Selective Frequency Link Adaptation on Rayleigh Fading Channel for OSTBC MIMO System with Imperfect CSIT using TLBO
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Abstract
Increasing the utilization of power and interference noise is very critical issue for wireless communication system. For the reduction of power utilization and noise interference used various adaptive technique such as link adaptive technique, selective frequency technique and diversity of antenna. Increase the life of power and reduces the value of inference improved the communication quality in wireless system. in this paper used teacher learning based optimization technique for selection of frequency for OSTBC-MIMO system. the proposed system reduces the value of inference and increase the capacity of channel. A TLBO approach for finding near optimum signaling for transmission. Prior to limiting, the channel estimates are assumed perfect and delay in obtaining these estimates is ignored to focus on the effects of limited feedback.

Keywords: - Selective Frequency CSI Link Adaption, MIMO, TLBO, STBC

Introduction
Selective frequency technique is important research area in the field of link adaptive communication technique. the selective frequency technique improved the efficiency of channel selection and increase the throughput of communication system[1,2]. With the rapid rising demand for high-rate and robust data services in recent years, the booming energy consumption has become a bottleneck at mobile terminals due to the size restriction of mobile terminals and the slow progress of battery technology [9]. Thus, in addition to SE, the energy efficiency (EE) of transmitter is becoming more and more influential for wireless communication. Given the amount of data required to be transmitted, the works in [10,12] optimize the transmission time for M-ary quadratic-amplitude modulation (MQAM) and M-ary frequency-shift keying adaptive modulation through exhaustive search with both static circuit power and power amplifier (PA) inefficiency considered. Link adaptation based on channel state information (CSI) is normally used to maximize the sum rate for a given total transmission power in a frequency-selective channel. It is well known that the optimal subcarrier power allocation is given by so-called water-filling. However, link adaptation can also be directed towards improved energy efficiency. proposed a scheme that adapts both the overall transmit power and its allocation using traditional selection of frequency to maximize the energy efficiency. This work provides more insight into how the overall transmit power should be chosen for optimal energy efficiency. In contrast to previous work, the circuit power consumption is modeled as a function of the sum rate, rather than as a constant. The power amplifier efficiency is further modeled as a function of the number of subcarriers used for transmission. Moreover, a fast and simple fixed point algorithm for finding the optimal power allocation is proposed. In order to achieve comparable performance to the average BER constraint with limited complexity, a non-linear optimization method is proposed. To further enhance the average spectral efficiency, adaptive power allocation schemes are considered to adjust the transmit power across the temporal domain or the spatial domain, depending on the specific situation. Provided the closed-form expressions of the average spectral efficiency, the optimal MIMO coding scheme that other the highest average spectral efficiency under the same circumstances can be identified. As we take into account the effect of imperfect channel estimation, the adaptation techniques are revised to tolerate interference introduced by the channel estimation errors. As a result, the degradation with respect to the average spectral efficiency is in proportion to signal-to-noise ratio (SNR). Section-I gives the introduction of the adaption technique. Section-II gives the MIMO model and Channel fading technique-III gives the information of TLBO. In section IV proposed model, in section V discuss comparative result Finally, in section-VI conclusion and future scope

II. MIMO SYSTEM
Let us consider user employs r antenna to receive signal transmitted from t antenna. The channels that link the t transmit and r receive antennas are characterized by an r×t matrix , which is assumed to follow the joint complex Gaussian distribution with mean matrix M and covariance matrix \( \Sigma \). Symbolically, we will write
H–CN_{t0M} \sum_{i}^{l} \Psi \) ……………………(1)

Where \( \Psi \) and \( \sum \) define the correlation structure at the transmit and receive ends, respectively. It is assumed that the intended signal is corrupted by \( l \) independent interferers, and the \( i \)-th interferer transmits its signal with antennas where \( i = 1, \ldots, l \). The desired information symbol \( b_{i} \) is weighted by the transmit beamformer before being fed to the transmit antennas. The transmit beamformer is normalized to have a unit norm so that the transmit energy equals \([3,4]\). The vector at the desired user’s receiver can, thus, be written as

\[ y = \mathbf{h}_{r} \mathbf{u} + \sum_{i=1}^{l} \mathbf{h}_{s} \mathbf{b}_{i} + \mathbf{n} \] ………………………(2)

Where \( \mathbf{h}_{r} \) is the \( r \times 1 \) channel matrix characterizing the links from the desired user’s \( r \) receive antennas to the \( ti \) transmit antennas of interferer \( i \); and is the symbols transmitted by interferer \( \mathbf{b}_{i} \) such that \( E[S, S] \) with denoting the average symbol energy and \( E[.] \) denoting expectation. In the way similar to defining \( \mathbf{H} \), we assume

\[ \mathbf{H}_{r} \mathbf{C}_{r} \mathbf{H}_{r}^{\dagger} \] ……………………………(3)

