DATA DETECTION WITH FUZZY C-MEANS BASED ON EM APPROACH BY MIMO SYSTEM FOR DIFFERENT CHANNEL'S ESTIMATION IN WIRELESS CELLULAR SYSTEM

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ABSTRACT

Classical wireless communication technologies are threatened with so many challenges for meeting the desires of ubiquity and mobility for the cellular systems. Hostile wireless channels features and restricted frequency bandwidths are obstacles in future generation systems. In order to deal with these limitations, different advanced signal processing approaches, such as expectation-maximization (EM) algorithm, SAGE algorithm, Baum-Welch algorithm, Kalman filters and their extensions etc. were proposed. In this paper, estimation of unknown channel parameter and detection of data at receiver end has been performed. MIMO Rayleigh and Rician channels are taken for wireless communication. To find the initial point for EM algorithm FCM clustering algorithm is used. In this work, algorithm is implemented using MATLAB R2012a. The performance matrices of the algorithm are bit error rate (BER) and mean square error (MSE) at different values of signal to noise ratio.

Keywords: Fuzzy C-Mean, MIMO system, Expectation Maximization Algorithm, semi blind channel estimation, channel state information, maximum a posterior.

I. INTRODUCTION

Nowadays, wireless communication demands high data with reliability. To achieve high data rate it is necessary to use wide spectral bandwidth, which makes system economical unfeasible. In order to minimize this problem, Multi input multi output system has been introduced. Several wireless technologies such as IEEE802.11n, IEEE802.16 etc. are using MIMO system.

A major challenge to MIMO system is to find the channel state information perfectly to detect the information in the system .Channel state information (CSI) can be acquired with the help of different channel estimation methods. CSI c a n be acquired u s i n g non-blind channel estimation techniques, this methodology results in loss of channel capacity, particularly in MIMO and fast fading channel. Blind channel estimation technique is also used for obtaining CSI but these techniques are less accurate have more complexity.

A substitute approach is to practice semi blind channel estimation technique, which is mixture of blind and non-blind channel estimation method. It exploits only few pilot carriers and other natural constraints to calculate the CSI. This method has been reviewed by many authors in the last two decades. In this paper, FCM based EM approach is used to compute the CSI [2-5] and then detection of data is performed with the help of Maximum a posterior (MAP) rule. We consider both Rayleigh and Rician MIMO channels.

Joint channel estimation of parameter and detection of data for MIMO systems using EM algorithm has established an excessive pact of courtesy in the last decade. EM algorithm is an iterative estimation algorithm that can derive the maximum likelihood (ML) estimates in the presence of hidden data ("incomplete data"). The basic function of EM is contains of two steps: Expectation (E) step, calculates the expectation of the log-likelihood function using the current evaluation of the factors. Maximization (M) step, computes factors maximizing the log-likelihood function.

The paper proposed EM algorithm which is used to find channel coefficients and noise variance. Initially channel coefficients for EM algorithm are obtained with support of FCM algorithm, which is a data grouping technique in which a data set is clustered into n groups and after calculating unknown parameter detection of data is performed using MAP rule.

We equate the performance of proposed method with the k-means-based EM algorithms [6]. The paper is organized as follows, Section II introduces fuzzy C-means technique and section III gives outline of EM algorithm. Section IV illuminates the proposed methodology, section V shows the simulated results and analysis and conclusions are summarized in Section VI.

II. FUZZY C- MEAN ALGORITHM

Fuzzy C Mean (FCM) is a data grouping method [14]. Data set is clustered into n groups. In this approach data point in the dataset fits to every cluster with some membership grade. Data point which locates close to centre of cluster has a high membership grade to that cluster and another data point that locates distant from the centre of a cluster has a low membership grade to that cluster. We define the objective function for FCM as follow

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} P^m_{ij} |x_i - \mu_j|^2$$

Here small m denotes real integer whose value greater then 1 & P_{ij} is membership grade of x_i in the cluster j and μ_j is the center of the cluster.center vector (μ_j) and distance matrix (D_{ij}) for each step is given by the equation's (1) & (2) respectively.

