i)} \quad (8)$$

$\hat{R}_{I+N}^{-1}(i)$ is a computationally costly matrix inversion . In later section reduce the complexity and to avoid matrix inversions the adaptive algorithms is introduced.

OKSPME robust beamforming method is used in adaptive beamforming technique that results in the proposed OKSPME-SP, which is more suitable in dynamic scenarios. To calculate the power consumed by the preferred signal along with its steering vector using similar recursions and procedure for the beamforming weights estimation is different as used in OKSPME. Example, with the use SG based adaptive recursions and a reformulated optimization problem in order for deriving expression for updating the weight which leads to decrease in the complexity in-accordance to magnitude when compared to OKSPME.

OKSPME-SG Adaptive technique:

Consider a problem of optimization as,

$$\underset{w(i)}{\text{minimize}} \quad w^H(i)(\hat{R}(i) - \hat{R}_1(i))w(i) \quad (9)$$

$$\text{subject to} \quad w^H(i)\hat{a}_1(i) = 1$$

here $\hat{R}_1(i)$ & $\hat{R}(i)$ are covariance matrix of the desired signal which is represented by x(i)xH(i) later it is modified by $\hat{\sigma}_1^2(i)\hat{a}_1(i)\hat{a}_1^H(i)$.

SG recursion can be expressed with,

$$w(i+1) = w(i) - \mu\frac{\partial L}{\partial w(i)}$$

and

$$L = w^H(i)(x(i)x^H(i) - \hat{\sigma}_1^2(i)\hat{a}_1(i)\hat{a}_1^H(i))w(i) + \lambda L(w^H(i)\hat{a}_1(i) - 1)$$

& μ is defined as the step size.

Substitute the value of L in equation (26) and assuming $w^H((i+1)\hat{a}_1((i+1) = 1$, the equation for λL can be stated as,

$$\lambda L = \frac{2(\hat{\sigma}_1^2(i)\hat{a}_1^H(i)\hat{a}_1(i) - y(i)x^H(i)\hat{a}_1(i))}{\hat{a}_1^H(i)\hat{a}_1(i)} \quad (10)$$

substitute λL in equation(19) again, for OKSPME-SG the weight update equation

When computing the weights, the adaptive SG recursion gives a matrix inversion that is necessary in OKSPME by this the computational complexity is reduced in OKSPME-SG. Another important thing is that, the step size μ should satisfy the condition $0 < \mu < \frac{1}{\hat{\sigma}_1^2(i)}$; to guarantee that I- $\mu\hat{\sigma}_1^2(i)\hat{a}_1(i)\hat{a}_1^H(i)$ always has a positive definite matrix then the equation is ensured to get a correct solution.

IV. RESULTS

The simulation outcome of the OKSPME technique proposed is compared with other existing RAB methods. Consider omni directional sensors in uniform linear arrays by means of the wavelength is partially spaced in order for creating every figures. To acquire all position of curve & to observe the snapshots that has a limit $i =$ 50, 100 repetition being executed. By approximating at $\theta_1 = 10^\circ$ and by assuming that the preferred signal will appear at 0dB for which the SINR (signal-to-interference-noise-ratio) is taken as a constant and $\theta_1 = -5^\circ, \theta_1 = +5^\circ$ is the angular sector for which the preferred signal is unspecified to appear. The result focuses on the output of beamformer SINR (-60dB to 60dB) performance versus number of snapshots.

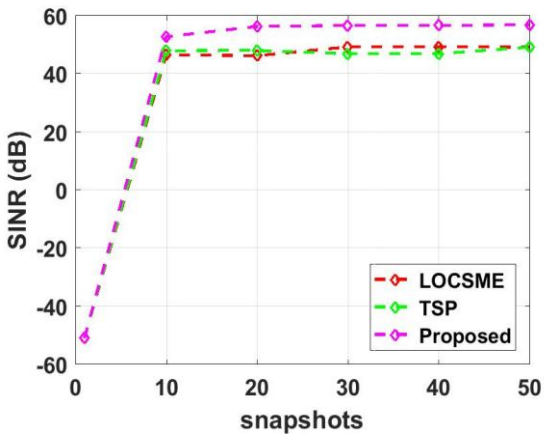

Figure: Graph of snapshots versus SINR (dB)

The steering vector for desired signal in case of coherent local scattering with time invariant is given as,

$$a_1(i) = P + \sum_{K=1}^{3} e^{j\varphi_k} b(\theta_k) \quad (26)$$

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Here P is the direct path & path which is scattered is denoted as b(θ_k) where k has the values 1, 2 and 3. In each simulation run the angles θ_k is selected without depending on other factors from a identical generator which has a constant mean of 10° along with the standard deviation having the constant

value 2°. φ_k(here k has the value 1, 2 &3) is the angle which is taken without depending on other angles and equivalently chosen in the interval between 0 to 2^{π}. Here the angles θ_k & φ_k changes their value in each trail and remains constant over the snapshots.