We assume the additive noise vector \( \mathbf{n} \) to \( r \times 1 \) complex Gaussian distribution of mean zero and covariance matrix \( \mathbf{R}_{n} \) conditioned on \( \mathbf{H}_{r} \). The covariance matrix of interference plus-noise component is given by

\[ \mathbf{R}_{c} = \sum_{i=1}^{l} E_{i} \mathbf{H}_{s} \mathbf{H}_{s}^{\dagger} + \mathbf{R}_{n} \] …………(4)

Now we take a closer look at the correlation structure of \( \mathbf{H} \) and \( \mathbf{H}_{r} \) in (2). The correlations of the matrices \( \mathbf{H} \) and \( \mathbf{H}_{r} \) are specified \( \sum_{i}^{l} \Psi_{i} \) by and \( \sum_{i}^{l} \Psi_{i} \), respectively. Physically, \( \sum \) and \( \sum_{i}^{l} \) represent the correlation matrices of incoming signal and interference at the receiver, respectively. Correspondingly, the transmit-antenna correlations for the desired user is characterized by the correlation matrix, whereas its counterpart for interferer is specified by the correlation matrix. The structure of these correlation matrices depends on channel’s fading characteristics, geometry and polarization of antenna arrays, and signal/interferers angle of arrival and spread.

### III. TLBO

This optimization method is based on the effect of the influence of a teacher on the output of learners in a class. It is a population based method and like other population based methods it uses a population of solutions to proceed to the global solution. A group of learners constitute the population in TLBO[16]. In any optimization algorithms there are numbers of different design variables. The different design variables in TLBO are analogous to different subjects offered to learners and the learners’ result is analogous to the ‘fitness’, as in other population-based optimization techniques. As the teacher is considered the most learned person in the society, the best solution so far is analogous to Teacher in TLBO. The process of TLBO is divided into two parts. The first part consists of the “Teacher phase” and the second part consists of the “Learner phase”. The “Teacher phase” means learning from the teacher and the “Learner phase” means learning through the interaction between learners. In the subsections below we briefly discuss the implementation of TLBO.

#### Initialization

Following are the notations used for describing the TLBO

- \( N \): number of learners in class i.e. “class size”
- \( D \): number of courses offered to the learners
- \( MAXIT \): maximum number of allowable iterations

The population \( X \) is randomly initialized by a search space bounded by matrix of \( N \) rows and \( D \) columns. The jth parameter of the ith learner is assigned values randomly using the equation

\[ x_{i}^{[j]} = m_{i}^{[j]} + \text{rand} \times (u_{i}^{[j]} - l_{i}^{[j]}) \] …………………………………(1)

where \( \text{rand} \) represents a uniformly distributed random variable within the range \( (0, 1) \), \( x_{i}^{[j]} \) and \( x_{i}^{[j]} \) represent the minimum and maximum value for jth parameter. The parameters of ith learner for the generation g are given by

\[ x_{i}^{[j]}(g) = m_{i}^{[j]} + \text{rand} \times (x_{i}^{[j]} - x_{i}^{[j]}) \] …………………………………(2)

#### III.1 Teacher phase

The mean parameter \( M^{[j]} \) of each subject of the learners in the class at generation \( g \) is given as

\[ M^{[j]} = [m_{1}^{[j]}, m_{2}^{[j]}, \ldots, m_{N}^{[j]}] \] …………………………………(3)

The learner with the minimum objective function value is considered as the teacher \( X_{g} \). Teacher for respective iteration. The Teacher phase makes the algorithm proceed by shifting the mean of the learners towards its teacher. To obtain a new set of improved learners a random weighted differential vector is formed from the current mean and the desired mean parameters and added to the existing population of learners.

\[ x_{\text{new}}^{[j]}(g) = \text{rand} \times (x_{\text{teacher}}^{[j]} - X_{g}^{[j]}) \] …………………………………(4)

TF is the teaching factor which decides the value of mean to be changed. Value of TF can be either 1 or 2. The value of TF is decided randomly with equal probability as,

\[ T_{F} = \text{rand} + \text{rand} \times (1 - \text{rand}) \] …………………………………(5)

Where TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm using Eq. (5). After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs better if the value of TF is between 1 and 2. However, the algorithm is found to perform much better if the value of TF is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria given by Eq. (5). If \( x_{\text{new}} \) is found to be a superior learner than \( X_{g} \) in generation \( g \), than it replaces inferior learner \( X_{g} \) in the matrix.

#### III.2 Learner phase

In this phase the interaction of learners with one another takes place. The process of mutual interaction tends to increase the
knowledge of the learner. The random interaction among learners improves his or her knowledge. For a given learner Xg , another learner Xg is randomly selected (i ≠ r). The ith parameter of the matrix Xnew in the learner phase is given as

\[ X_{\text{new}}^i = \begin{cases} \mathbf{x}^i + \mathbf{r} & \text{if } f(x^i) > f(x^j) \text{ and } j \neq i \text{ and } j \neq r \smallskip \mathbf{x}^i + \mathbf{r} & \text{otherwise} \end{cases} \]

III.3 Algorithm termination
The algorithm is terminated after MAXIT iterations are completed.

