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Performance Analysis of MIMO-QR-OSIC receiver design Using HSPA$^+$ technology

M.Shashidhar
Department of ECE,
Vaagdevi College of
Engineering, Warangal-05, India.
Email:sasi47004@gmail.com

K.Kishan Rao
Department of ECE, Director,
Vaagdevi Group of Colleges,
Warangal-05, India,
Email:kishanrao6@gmail.com

P.V.D. Soma sekhar Rao
Department of ECE,
JNTU College of Engineering,
Hyderabad, India
Email:pvds_sekhar@hotmail.com

Abstract: **In this paper, we investigate the QR-OSIC (Order successive interference cancellation) receiver design for the transmitter-side power allocated Multi-Input Multi-Output (MIMO) system. Based on the properties of the Q-function and ordering results, we develop the efficient ordering algorithms in combination with the Power Allocation (PA) scheme. We derive new detection ordering strategy and schemes from joint transceiver design. To obtain a closed-form solution, a QR-factorization based approach will be employed in our study. First, we provide the Bit Error Rate (BER) minimization condition, derived from the convexity of the Q-function in the PA scheme. It is demonstrated that the ordering strategy, which makes the channel gains converge to their geometric average, achieves the improved error performance. Based on this observation, we develop the two ordering algorithms, which are identical except for the threshold adaptation. The basic algorithm determines the detection-order using the geometric mean as a constant threshold, whereas the modified ordering scheme for robust convergence adaptively updates the threshold by taking into account the previous ordering results. From the convexity of the Q-function, we further derive the ordering strategy that makes the channel gains converge to their geometric mean. Based on this approach, the fixed ordering algorithm is first designed for which the geometric mean is used for a constant threshold. To further improve the performance, the modified scheme employing adaptive thresholds is developed using the correlation among ordering results. Theoretical analysis and simulation results show that proposed ordering schemes using QR-decomposition not only require a reduced computational complexity compared to the conventional scheme, but result in improved error performance.**

***Keywords*-MIMO, QR-OSIC, Power allocation, Non data aided**

1. INTRODUCTION

Wireless communications undergoes a dramatically change in recent years. More and more people are using modern communication services, thus increasing the need for more capacity in transmissions. Since bandwidth is a limited resource, the strongly increased demand in high transmission capacity has to be satisfied by a better use of existing frequency bands and channel conditions. One of the recent technical breakthroughs, which will be able to provide the necessary data rates, is the use of multiple antennas at both link ends. These systems are referred to as multiple-input multiple-output (MIMO) wireless systems.

MIMO technology, through the use of multiple antennas at the transmitter and receiver sides, has been an area of intense research for its promise of increased spectral efficiency and reliability. The MIMO, a multi antenna system, answers the question of how to achieve the higher data rates, wider coverage, and increased reliability all without using additional frequency spectrum. The combination of multiple antennas system with multiple carrier system gives an excellent performance.

While Data Aided (DA) algorithms achieve good performance, transmission of training sequences contributes to overheads and reduces overall data rate. Further, the receiver needs to know the starting point of the training sequences and hence frame synchronization is required even before symbol timing can be estimated, thus further complicating the receiver. Non Data Aided (NDA) algorithms work by extracting the timing estimate from the received signal without using any training sequence.

Since NDA methods usually make use of second order statistics, they require longer observation lengths and are computationally intensive. However they provide several benefits as the data rate is not compromised and the need for frame synchronization at the physical layer is obviated. Further, if the receiver is resourceful (e.g. a base station), NDA methods allow us to trade-off receiver complexity with the performance of estimator simply by changing the observation length and without compromising data rate, unlike DA estimators.

The transmission in wireless communication is typically organized in packets, with a training sequence at the beginning of the packet, to allow for the channel estimation and coherent detection at the receiver. When the transmitter is unaware of the channel and the receiver does not give the feedback details Phase and Magnitude information, we speak of „open-loop" transmission. It is good match for the wireless MIMO channel that is time varying, and the rate of feeding back channel information might be low. The major potentiality of MIMO can be exploited by BLAT ordered successive interference cancellation (B-OSIC) detector also called as V-BLAST. In B-OSIC a procedure is followed by taking a data stream having with high SINR and it is subtracted from received In Section – II design of QR-OSIC receiver structure is explained. In Section-III Comparing of Existing algorithm with Proposed algorithm

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I- QR-OSIC RECEIVER DESIGN FOR MIMO SYSTEM

Let M_t is the number of transmitting antenna's and N_r be the receiving antenna's for a MIMO system for any existing channel condition based on fading

For flat folding MIMO channel Can be expanded as a Matrix H of order M_t X N_r. Let h_{ji} indicates the channel gain of transmitting and receiving antenna for i & j variables.

