Channel Estimation in 5G Technology: Gaussian Mixture Learning Approach with Compressed Sensing

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Abstract

Massive MIMO-OFDM is a powerful and long-lasting solution for future 5G wireless applications. It provided substantial improvements in latency and reliability, allowing for a more significant number of user participation at high data rates. Reduced pilot overhead is required to acquire accurate channel knowledge. Compressed sensing is one of the uppermost approaches to solving this challenge. The sparsity level between the communication channels is strengthened by sparse channel estimation, increasing channel estimation performance by decreased pilot overhead. Non-zero vector distributions can perform this by considering the Gaussian mixture and learning their properties employing the expectation-maximization technique. The simulation results validated the suggested channel estimation approach with minimal pilot overhead and demonstrated the system's excellent symbol error rate (SER) performance.

Keywords
Massive MIMO-OFDM, Gaussian Mixture, Compressed sensing, EM Learning

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Introduction

Massive MIMO-OFDM offers reliability and high data rates for 5G [1]. Channel information poses challenges for optimal system performance. Enhancements in this area are crucial for achieving the technology's full potential in meeting wireless communication demands effectively. Consequently, utilizing suitable estimate methods for the channels between the sending and receiving antennas is necessary. An accurate channel estimation can be obtained using the correct training sequence design.

We applied compressed sensing-aided (CS-Aided) technique to assess channel sparsity in massive MIMO-OFDM system [2]. Although communication channels are naturally sparse, they are frequently treated as zero coefficients for channel impulse response (CIR). This method enhances channel property understanding efficiently by reducing pilots. It outperforms traditional methods. Previous studies explored Greedy algorithms and Bayesian compressed sensing techniques.

The sparsity adaptive matching pursuit (SAMP) [3] produces outstanding results in several applications without channel sparsity. Because SAMP uses a fixed step size, there is a gap between convergence speed and recovery precision. OFDM, a modulation scheme, reduces interference by converting serial data into parallel streams with multiple frequencies. It enhances data transmission efficiency by minimizing cross-talk. Sparse and dense vectors are utilized in OFDM's massive MIMO compressed sensing channel estimation [4]. Non-zero and zero vectors compensate for specific indices. The LS technique is employed for reconstructing sparse signals, ensuring perfect sparse recovery.

The expectation-maximization (EM) algorithms [5] are often used to determine parameters using a Gaussian methodology. The expectation step is optimized with GAMP for reduced computation complexity in i.i.d. distributed random signals. FITRA is designed for sparse representation, demonstrating a high convergence rate [6]. It incorporates a regularization parameter for MUI cancellation and method standardization, enhancing its operational efficiency. This algorithm offers a robust solution for tasks requiring efficient and accurate sparse representation.

In a study, compressed sensing with Gaussian mixture models was enhanced and compared for downlink massive MIMO-OFDM systems, focusing on ZF precoding. The research aimed to improve system performance and efficiency in handling massive MIMO communication with OFDM modulation. The signal was processed through truncated and Bernoulli Gaussian mixing to estimate error performance.

The suggested techniques give a significant improvement in terms of computational difficulty, according to simulation results. The remainder of this work is divided as follows. The downlink and noise estimation models are discussed in the second section. The third portion addresses training sequence design and estimating principles for existing techniques.. The OMP and Bayesian techniques are examined in the fourth part [7]. Practical issues are covered in the fifth section, and the sixth section concludes.

Methodology

The Base Station (BS) is designed with M transmitting antennas to facilitate signal transmission. Alongside these antennas, K distinct single-element antenna systems operate autonomously. The system's overall effectiveness is determined by the total number of OFDM pilot tones, denoted as N. This configuration enables efficient communication and signal processing in wireless networks. Data transmission and guard band are two categories within the available set of pilot tones. In order to ensure the desired condition, the pilot symbols for each user are carefully chosen and integrated into the $K \times 1$ signal vector of $x(n)$. This vector represents the transmission at the n^{th} symbol time and includes both the pilot tones and the data vector. By satisfying the condition $\mathbb{E}\{\|\mathrm{x}(n)\|_2^2\} = 1$, the overall energy of the signal is normalized to a value of 1. Consequently, the pilot tone should adjusted as $x(n) = 0_{K\times 1}$.