$$\mu_j = \sum_{k=1}^{N} P_{ij}^{m'} \quad X \quad x_{ij} \sum_{k=1}^{N} P^{m'}_{ij} \qquad (1)$$

$$D_{ij} = [\sum_{j=1}^{m} [x_{ij} - \mu_j]^2]^{(1/2)} \qquad (2)$$

Membership grade for the Kth step is updated using equation

$$P^{r-1}_{ij} = \sum_{j=1}^{\mu} [D^k_{ir} / D^r_{jr}] 2/(m'-1) \qquad (3)$$

If $\| P(r+1) - P r \| < \delta$ then iteration STOPS: else update the cluster centroid and the membership grades for data point iteratively till termination criteria achieved.

δ is a termination condition which lies between 0 and 1, and r is the number of iteration convergence of this procedure is arises at local minimum or a saddle point of Jm.

The steps of algorithm are as follows:-

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Step 1: Initialize membership grade p = [Pi j] matrix, P (0)

Step 2: At k-step: calculate the centroid vectors and distance vector from (1) and (2) with help of p (k)

Step 3: Update p(r), p(r+1)

Step 4: If || p (r+1) - p (r)|| < δ then STOP;

Otherwise return to step 2.

FCM shifts the cluster centres to the "exact" location within a dataset iteratively. p is membership grade between data and centroid of cluster whose value lies between 0 and 1.

III. EXPECTATION MAXIMIZATION ALGORITHM

The EM (Expectation-Maximization) algorithm has been usually applied in a huge number of regions that pact with unknown factors disturbing the result, such as signal processing, genetics etc. The EM is iterative technique for calculating maximum likelihood (ML) estimates of a channel. It is one of a semi-blind technique.

The EM algorithm is mainly beneficial for channel estimation when existing data is incomplete or hidden. Incomplete data may be challenging in the circumstances where the data on the transmitted signals is unavailable or insufficient. This method contains of dormant variables in addition to unknown parameters and observed data values i.e. there are some lost values between the data. First we take derivatives of the likelihood function with respect to all the unknown parameters and then by solving the resulting equations simultaneously, we find the maximum likelihood solution.

The set of detected data is denoted by x, the set of all hidden variables by z and set of unknown parameters to be estimated is denoted by Ө. Log likelihood function is calculated by

$$l_n P (x/ Ө) = \sum_z P (x,z/ Ө) \qquad (4)$$

Firstly we have to initialize EM by some initial values of unknown parameters then EM algorithm executes in two steps: In the expectation step, or E step, the existing values of the parameters are used to calculate the posterior probabilities, or responsibilities given in equation (5). Then in the maximization step, or M step, again calculation of the unknown parameters such as means, covariance, and mixing coefcients will take place using the equations (6), (7), and (5) respectively. firstly, new means is calculated by using equation (6) and with the help of these new values we evaluates the covariance using equation (7), these updated parameters resulting from both E step and M step are assured to increase the log likelihood function This process is iteratively repeat until a stopping criterion is satised. Each iteration of EM algorithm increases the value of log-likelihood function [9] that implies that the EM algorithm will converge irrespective of the initial value of the parameters. Convergence properties of EM algorithm in details can be found in [9], [13].

(E-step) computes.

$$T^{(t)}_{j,i} = \{ Т^{(t)}_j f (x_i | \mu^{(t)}_j , \sigma^{(t)}_j) \} \div \{ \sum_i^k Т^{(t)}_k f (x_i | \mu^{(t)}_k , \sigma^{(t)}_k) \} \qquad (5)$$

Here $T^{(t)}_{j,I}$ gives the probability of ith sample to belong into the jth distribution.