Z $\{Z_1, Z_2 \ldots\ldots\ldots Z_{mr}\}^T$ of $M_{r\ X\ 1}$,is the received signal Vector expressed as

$$Z = \sqrt{\frac{B_s}{M_t}}.Hkw + r \qquad \ldots\ldots..$$

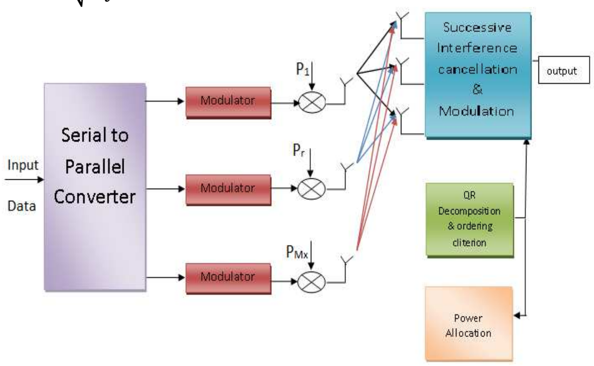

Figure 1. MIMO transmission model with QR-OSIC receiver

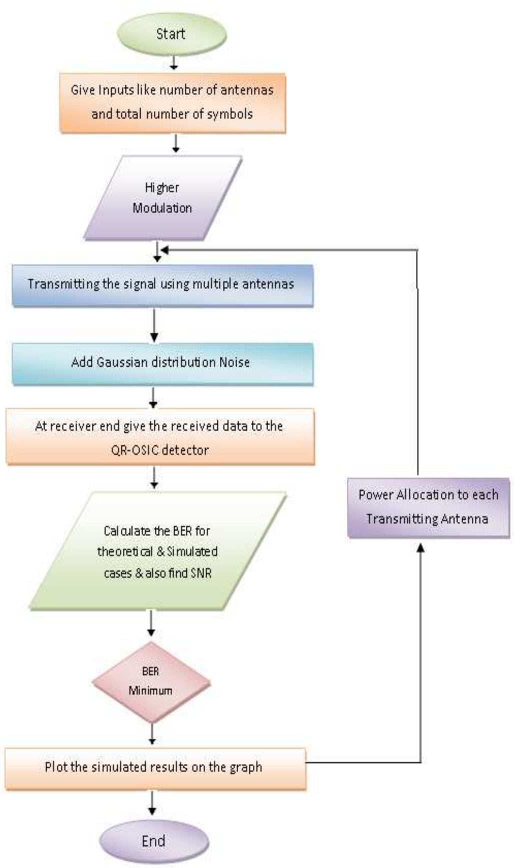

Figure 2.QR_OSIC receiver design flow chart

W = $\{W_1, W_2 \ldots\ldots\ldots W_{mt}\}^T$ of order M_t X 1 is the transmitting antenna Signal vector .

V = $\{V_1, V_2 \ldots\ldots\ldots W_{mr}\}^T$ be the M_r dimensional noise vector with variance of ∞_x^2 of Complex zero mean Gaussian distribution.

The total transmitted signal energy represented as B_S for transmitting antenna M_t and K = $\sqrt{M_t}$.The Diag (k_1, k_2 …….. k_{mt}) represents preceding matrix of individual power allocation power of k_1 k_2 ……..

For MMSE QR detector signal model is expressed as (Mt+Mr)xMt augmented channel matrix Ĥ and (Mt+Mr)x1 extended receive vector Z. and for zero matrix o_{nt},1 is shown as Mtx1 can be written as

$$\widetilde{H} = \begin{bmatrix} H \\ \sigma_n I_{Mt} \end{bmatrix} \text{Q'R' and } \tilde{Z} = \begin{bmatrix} z \\ o_{nt}, 1 \end{bmatrix} \qquad (1)$$

SNR can be determined by upper triangular matrix T" which is shown differently and represented by detecting order. For k_{th}data stream post detector SNR is

$$p_j = \frac{B_s}{\sigma_r^2} k_j^2 \overline{T_{j,J-1}}^2 \quad k = 1,2 \ldots \ldots Mt \qquad (2)$$

This system explains BER minimized allocation of power transmitter that can be performed using QR decomposition based on OSIC detection.

For each data stream allotted in transmission power K_j for each data stream based on feedback in transmitter of diagonal elements T_{jj} by using diagonal power allocation matrix independently encoded symbols precoded first passed from M_t data stream[64]. The operations of QR-OSIC receiver in which transmit symbols are detected sequentially by following designated detection order.