The feasibility of detecting the signal within the guard band is limited. To overcome the challenges posed by collaborative sensing among users and mitigate multi-user interference (MUI) at the base station (BS), it is advisable to employ the Zero-Forcing (ZF) pre-coding spatial signal technique.

The pre-coding sparse signal vector can be expressed as the signal vector on the n^{th} pilot tone

$$\boldsymbol{s}(n) = \boldsymbol{P}(n)x(n) \tag{1}$$

The pre-coded vector for the n^{th} sub-carrier with M antennas is denoted as $\boldsymbol{s}(n) \in \mathbb{C}^{M\times 1}$, while the pre-coding channel matrix for the n^{th} OFDM pilot tone is represented as $\boldsymbol{P}(n) \in \mathbb{C}^{M\times K}$. These vectors are essential in obtaining the ZF pre-coding spatial channel vector matrix. It is important to note that K is much smaller than M in this context.

$$\boldsymbol{P}_n^{ZF} = \boldsymbol{X}_n^H(\boldsymbol{X}_n\boldsymbol{X}_n^H)^{-1} \tag{2}$$

In the context of MIMO channels, $\boldsymbol{P}_n^{ZF}$ is utilized to provide both the inverse and pseudo-inverse of the n^{th} pilot tone matrix, denoted as $\boldsymbol{P}(n)$. The vectors of M antennas are rearranged for OFDM purposes, and post-coding with inverses is applied to the n^{th} pilot tone in the MIMO channel matrix to maintain accuracy.

$$[\boldsymbol{a}_1 \dots \boldsymbol{a}_M] = [\mathbf{h}_1 \dots \mathbf{h}_M]^T \tag{3}$$

The vector $\mathbf{h}_m \in \mathbb{C}^{N\times 1}$ represents the frequency-domain samples received at the m^{th} antenna. The samples are converted into time-domain signals employing an inverse discrete Fourier transform (IDFT). In order to mitigate the occurrence of inter-symbol interference (ISI), a cyclic prefix (CP) is appended to the signals that are transmitted via the antennas. This technique helps ensure that the transmitted data's integrity is maintained, thereby reducing the likelihood of errors or distortions during the communication process. Afterward, the signals that change over time are converted into analog form to make it easier to send them through the channel.

Following the removal of the CPs, the frequency-domain signals are acquired through the utilization of the Discrete Fourier Transform (DFT). This process allows for the analysis and representation of the signals in the frequency domain, providing valuable insights into the underlying characteristics of the data. The transformed N-point DFT received vector, which includes K user signals, is denoted by

$$\mathbf{F}(n) = \frac{1}{\sqrt{N}}\exp^{\left(-\frac{j2\pi \mathrm{n}}{N}\right)} \qquad 0 \le n \le N-1 \tag{4}$$

The signal is characterized by K user symbols denoted as $\mathbf{X}(n)$, with $\mathbf{X}(n)$and $\mathbf{h}(n)$ being vectors representing channels in $\mathbb{C}^{N\times 1}$ and $\boldsymbol{z}(n)$ indicating the receiver noise associated with the n^{th} transmitted symbol.

$$\boldsymbol{y}(n) = \mathbf{X}(n)\mathbf{h}(n) + \boldsymbol{z}(n) \tag{5}$$

The MUI signal, represented by the received signal vector, is observed to be error-free, denoted as $\boldsymbol{y}(n) = \mathbf{h}(n) + \boldsymbol{z}(n)$, It is crucial to maintain precise alignment and mathematical accuracy while integrating equations (1), (2), and (4) into the ZF pre-coding scheme.