IV PROPOSED SYSTEM
The proposed frequency selection consists of two basic coefficients; one is frequency selector filter and one TLBO. The purpose of filter is to receive the distorted output from the channel and will form two separate and independent patterns, one for {+1} and next for {-1}. The purpose of the TLBO is to optimize the cost function and thereby minimizing the error. The frequency selector is two coefficients one is low adaption of power and another is high power adaption. These two coefficients include the input unit, the pattern unit, the summation unit and the output unit. The input unit contains a number of input image data and the pattern unit node equal the number of training data, the output unit represents the significant results. The raw frequency is divided into k signals, which represent the k situations to be explained. Each signal has m-dimensional observations, i.e. \( X = \{X_1, X_2, \ldots, X_m\} \). The following selection rules satisfy the raw data into k signals:[12]

\[ h_i c_i f_i(X) > h_j c_j f_j(X) \quad \forall \quad j \neq i , \]

Where \( h_i \) is the prior FS of signal k; \( c_i \) is the representative center that belongs to the signal k, but the loss function has been a miscarriage of justice; and \( f_i \) is the FS density function of signal k.

The FS density function for each signal can be expressed as follow:

\[ f_i(x) = \frac{1}{(2\pi)^d \sigma^d} \sum_{j=1}^{N_i} \exp \left[ -\frac{(x - x_{ij})^t(x - x_{ij})}{2\sigma^2} \right] \]

Where \( f_i(x) \) denotes the dimension of training vector, \( \sigma \) is the smoothing parameter and \( d \) is the dimension of training vector. \( N_i \) Denotes the total number of training vector in category i, and \( x_{ij} \) is the value vector and \( x \) is test vector.

When a new input image \( X \) is added, the pattern unit will be calculated with the individual weight vector \( W^p \) of the product to make a nonlinear transformation to \( Z_i \):

\[ Z_i = X \cdot W^p . \]

The FS of neural network with back propagation networks can approximate any continuous nonlinear function. In this paper, we use the Gaussian function as the activation function:

\[ P(Z_i) = \exp \left[ \frac{Z_i - 1}{\sigma^2} \right] \]

With the above equation, \( X \) and \( W^p \) have been normalized with their unit length:

\[ P_i(X) = \exp \left[ -\frac{(X - W^p)^t(X - W^p)}{2\sigma^2} \right] \]

The summation unit will be calculated from the pattern unit by summarizing and averaging the output of \( N_i \) neurons to generate an output FS vector, i.e.

\[ S_i(X) = \frac{1}{N_i} \sum_{j=1}^{N_i} \exp \left[ \frac{(X - W^p)^t(X - W^p)}{2\sigma^2} \right] \]

Finally, one or many larger values are chosen as the output unit that indicates these data points are in the same signal via a coefficient transfer function from the output of summation unit [7], i.e.

\[ O(X) = \arg \max(S_i(X)), \quad i = 1, 2, \ldots, m \]

V SIMULATION OF SYSTEM
Computer simulations are conducted to demonstrate the effectiveness of the proposed TLBO in STBC-OFDM systems. Simulations are done in MATLAB using the Rayleigh channel model, comparison of proposed method with zero forcing condition and CSIT is analyzed. Here in, quadrature phase-shift keying (QPSK) modulation is used, the number of subcarriers is set as \( N = 64 \), and the length of CP is always chosen to be longer than the maximum length of the multipath fading channel.
Figure 1 Performance analysis of BER and SNR of 2*2 MIMO system for number of tapes=10

Figure 2 Performance analysis of BER and SNR of 4*4 MIMO system for number of tapes=10

Figure 3 Performance analysis of BER and SNR of 4*4 MIMO system for number of tapes=10 for adaptive Model and TLBO

Figure 4 Performance of STBC - OFDM System with TLBO scheme for various diversity constrains
VI  CONCLUSION AND FUTURE SCOPE

In this paper proposed a new methodology TLBO average weighted for improvement of BER and reduction of noise interference. Our proposed methodology performs on MIMO STBC-OFDM system model for balanced and unbalanced combination of multiuser system. The evaluation of parameters used three conditions ZF, MMSE, TLBO average weighted. TLBO average weighted shows better result in comparison of Pre FFT combination of STBC OFDM with TLBO fair Condition. Future works can be done in the direction of reducing the complexity of our designed Optimized Adaptive TLBO Criteria for STBC-OFDM with Multiple Diversity Constraints system. Work can be done to use the proposed TLBO Average Weighted criteria can be used with MC-CDMA.

REFERENCES