MMSE DETECTOR

MMSE detector reduces the mean squared error between the out put of the transmitted symbols which results in filter matrix.

The filter output is

$$G_{MMSE} = (H^H H + \sigma_n^2 I_{N_t})^{-1} H^H \qquad (3)$$

The errors which are estimated of different layer leads to the main diagonal elements of the covariance matrix

$$\phi_{MMSE} = E\left\{\left(\hat{s}_{MMSE} - s\right)\left(\hat{s}_{MMSE} - s\right)^H\right\}$$

(4)

$$= \sigma_n^2 (H^H H + \sigma_n^2 I_{N_t})^{-1}$$

With the definition of a an (M_t+M_r) x M_t augmented channel matrix , an (M_t+M_r) X 1 extended receive vector $\overline{y}$ and an M_t X 1 zero matrix $0_{N_t,1}$ can be written as

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$$\bar{H} = \begin{bmatrix} H \\ \sigma_n I_{N_t} \end{bmatrix} \rightarrow ordering\ \bar{Q}\bar{R}\ and\ \bar{y} = \begin{bmatrix} y \\ 0_{Nt,1} \end{bmatrix}$$

the output of the MMSE filter now can be rewritten as

$$\hat{S}_{MMSE} = (H^H H)^{-1} \bar{H}^H \bar{y} = \bar{H}^+ \bar{y}$$

Furthermore, the error covariance matrix becomes

$$\phi_{MMSE} = \sigma_n^2 (\bar{H}^H \bar{H})^{-1} = \sigma_n^2 \bar{H}^+ \bar{H}^{+^H} \quad (5)$$

Comparing last two equations to the corresponding expression for linear zero-forcing detector in previous topic, the only difference is that the channel matrix H has been replaced by $\bar{H}$. This observation is extremely important for incorporating the MMSE criterion into the SQRD based detection algorithm[65],[66]. All paragraphs must be indented and justified, i.e. both left-justified and right-justified.

PRECODING FOR ORDINARY DETECTOR MMSE QR DETECTION

By observing the equation of post detection SNR channel gains are effected by power allocation of transmitter and error rate. Based on the properties of Q-Function and ordering results and the ordering strategy is determined. To extend the MMSE criterion w.r.t to QR based detection,[67] it is similar just like ZF and MMSE detection Section. We introduce the QR decomposition of the extended channel matrix as

$$\bar{H} = \begin{bmatrix} H \\ \sigma_n I_{N_t} \end{bmatrix} = \bar{Q}\bar{R} = \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} \bar{R} = \begin{bmatrix} Q_1 \bar{R} \\ Q_2 \bar{R} \end{bmatrix}$$

where the (M_t+M_r) x M_t matrix $\bar{Q}$ with orthogonal columns was partitioned into Q1and Q2 $\bar{Q}^H \bar{H} = Q_1^H + \sigma_n^2 Q_2^H = \bar{R}$ holds and from the relation $\sigma_n I_{N_t} = Q_2 \bar{R}$ it follows that

$$\bar{R}^{-1} = \frac{1}{\sigma_n} Q_2$$

i.e., the inverse $\bar{R}^{-1}$ is a by-product of the QR decomposition and Q_2 is an upper triangular matrix. This relation will be useful for the post-sorting algorithm Using above equations, the filtered receive vector becomes

$$\hat{S} = \bar{Q}^H \bar{y} = Q_1^H y = \bar{R}S - \sigma_n Q_2^H S + Q_1^H \quad (6)$$

The 2nd term on the right hand side of above equation together with the lower triangular matrix Q_2^H constitutes the remaining interference that are not able to be removed through the successive interference cancellation method. This aspects out the trade-off between noise amplification and interference suppression.

The ultimate detection sequence now maximizes the sign-to-interference-and-noise ratio (SINR) for every layer, leading to minimal estimation error for the corresponding detection step. The estimation error of the special layers in the first detection step correspond to the diagonal factors of the error covariance matrix

$$\phi = \sigma_n^2 (\bar{H}^H \bar{H})^{-1} = \sigma_n^2 \bar{R}^{-1} \bar{R}^{-H}$$

The estimation error after ideal interference cancellation is given by $\sigma_X^2 / |\overline{r}_{k,k}|^2$. for this reason, it's once more most appropriate to prefer the permutation that maximizes $|\bar{r}_{k,k}|$ in every detection step. The algorithm proposed within the next part determines an optimized detection sequence within a single sorted QR Decomposition & thereby tremendously reduces the computational complexity in comparison to typical MMSE-BLAST algorithm[68]

Q-FUNCTION

In statistics, the Q-function is the tail probability of the distribution. In other words, Q(x) is the probability that a standard normal random variable will obtain a value larger than x. Other definitions of the Q-function, all of which are simple transformations of the normal cumulative distribution function, are also used occasionally[72].