The mathematical representation of the transmitted pilots from the n^{th} antenna can be expressed as a column vector $(\mathbf{X}_P = \mathbf{X}_{p_1}, \mathbf{X}_{p_2}, \dots, \mathbf{X}_{p_{N_P}})^T \in \mathbb{C}^{N_P \times 1}$. The pilot locations can be abbreviated as $[p_1, p_2, \dots, p_{N_P}]$, and the n^{th} antenna receives a signal which can be expressed as

$$\boldsymbol{y}(n) = \sum_{i=1}^{L} \operatorname{diag} \mathbf{F}(n)\boldsymbol{s}(n) + \boldsymbol{z}(n) \tag{6}$$

Our system model includes 256 base station antennas catering to 128 users. It operates with a 16-QAM constellation and 32 OFDM pilot tones, enhancing communication system efficiency and performance. Because BS has hundreds of transmit antennas, the performance of their channels is significantly degraded, and the pilot overhead to estimate the channels is also large. As a result, it's critical to reduce the high pilot overhead associated with higher data rates.

CS-Based Channel Estimation

Create a DFT signal matrix for the n^{th} antenna in a large MIMO-OFDM system, taking into account the noise. The signal denoted as

$$\boldsymbol{y}_P = \sum_{i=1}^{L} \operatorname{diag}(\mathbf{X}_P)\mathbf{F}_P\mathbf{h}_n + \boldsymbol{z}_P \tag{7}$$

The proposed method for channel estimation in a massive MIMO-OFDM system is centered on estimating the unknown vector h(n) through the use of iterative greedy reconstruction techniques [3]. Applying the proposed CS recovery approach aids in estimating the unknown vector within the massive MIMO-OFDM system. Greedy iteration reconstruction techniques have illustrated [8] significant potential in improving the accuracy and efficiency of channel estimation in OFDM systems.

However, many traditional greedy algorithms demand priori information from the receiver. Furthermore, greedy iteration algorithms have inaccuracies and need additional processing resources. The proposed method for recovering CS does not necessitate any prior understanding of the channel state. This approach relies on a specific threshold for iteration and aligns with the concept of Partial Common Support Information (PCSI) [9]. By not requiring knowledge of the channel level beforehand, this technique offers a more accessible and efficient way to recover CS.

The expression for the PCSI of the n^{th} receive antenna can be represented as follows:

$$\mathbf{I}_n = \sum_{n=1}^{L} \mathbf{I}_n + (n-1)L \tag{8}$$

Large datasets pose several challenges when applying Orthogonal Matching Pursuit (OMP) algorithm. These challenges include high computational complexity, which can result in increased processing time and resource requirements. Additionally, storing such large datasets can be expensive, adding to the overall cost of implementing OMP. Moreover, the need for multiple k iterations to estimate the coefficients of q can further exacerbate the computational burden and slow down system performance.

Algorithm I:
CS-Based Massive MIMO-OFDM Channel Estimation [10]

Input: The first formulations A_n, Y_P and I_n are selected.

1. Initialize$\Lambda_0 = \mathrm{I}_n, \mathrm{A}_0 = \mathrm{A_n}|_{\Lambda_0}, \mathrm{r}_0 = Y_P - \mathrm{A}_0(\mathrm{A}_0{}^T \mathrm{A}_0)^{-1} \mathrm{A}_0{}^T Y_P, t = 0$ and $\varepsilon \approx 0$.
2. $t = t + 1$
3. $\lambda_t = \arg \max_{j \in 0, NL-1} (|\mathrm{r}_{t-1}{}^T \mathrm{A_n}|)$
4. $\Lambda_t = \Lambda_{t-1} \cup \{\Lambda_t\}$
5. $\mathrm{A}_t = \mathrm{A}_{t-1} \cup \mathrm{A_n}|_{\lambda_t}$
6. $\hat{\mathbf{h}}_{n,t} = \arg\min \left\| Y_P - \mathrm{A}_t \hat{\mathbf{h}}_{n,t} \right\| = (\mathrm{A}_t{}^T \mathrm{A}_t)^{-1} \mathrm{A}_t{}^T Y_P$
7. $\mathrm{r}_t = Y_P - \mathrm{A}_t \hat{\mathbf{h}}_{n,t}$

End while

Output: estimate the CIR $\hat{\mathbf{h}}_{n,t}$.