At first, the proposed method is compared with other RAB methods like comparing the variance of noise and their complexity. M = 12 is number of sensors and k = 3 is source of the signal along with the preferred signal being set. A 20dB interference noise ratio is also set and show the SINR performance versus snapshot with 50 in Figure. And also two interferers are arranged in the direction $\theta_2 = 30^{\circ}$ and $\theta_3 = 50^{\circ}$, respectively. User defined parameters such as μ being the step size & also neglecting λ being wavelength are adjusted to achieve good output performance.

The beam space algorithm will fix the dimension D = 4 but proposed technique can achieve better performance than the beam space approach and also has comparable or improved output compared to LOSCME technique.

In case of incoherent local scattering with time-variant the steering vector is given as,

$$a_1(i) = s_{0(}i)P + \sum_{K=0}^{3} s_{k(}i)b(\theta_k) \quad (7.19)$$

Where $s_k(i)$ (k=0 ,1 , 2, 3,)are the independent and identically distributed Gaussian random variables with zero mean complex value that is taken from random generator which is not dependent on other factors. For every run to run and from every snapshot to snapshot the $s_k(i)$ changes. Thus in incoherent scattering with time variant nature results in environmental uncertainties in the system that leads to increase in the steering vector mismatch.

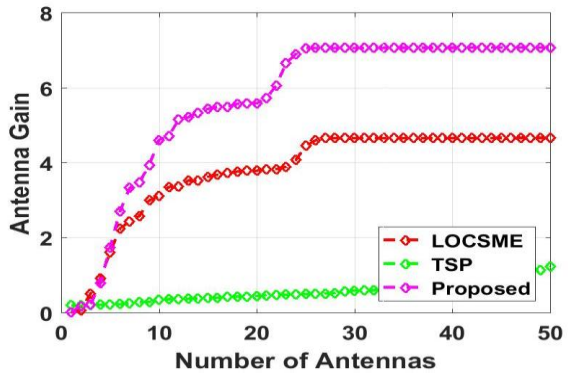

Figure: Graph of the number of antennas versus antenna gain

Antenna gain is defined as the ratio of intensity (measured in power per unit surface area) radiated by the antenna in the direction of its maximum output to the intensity radiated by a isotropic antenna at the same distance that radiates equal power in all directions. Antenna gain measures the degree directivity of antennas radiation pattern. If higher is the antenna gain the power is radiated more in one particular direction, whereas the low antenna gain will radiate in wider angle /direction. If the antennas used at transmitter and or at the receiver side is more better is the data rate, increases the capacity and decrease in the required uplink and downlink transmit power. In this example number of antenna is considered to be 50 antennas and antenna gain at 8 dB. In the proposed OKSPME method, higher is the antenna gain with increase in number of antennas in comparison with LOCSME and other RAB algorithms.

V. CONCLUSION

In this work the OKSPME algorithm is proposed that is anchored from the mismatching the estimation done regarding the cross correlation and also the Krylov subspace that is orthogonal. The OKSPME-SG is a low complexity RAB algorithm that is developed in order for allowing to use weights in a beamformer so that it may be upgraded for better despite of not inverting the matrix. This proposed algorithm gives the details about the forming the vector for the steer performed and this needs to be calculated by MSE analyzed with the help of RAB which is dependent only in the case of an angle sector that is assumed previously besides having a good amount of information regarding the other factors as well. Having this information, Computation complexity of the OKSPME is compared with the LOSCME and some of the other existing algorithms. The simulation result depicts the fact which showcases algorithm that is being proposed is vigorous in opposition to the various parameters being picked up that are completely user dependent along with the uncertainties in the environment surrounded which achieves the best output SNR performance mainly for high or medium input values of SNR and higher the antenna gain.

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