- Definition and basic properties

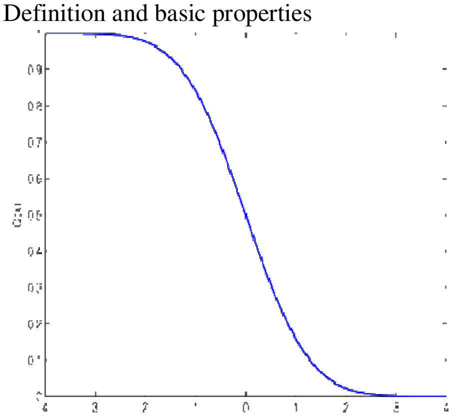

Figure 5: A plot of the Q function

Formally, the Q-function is defined as

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} \exp\left(-\frac{u^2}{2}\right) du \quad (7)$$

Thus,

$$Q(x) = 1 - Q(-x) = 1 - \Phi(x),$$

Where $\Phi(x)$ is the cumulative distribution function of the normal Gaussian distribution. The Q-function can be expressed in terms of the error function as

$$Q(x) = \frac{1}{2} - \frac{1}{2} erf\left(\frac{x}{\sqrt{2}}\right) = \frac{1}{2} erfc\left(\frac{x}{\sqrt{2}}\right)$$

Bounds:-

- The Q-function is not an elementary function. However, the bounds

$$\frac{x}{1+x^2} \cdot \frac{1}{\sqrt{2\pi}} e^{-x^2/2} < Q(x) < \frac{1}{x} \cdot \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \qquad x > 0,$$

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become increasingly complex for large x, and are often useful. Using the substitution $v = u^2 / 2$ and defining

$$a_1 = \langle e_1, a_1 \rangle e_1$$

$$a_2 = \langle e_1, a_2 \rangle e_1 + \langle e_2, a_2 \rangle e_2$$

$$a_3 = \langle e_1, a_3 \rangle e_1 + \langle e_2, a_3 \rangle e_2 + \langle e_3, a_3 \rangle e_3$$

$$a_k = \sum_{j=1}^{k} \langle e_j, a_k \rangle e_j$$

The upper bound is derived as follows:

$$Q(x) = \int_x^\infty \varphi(u)du$$

$$< \int_x^\infty \frac{u}{x}\varphi(u)du = \int_{x^2/2}^\infty \frac{e^{-v}}{x\sqrt{2\pi}}dv = -\frac{e^{-v}}{x\sqrt{2\pi}}\Big|_{x^2/2}^\infty = \frac{\varphi(x)}{x}.$$

Similarly, using $\varphi'(u) = -u\varphi(u)$ and using the quotient rule,

$$1 + \frac{1}{1+x^2} Q(x) = \int_x^\infty \left(1 + \frac{1}{x^2}\right)\varphi(u)du$$

$$> \int_x^\infty \left(1 + \frac{1}{u^2}\right)\varphi(u)du = -\frac{\varphi(u)}{u}\Big|_x^\infty = \frac{\varphi(x)}{x}.$$

Solving for $Q(x)$ provides the lower bound.

- Chernoff bound of Q-function is

$$Q(x) \leq \frac{1}{2} e^{-\frac{x^2}{2}}, \qquad x > 0$$

QR-DECOMPOSITION

In linear algebra, a QR decomposition (often known as a QR factorization) of a matrix is a decomposition of a matrix A right into a product A=QR orthogonal matrix Q and an upper triangular matrix R. QR decomposition is regularly used to solve the linear least squares difficulty[73], and is the basis for a precise eigen value algorithm, the QR algorithm.