The number of iterations in CS-based methods (Static or Dynamic LS, OMP, CS-Aided, and BCS) is determined by the channel's sparsity level. Still, the suggested technique stops iteration only when the residual is less than 0. As a result, the correctness of the recovery is guaranteed. Furthermore, when reliable partial common support information is obtained, the number of repeats is minimized, resulting in reduced the suggested method's computational cost.

Utilizing the expectation-maximization (EM) method, we have developed a systematic approach for accurately estimating noise variance and Gaussian mixture parameters (GM) parameters. This approach significantly enhances the accuracy of modeling complex data distributions by iteratively updating parameters based on observed data. The GAMP algorithm efficiently manages EM updates, resulting in reduced computational complexity. To achieve accurate parametric estimation when dealing with an independent and identically distributed zero-mean Gaussian distribution, it is recommended to utilize EM-TGM-AMP and EM-BGM-AMP algorithms.

Gaussian Mixture GAMP

Bayati. et all proposed the generalized AMP (GAMP) method to solve random Gaussian noise. The suggested method does not require familiarity with $p_X(.)$ or the assumed noise variance, yet it delivers exceptional recovery results under these conditions. The coefficient in $\boldsymbol{x} = [x_1, x_2, \dots, x_N]^T$ approaches the i.i.d distribution with marginal probability density function can be written as in this Gaussian-mixture GAMP technique.

$$p_X(x; \lambda, \boldsymbol{\omega}, \boldsymbol{\theta}, \phi) = (1 - \lambda)\delta(x) + \lambda \textstyle\sum_{l=1}^{L} \omega_l \mathcal{N}(x; \theta_i, \phi_i) \quad (9)$$

Substitute the hypothesized parameters (3) into (8) to produce a further estimate of GM-GAMP, and the simplified formula becomes

$$p_{X|\boldsymbol{Y}}(x_i|\boldsymbol{y}; \hat{r}_i, \mu_i^r, \boldsymbol{q}) = \left[(1 - \lambda)\delta(x_i) + \lambda \sum_{l=1}^{L} \omega_l \mathcal{N}(x_i; \hat{r}_i, \mu_i^r)\right] \frac{\mathcal{N}(x_i; \hat{r}_i, \mu_i^r)}{\varsigma_i}$$

$$= \left[(1-\pi_i)\delta(x_i) + \pi_i \sum_{l=1}^{L} \overline{\beta}_{i,l} \mathcal{N}(x_i; \gamma_{i,l}, v_{i,l})\right] \quad (10)$$

In (10) $\pi_i$indicates posterior support probability values, $\Pr\{x_i \neq 0|\boldsymbol{y};\boldsymbol{q}\}$ of GM-GAMP approximation.
The factor that has undergone normalization can be denoted in a more standardized manner for clarity and consistency in calculations.

$$\varsigma_i \triangleq \int_{\boldsymbol{X}} p_X(x;\boldsymbol{q}) \mathcal{N}(x, \hat{r}_i, \mu_i^r) = (1-\lambda)\mathcal{N}(0; \hat{r}_i, \mu_i^r) + \lambda \sum_{l=1}^{L} \omega_l \mathcal{N}(0; \hat{r}_i - \theta_l, \mu_i^r + \phi_l) \quad (11)$$