(M-step) computes

$$Т^{(t+1)}_j = 1/N \sum_{i=1}^N T^{(t)}_{j,I} \qquad (6)$$

$$\mu^{(t+1)}_j = [\sum_{i=1}^N T^{(t)}_{j,I} x^t_I] \div [\sum_{i=1}^N T^{(t)}_{j,i}] \qquad (7)$$

$$\sigma^{(t+1)}_j = \sum_{i=1}^N T^{(t)}_{j,I} (x_i - \mu^{(t+)}_j) (x_i - \mu^{(t+1)}_j)^T (\div) \sum_{i=1}^N T^{(t)}_{j,i} \qquad (8)$$

The EM algorithm comprises of following steps:

Step 1: Initialize unknown parameter by some values (centre, covariance, mixing coefficient)

Step 2: At E-step: computes the prior probability using the current parameter from eq.4

Step 3   M-step: Evaluate the unknown parameters (mean and covariance) with the help of the calculated posterior probability from equation (7) and (8)

Step 4: Determine the log likelihood function and check for convergence of either the parameters or the log likelihood function

If convergence criterion is not fulfill then return to step2.

IV. METHODOLOGY

EM based iterative receiver for joint estimation of parameter and detection of data is proposed. Here Unknown parameters are channel coefficient (μ), noise variance () and mixing coefficient (S) .We assume that the receiver is aware of the first block in the transmitted frame. FCM algorithm is used here to find initial point and quick Convergence of EM algorithm.

EM algorithm is initialized with estimated channel coefficients from fuzzy C means method and some initial values of noise variance and mixing coefficient then algorithm perform E-step ,in which it calculates posterior probability by using current estimated values then M-step re-estimate unknown parameters. E-step and M-step repeats iteratively until convergence criteria are satisfied.

After estimating the parameter set, the nth symbol is detected by MAP (maximum a posterior) rule The entire procedure is summarized in Algorithm where the convergence criteria are set as the amount of change (in percentages) in the estimated parameters. The procedure of method via flowchart is shown in Fig. 1

Algorithm for Estimation of unknown algorithm parameter and detection of data using the FCM based EM. Begin

Step-A Find **initial estimate of μ** for the EM algorithm from the method of **FCM:**

Initialize μ with some initial values

While Convergence criterion is not satisfied do

Step 1: Find **μ** using (1); Step 2: Re-estimate $P_{I,j}$ using (3); **End**

Step-B Estimate the parameter set ϴ, using the EM Algorithm.

Initialize μ with the result of FCM algorithm and initialize σ   and Ʈ

While Convergence criterion is not satisfied do E-Step: Find posterior probability using (4);

M Step: Re-estimates μ, Z and S using (7), (6), and (5); End

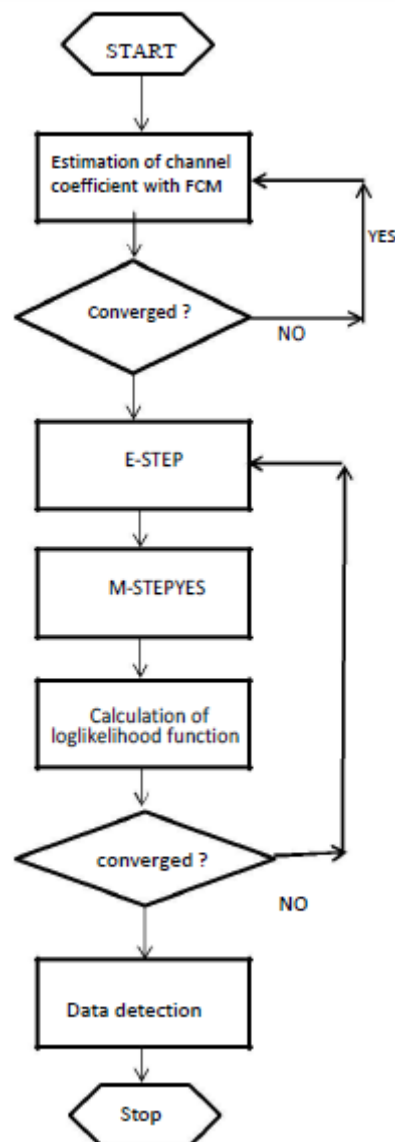**Step-C perform symbols detection by using MAP rule**

End.