If A has linearly independent columns (say n columns), then the first n columns of Q type forms an ortho normal basis for the column area of ASQUARE MATRIX

Any real square matrix A may be decomposed as

$$A = QR,$$

The place Q is an orthogonal matrix (its columns are orthogonal unit vectors that means $Q^TQ = I$) and R is an upper triangular matrix (also referred to as right triangular matrix). This generalizes to a complex square matrix A and a unitary matrix Q. If A is invertible, then the factorization is specified if we require that the diagonal elements of R are positive

RECTANGULAR MATRIX

More often, a difficult m×n matrix A, with m ≥ n, because the fabricated from an m×m unitary matrix Q and an m×n upper triangular matrix R. Because the bottom (m−n) rows of an m×n upper triangular matrix consist wholly of zeroes, it is almost always useful to partition R, or each R and Q as

$$A = QR = Q\begin{bmatrix} R_1 \\ 0 \end{bmatrix} = \begin{bmatrix} Q_1 & Q_2 \end{bmatrix}\begin{bmatrix} R_1 \\ 0 \end{bmatrix} = Q_1R_1$$

where R_1 is an n×n upper triangular matrix, Q_1 is m×n, Q_2 is m×(m−n), and Q_1 and Q_2 both have orthogonal columns.

COMPUTING THE QR DECOMPOSITION

There are a few ways for certainly computing the QR decomposition, comparable to by the use of the Gram–Schmidt method, Householder transformations, or Givens rotations. Each and every has a quantity of benefits and drawbacks.

USING THE GRAM–SCHMIDT PROCESS

Consider the Gram–Schmidt process applied to the columns of the full column rank matrix A=[a_1,……a_n] , with inner product <v,w>=v^Tw (or) <v,w>=v^*w for the complex case.

Define the projection: $$\mathrm{proj}_e a = \frac{\langle e, a \rangle}{\langle e, e \rangle} e$$

$$u_1 = a_1, \qquad e_1 = \frac{u_1}{\|u_1\|}$$

then: $$u_2 = a_2 - \mathrm{proj}_{e_1} a_2, \qquad e_2 = \frac{u_2}{\|u_2\|}$$

$$u_k = a_k - \sum_{j=1}^{k-1} \mathrm{proj}_{e_j} a_k, \qquad e_k = \frac{u_k}{\|u_k\|}$$

We then rearrange the equations above so that the a_s are on the left, using the fact that the $\mathbf{e}_i$ are unit vectors:

$$a_1 = \langle e_1, a_1 \rangle e_1$$

$$a_2 = \langle e_1, a_2 \rangle e_1 + \langle e_2, a_2 \rangle e_2$$

$$a_3 = \langle e_1, a_3 \rangle e_1 + \langle e_2, a_3 \rangle e_2 + \langle e_3, a_3 \rangle e_3$$

$$a_k = \sum_{j=1}^{k} \langle e_j, a_k \rangle e_j$$

Where $\langle e_i, a_i \rangle = \|u_i\|$.

This can be written in matrix form: $A = QR$

Where $$Q = [e_1, \ldots\ldots, e_n] \quad and \quad R = \begin{pmatrix} \langle e_1,a_1 \rangle & \langle e_1,a_2 \rangle & \langle e_1,a_3 \rangle & \cdots \\ 0 & \langle e_2,a_2 \rangle & \langle e_2,a_3 \rangle & \cdots \\ 0 & 0 & \langle e_3,a_3 \rangle & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

EXPLANATION OF BER PERFORMANCE

The average BER minimization for a power allocation scheme beneath a channel matrix regarding QR in decomposition. In information move no error propagation, successive cancellation is proposed. In greater modulation allocation of energy is expressed in phrases as

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Minimize $\frac{1}{M_t}\sum_{j=1}^{M_t} R\left(\sqrt{2r_t}k_j \text{Tij'}\right)$

$$\approx \frac{1}{M_t}\sum_{k=1}^{M_t} R\left(\sqrt{2\rho_k}\right)$$

$s.t = \sum_{j=1}^{M} k_j^2 = 1$

$$\overline{T_{JJ}} \geq 0 \qquad j \in (1,2 \ldots \ldots M_t)$$

Where $\mathrm{R(w)} = \frac{1}{\sqrt{2\pi}}\int_{\mathrm{w}}^{\infty} \mathrm{e}^{-\mathrm{t}^2}\,\mathrm{dt}$ and $r_t = \sqrt{\frac{B_s}{\sigma_r^2}}$

If $\overline{T_{\iota J}} \geq 0$ it is acquired from the jth column of the channel matrix which is augmented. By using taking specified constant with cancellation the common BER of idle power allocation may also be estimated. By using taking the channel reap T_{jj} and allocating energy Kj put up detection SNR Pk and BER is derived from eq4. The BER minimized through QR-OSIC receiver due to convexity property of Q perform. By means of detection ordering of the QR-OSIC all diagonal elements of the matrix T¯ are equal to their common data stream given by

$$\mu = \sqrt[M_t]{\det(\bar{T})} = \sqrt[M_t]{\prod_{j=1}^{M_k} \overline{T_{JJ}}} \qquad (8)$$

When K_j and $\overline{T_{JJ}}$ variables makes product at the transmitter for them power allocation is same for all data stream. By several spatial temporal properties the real MIMO channel is characterized with respect to following conditions. By optimality condition it is not practical,if different detecting order is taken into consideration that reflects to $\overline{T_{JJ}}$ due to its T<j will be differently arranged. The improved BER performance can be accurate depending on PA scheme with estimating detection order strategy.