The Gaussian probability density function multiplication rule can be used to calculate (10) and (11). The dependent variables in (12) can be expressed as follows:

$$\pi_i \triangleq \frac{1}{1+\left(\frac{\sum_{l=1}^{L}\beta_{i,l}}{(1-\lambda)\mathcal{N}\left(0;\hat{r}_i,\mu_i^r\right)}\right)^{-1}} \quad (12)$$

$$\gamma_{i,l} \triangleq \frac{\frac{\hat{r}_i}{\mu_i^r} + \theta_l/\phi_l}{\frac{1}{\mu_i^r} + 1/\phi_l} \text{ and } v_{i,l} \triangleq \frac{1}{\frac{1}{\mu_i^r} + 1/\phi_l} \quad (13)$$

$$\beta_{i,l} \triangleq \lambda \omega_l \mathcal{N}(0; \hat{r}_i; \theta_l, \mu_i^r + \phi_l) \text{ and } \overline{\beta}_{i,l} \triangleq \frac{\beta_{i,l}}{\sum_{l=1}^{L}\beta_{i,k}} \quad (14)$$

To ensure realistic implementations, GAMP approximation combines with L-term Gaussian Mixture. The AMP algorithm [12] accurately approximates the central-limit theorem and the independently identically distributed zero-mean Gaussian A·

EM Learning of the Prior Parameters

Let's look at the expectation-maximization (EM) algorithm for learning the priori parameters $\boldsymbol{q} \triangleq (\lambda, \boldsymbol{\omega}, \boldsymbol{\theta}, \phi, \psi)$. At each repetition, the highest likelihood $p(\boldsymbol{y};\boldsymbol{q})$ increased the lower bound. The following EM technique uses the preceding illustration to approximate the priori parameters.

$$\int_x \hat{p}(x) \ln p(\boldsymbol{y};\boldsymbol{q}) = \int_x \hat{p}(x) \ln\left(\frac{p(\boldsymbol{x},\boldsymbol{y};\boldsymbol{q})}{\hat{p}(x)} \frac{\hat{p}(x)}{p(\boldsymbol{x}|\boldsymbol{y};\boldsymbol{q})}\right)$$

$$E_{\hat{p}(x)}\{\ln p(\boldsymbol{x},\boldsymbol{y};\boldsymbol{q})\} + H(\hat{p}) + D\left(\hat{p} \| p\boldsymbol{x}|\boldsymbol{y}(\cdot\,|\boldsymbol{y};\boldsymbol{q})\right) \quad (15)$$

The notation $E_{\hat{p}(x)}\{\cdot\}$ is used to represent the expectation, while $H(\hat{p})$ stands for entropy, and $D(\hat{p}\|p)$ signifies the Kullback-Leibler (K-L) divergence. This scenario explicitly defines The EM bounds as $(\boldsymbol{q} = \boldsymbol{q}^n)$and $(\hat{p} = \hat{p}^n)$, expectation$\ln p(\boldsymbol{y};\boldsymbol{q}^n) - D(\hat{p}\| p_{\boldsymbol{X}|\boldsymbol{Y}}(\cdot\,|\boldsymbol{y};\boldsymbol{q}^n)$, afterwards the maximized function described as $\hat{p}^n(\boldsymbol{x}) = p_{\boldsymbol{X}|\boldsymbol{Y}}(\boldsymbol{x}|\boldsymbol{y};\boldsymbol{q}^n)$, maximization $E_{\hat{p}(x)}\{\ln p(\boldsymbol{x},\boldsymbol{y};\boldsymbol{q})\} + H(\hat{p}^n)$, after that the maximized function produces as $\boldsymbol{q}^{n+1} = \arg\max_{q} \hat{\mathrm{E}}\{\ln p(\boldsymbol{x},\boldsymbol{y};\boldsymbol{q})|\boldsymbol{y};\boldsymbol{q}^n\}$. Where $\hat{\mathrm{E}}$ indicates that the posterior approximation is being used. Additionally, the noise variance ψ can be updated by considering the calculation of $\boldsymbol{q}^n$. This update can be implemented by

$$\psi^{n+1} = \arg\max_{\psi>0} \sum_{m=1}^{M} \int_{x} p_{Z|\boldsymbol{Y}}(z_m|\boldsymbol{y};\boldsymbol{q}^n)\,.\ln p_{\boldsymbol{Y}|Z}(y_m|z_m;\psi) \quad (16)$$

The optimal parameter is ψ in which the derivative of the sum value is zero, allowing the following noise variance parameter to be obtained.