Figure: Flow –chart of unknown channel estimation and data detection with proposed method

V. RESULT AND PERFORMANCE

Comparison of the performance of which is FCM based EM algorithm with the K-means based EM algorithm for different modulation techniques is done in this section. This method is applicable for both Raleigh & Recian MIMO fading channels. Mean square error rate are considered as the performance matrices for the result analysis. For simulation purpose we considered the number of transmitted antenna and received antenna should be equal to =2.
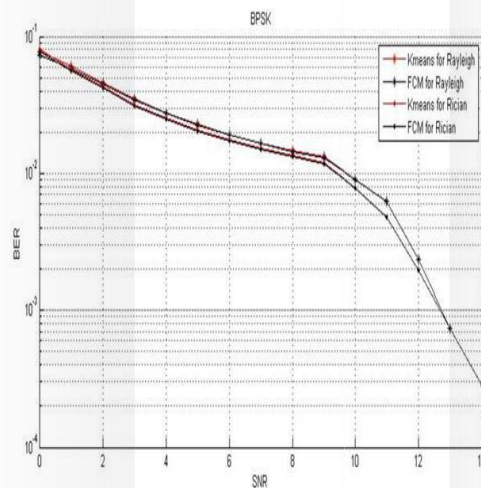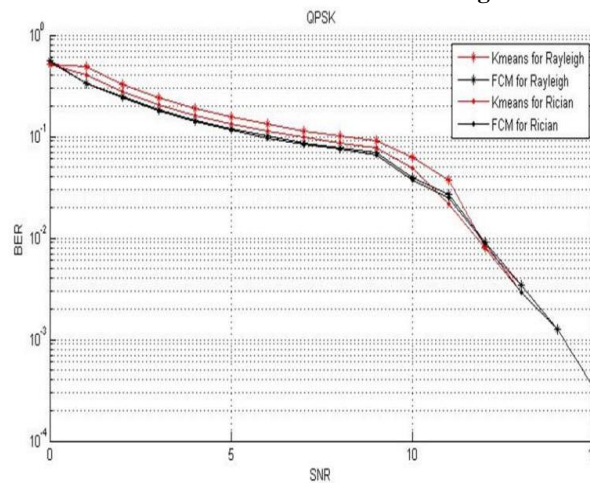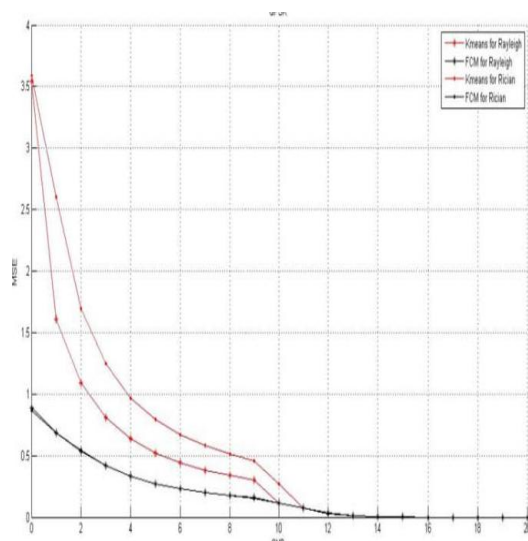
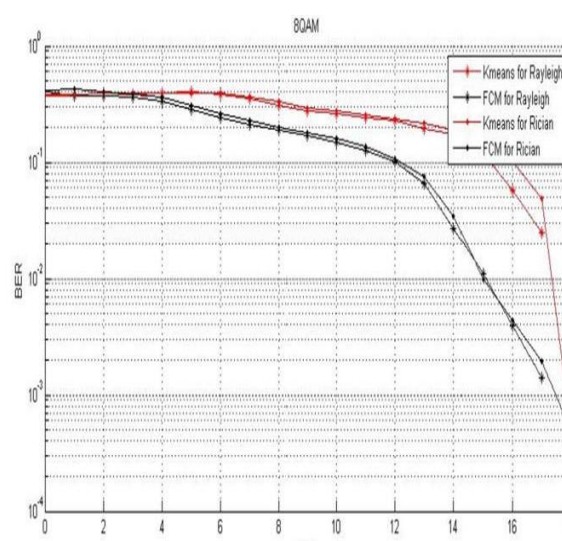**Fig2.BER Vs SNR for BPSK Modulation for Raleigh & Rician MIMO – channels**
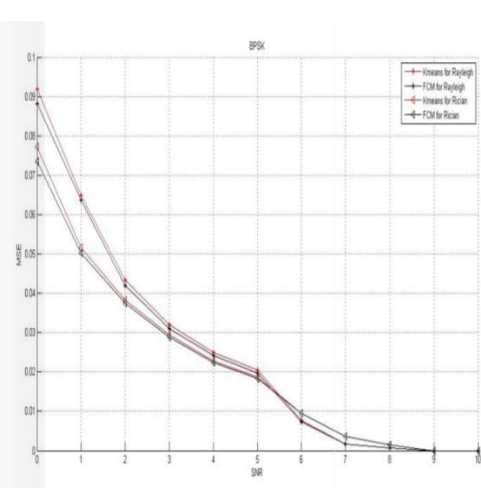
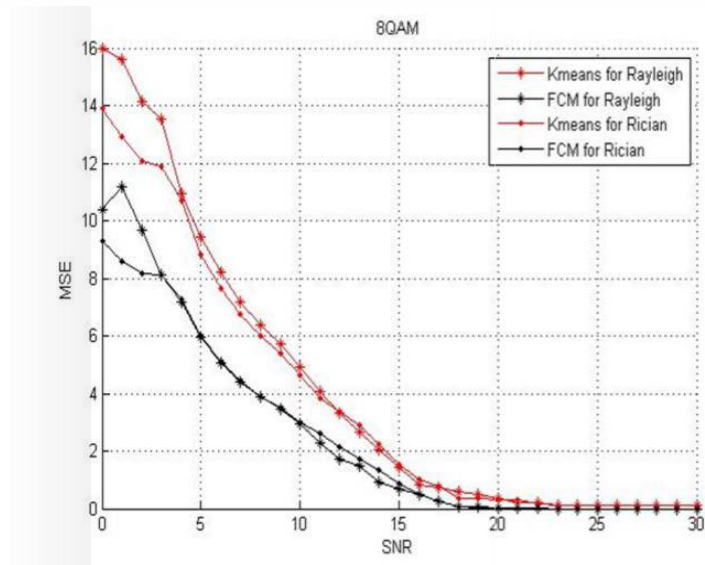**Fig 3.MSE Vs SNR for BPSK Modulation for Raleigh & Rician MIMO – channels**