STRATEGY & ALGORITHM

When two variables k_j and T_{ij}' produced is maximized by simplifying due to that average BER is minimized. $k_j\overline{T_{11}}$

$$k_1\overline{T_{11}} = k_2\overline{T_{22}} = k_{Mt}\overline{T_{Mt\,Mt}}$$

$\sum_{j=1}^{Mt} k_j^2 = 1 \quad 0 < k_j < 1$

From the properties taking into consideration

$K_1\overline{T_{1,1}} = K_2\overline{T_{2,2}} = \sqrt{1-k_1^2}\det\left(\frac{\bar{T}}{\overline{T_{11}}}\right)$

$k_1^2 = det^2\left(\frac{\bar{T}}{\overline{T_{11}^4}}\right) + det^2(\bar{T})$ and

Max $K_1\overline{T_{1,1}}$ =max $K_1^{\,2}\overline{T_{1,1}}^2$.

The two transmit antennas problem can be written as

Maximize $\frac{\overline{T_{1,1}}^2 . det^2(\bar{T})}{\overline{T_{1,1}}^4 . det^2(\bar{T})} = \Phi(\overline{T_{1,1}})$ Such that $K_1\overline{T_{1,1}} = K_2\overline{T_{2,2}}$, $R_1^2 + k_2^2$.

If differential calculus is applied to $\Phi(\overline{T_{1,1}})$

$$Z\overline{T_{11}}\left(\overline{T_{11}}^4 - \det(\bar{T})\right) = 0$$

$$\overline{T_{11}} = \sqrt{\det(\bar{P})} = \mu \qquad (9)$$

If $K^2\,\overline{T_{JJ}}$ α ρ_j then $\overline{T_{JJ}}$ approaches to μ if ρ_j is increasing.

Higher post detection SNR can be carried when $\overline{T_{\iota J}}$ converge to μ delivers the ordering strategy. Let us extend the system with M_t antennas. A fixed ordering algorithm has been used to establish to satisfy the desired strategy. The channel gain can be minimized by $|\overline{T_{JJ}} - \mu|$ for all j.

$$j_p = \arg \underset{q}{min} |\overline{T_{qq}} - \mu|$$

$$q \in \{j_1, \ldots.. j_{p-1}\} = \mu = \sqrt[M_t]{\det(\bar{T})}$$

Transmit elements are rearranged as its subscript implies the reverse order in which the elements are to be detected. Then permutated sequence of them is given by order $\{j_1, \ldots.. j_{mt}\}$. The robust convergence can be achieved by employing adaptive criterion for modified ordering algorithm. If m_t=3 system by taking into consideration of selecting an element 1 as j_1. The result will be different in $\overline{T_{11}}$ if element 2 & 3 are selected. When value of j_2, j_3 are decided which effects the remaining sets. Channel gains are calculated as

$$\mu = \sqrt[M_r]{\prod_{jp=1}^{M_t} \overline{T_{pl-pl}}} \qquad (10)$$

From the previously determined channel gains adaptive ordering design is proposed by which controlling of the weights are done by renewing the thresholds. In fixed method different variables threshold are substituted then it is defined as

$$j_1 = \arg \underset{q}{min} |\overline{T_{qq}} - \mu_p|$$

$$\mu_p = \mu = \mu_{p+1} = \frac{M_t - p + 1}{M_t - p}\sqrt{\frac{\mu_p}{T_{pp}}\frac{N}{FP} + 1} \qquad (11)$$

From above equations μ_p denote the threshold for j_p.

The decided features which can be already made up are extracted by means of decreasing size of constant ordering method. By way of this adaptive ordering algorithm can be determined . The channel gain is enabled by way of adaptive ordering algorithm which is adjusted by way of μp+1 on the reverse sides if Tjj'-μ with distribution to at least one part serially[69]. Due to converge of μ is done for extra channel positive factors, the efficiency of QR-OSIC receiver is complexity of computations can be decreased.[70],[71].

II-i) EXISTING ALGORITHM OF MIMO-QR-OSIC

1. $\bar{R} = O_{Nt}, \bar{Q} = \bar{H},\ K = \{1,2, \ldots. N_t\}, \mu_l = \mu$
   Initialize $\bar{R}$ (zero Matrix), $\bar{Q}$ which is equal to $\bar{H}$ matrix, permutation sequence Nt, Geometric Mean $\mu = (\overline{R_{1,1}} = \sqrt[Nt]{det\bar{R}})$
2. For i =1,2,… .N_t
3. $\tau_i = \|\bar{Q}(:,i)\|^2$ Calculate matrix each and every column norm τ
4. *end*
5. For *l*=1,2,…. .N_t
6. $k_l = \arg\min\left|\sqrt{\tau}\,\mathrm{w} - \mu_l\right|$
   Initialize *l* value as 1.

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Calculate the min norm element(k_l) of $,\bar{Q}$ matrix column.
Increment l value with 1 after completion of step 15 and repeat step 6 to 11

7. $\mu_{l+1} = \mu: fixed$

$$\mu_{l+1} = \sqrt[\frac{N_t-l+1}{N_t-1}]{\mu_l/R_{l,l} - N_t - l + 1} : Adaptive$$

Calculate fixed or adaptive threshold(μ_2).

8. $\bar{R}(:,l) \leftrightarrows \bar{Q}(:,k_l)\,, \tau_l \leftrightarrows \tau_{kl}$
Exchange the l column (l=1) of $\bar{R}$ matrix with $\bar{Q}$ matrix column(k_l) ($\bar{Q}$ matrix columns min norm column).
Exchange the $\bar{Q}$ matrix column (l,k_l) norm,
when l=1=> exchange R matrix first column norm.
$K(l) \leftrightarrows K(kl)$
Exchange permutation vector element $\bar{Q}(1{:}N_r + l - 1, l) \leftrightarrows \bar{Q}(1{:}N_r + l - 1, kl)$
Exchange $\bar{Q}$ matrix 1 to $N_r + l - 1$ rows and column with $N_r + l - 1$ rows and kl columns
i.e., when l=1 $\bar{Q}(1{:}N_r + l - 1{,}1) \leftrightarrows \bar{Q}(1{:}N_r + l - 1{,}kl$

$$\bar{Q}(1{:}N_r, 1) \leftrightarrows \bar{Q}(1{:}N_r, kl)$$

Exchange $\bar{Q}$ matrix first column to Nr rows with the $\bar{Q}$ matrix column which has min norm element.

9. $\bar{R}(l,l) = \sqrt{\tau_l}$
Select diagonal element as $\sqrt{\tau_l}$
When l=1 =>$\bar{R}(1,1)$ *will be* $\sqrt{\tau_l}$.

10. $\bar{Q}(:,l) = \bar{Q}(:,l)/\bar{R}(l,l)$
Divide 1 column elements of $\bar{Q}$ matrix with $\sqrt{\tau_l} = \bar{R}(l,l)$
When l=1 divide $\bar{Q}$ matrix first column elements with $\bar{R}(l,l)$.

11. For m=l+1,…. N_t
12. $\bar{R}(l,m) = \bar{Q}^H(:,l).\bar{Q}(:,m)$

13. $\bar{Q}(:,m) = \bar{Q}(:,m) - \bar{R}(l,m).\bar{Q}(:,l)$
Find the $\bar{R}$ matrix remaining row elements using formula.
Find the $\bar{Q}$ matrix remaining column elements using formula.
After calculating the $\bar{R}$ matrix one row element, calculate the $\bar{Q}$ matrix corresponding column total elements.

14. $\tau_m = \tau_m - \bar{R}^2(l,m)$
Calculate the norm according to changes in $\bar{R}$ matrix, $\bar{Q}$ matrix elements. Increment m value with 1.
Repeat steps 12,13 &14 until m=N_t.
15. End (when m>N_t)
When m>N_t end the procedure to calculate the $\bar{Q}$ matrix column elements & $\bar{R}$ matrix row elements. Increment l value with 1 & repeat step 6 to step 11

16. End (when l >N_t)
End the procedure when l value is greater than N_t

ii) PROPOSED ALGORITHM

1. $\bar{R}, \bar{Q}, k, \mu$ initializtion from existing algorithm output.

2. For i= N_t , …1

3. $\tau_i = \|\bar{Q}(:,i)\|^2$
4. *end*
Calculate the $\bar{Q}$ matrix each and every column norm τ.
(N_t, N_{t-1}, …..1 column norms)

5. For l= N_t , …1

6. kl =arg min |√τ w-μ_l |
Initialize l value as N_t.
Calculate the min norm element (kl) of $,\bar{Q}$ matrix column.