Fig4.BER Vs SNR for QPSK Modulation for Raleigh and Rician MIMO channels

Fig5: MSE Vs SNR for QPSK Modulation for Raleigh and Rician MIMO channels

Fig6: BSE Vs SNR for 8QAM Modulation for Raleigh and Rician MIMO channels

Fig7: MSE Vs SNR for 8QAM Modulation for Raleigh and Rician MIMO channels

Fig 6 and fig 7 shows comparison of b 8PSK for both MIMO channels in terms respectively. For both the parameter FCM better result for both channels

VI. CONCLUSION

From the result of analysis. In this paper iterative expectation maximization algorithm with FCM is proposed for parameters estimation and data detection in Multiple Inputs with Multiple outputs system (MIMO method).in this method we consider that the receiver don't have any knowledge of the channel co-efficients.The algorithm Is evaluated for both MIMO Rayleigh and Rician fading channels with different modulation techniques or schemes like BPSK, QPSK and 8QAM. We compare the performance method with the k-means based EM algorithm in terms of BER and MSE at different values of signal to noise ratio(SNR).FCM and EM based algorithm gives better performance than the K-mean based EM algorithm. As the noise in the system increases the performance of FCM based EM algorithm also increases with respect to K-mean based EM algorithm. Whereas the complexity of proposed method require 2 or 3 iterations of the EM algorithm to converge and it doesn't require any matrices inversion trellis's search.

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