7. $\mu_{l-1} = \mu: fixed$
8. $\mu_{l+1} = \sqrt[\frac{N_t-l+1}{N_t-1}]{\mu_l/R_{l,l} - N_t - l + 1}$ adaptive
Calculate fixed/ adaptive threshold value ($\mu_{\mathrm{Nt}-1}$)

9. $\bar{R}(:,l) \leftrightarrows \bar{Q}(:,kl)\,, \tau_l \leftrightarrows \tau_{kl}$
Exchange Nt column in $\bar{R}$ matrix with $\bar{Q}$ matrix kl column where kl is the min norm element column of $\bar{Q}$ matrix columns.
Exchange the norm τ value according to column change of $\bar{R}$ & $\bar{Q}$ matrix.
τ_{Nt} with norm of kl value.
$k(l) \leftrightarrows k(kl)$
Exchange permutation vector element also.

$$\bar{Q}(1{:}N_r + l - 1, l) \leftrightarrows \bar{Q}(1{:}N_r + l - 1, kl)$$

Exchange $\bar{Q}$ matrix 1 to $N_r + l - 1$ rows and column with $N_r + l - 1$ rows and kl column elements.

10. $\bar{R}(l,l) = \sqrt{\tau_l}$
Select diagonal element as $\sqrt{\tau_l}$
When l=N_t =>$\bar{R}(\mathrm{Nt},\mathrm{Nt})$ *will be* $\sqrt{\tau_{\mathrm{Nt}}}$

11. $\bar{Q}(:,l) = \bar{Q}(:,l)/\bar{R}(l,l)$
Divide N_t column elements of $\bar{Q}$ matrix with diagonal element.
for l=N_t => $\bar{Q}$ matrix N_t column elements with $\bar{R}(l,l)$

12. For m=*l,l-1*

13. $\bar{R}(l,m) = \bar{Q}^H(:,l).\bar{Q}(:,m)$
    Calculate $\bar{R}(l,m)$ element with formula
    l= N_t => m= N_t =>$\bar{R}(\mathrm{Nt},\mathrm{Nt})$ element will be calculated.

14. $\bar{Q}(:,m) = \bar{Q}(:,m) - \bar{R}(l,m).\bar{Q}(:,l)$
    Calculate $\bar{Q}$ matrix m column elements using formula
    l= Nt => m= Nt=> $\bar{Q}(:,m) = \bar{Q}(:,Nt)$
    Q matrix Nt column elements will be calculated.

15. $\tau_m = \tau_m - \bar{R}^2(l,m)$

Calculate the threshold according to calculation of $\bar{R}$ element, $\bar{Q}$ column element.

16. Decrement m value with 1.
    column element. Decrement m value with 1.
    Repeat steps 12,13 &14 until *m=l-1*

17. End (when *m=l-1)*
    When m=*l*-1, end the procedure to calculate row elements &
    column elements. Decrement l value with 1 & repeat step 6 to step 11
18. End.

SIMULATION RESULT

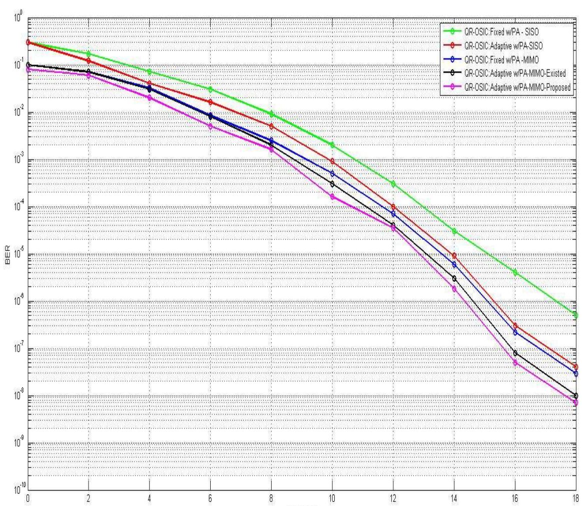

Figure 6 BER vs SNR with SISO&MIMO for fixed and adaptive power allocation

CONCLUSION

Performance of MIMO-QR-receiver design is compared with existing and proposed algorithm based on fixed power and adaptive power allocation. The Average BER performance of SISO with one transmit and receive antenna and MIMO systems with two transmit/receive antennas are compared as shown in Figure 6 at SNR=18dB the BER is $9\text{x}10^{-9}$ for MIMO-adaptive power allocation (Existing Method)and the BER is $7\text{x}10^{-9}$ for MIMO adaptive power allocation(Proposed Method).The efficiency is increased by 77%.

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