$$\psi^{n+1} = \frac{1}{M}\sum_{m=1}^{M}(|y_m - \hat{z}_m|^2 + \mu_m^z) \quad (17)$$

EM Updates of BGM Case

Assuming that the Bernoulli-Gaussian marginal pdf and the ℓ_1 GM model can be reduced to (17), the result is $p_X(x;\lambda,\omega,\theta,\phi) = (1-\lambda)\delta(x) + \lambda\mathcal{N}(x;\theta,\phi)$. It should be noted that in this case there is no need to find the weight because there is only one weight, so the previous criterion can be expressed by $q^n \triangleq (\lambda^n, \theta^n, \phi^n, \psi^n)$.

$$\lambda^{n+1} = \arg \max_{\lambda\in(0,1)} \sum_{i=1}^{L} \widehat{\mathrm{E}}\{\ln p_X(x_i;\lambda,q^n)|y;q^n)\} \quad (18)$$

The parameter ψ is considered optimal since the derivative of the sum value is zero, thereby establishing the noise variance parameter.

$$\lambda^{n+1} = \frac{1}{L}\sum_{i=1}^{L}\pi_i \quad (19)$$

The updated θ, ϕ EM parameters are expressed in the same way as (19).

$$\theta^{n+1} = \frac{1}{\lambda^{n+1}N}\sum_{i=1}^{L}\pi_i\,\gamma_{i,1} \quad (20)$$

$$\phi^{n+1} = \frac{1}{\lambda^{n+1}N}\sum_{i=1}^{L}\pi_i\left(\left|\theta^n - \gamma_{i,1}\right|^2 + v_{i,1}\right) \quad (21)$$

Apply Leibniz's integral principle to interchange differential and integral points, and use this $\delta(x) = \mathcal{N}(x;0,\varepsilon)$ to randomly assign a Dirac approximation of $\varepsilon > 0$, then solve, with a coefficient equal to λ increasing. As discussed in Section III, all differential equations and integral equations can be interpreted in series.

The EM-BGM-AMP algorithm is used to predict the performance of large CS-based MIMO-OFDM channels, as shown below.

Algorithm II: EM-BGM-AMP

Initial value L, $\hat{x}^0 = 0$, and unknown parameters q^0. For $n = 1$ to N_{max} do
Generate $\hat{x}^n, \hat{z}^n$, $(\mu^z)^n$, π^n, $\{\beta^{n,k}, \gamma_k^n, v_k^n\}_{k=1}^M$through BGM-GEMP with q^{n-1}. if $\|\hat{x}^n - \hat{x}^{n-1}\|_2^2 < \tau_{EM}\|\hat{x}^{n-1}\|_2^2$ then
Break
end if
Determine λ^n from π^{n-1}.
For $k = 1$ to M do
When the sparse mode value is turned on
Determine θ_k^n from $\pi^{n-1}, \gamma_k^{n-1}, \{\beta_l^{n-1}\}_{l=1}^M$.

end if
Compute ϕ_k^n from π^{n-1}, $\theta_k^{n-1}, \gamma_k^{n-1}$, $\{\beta_l^{n-1}\}_{l=1}^M$.
Compute ω^n from π^{n-1} and $\{\beta_l^{n-1}\}_{l=1}^M$.
End
Compute ψ^n from $\hat{z}^n$ and $(\mu^z)^n$.
end

EM Updates of TGM Case

The advantage of the GAMP technique is that it provides approximations of the likelihood functions $p(y;q)$ through $\hat{p}^n(x) = p_{X|Y}(x|y;q^n)$ and the EM creates a fresh estimate of $q(x)$ and ψ , as well as posterior approximations of the other relevant variables and the determination of the boundary parameter v. The following is a summary of the proposed approach provided by the algorithm. The posterior approximations are not repeated here for the sake of brevity; new noise variance updates are included.

$$\psi^{n+1} = \sum_{m=1}^{M} p_{Z|Y}(z_m|y;q^n) \ln p_{Y|Z}(y_m|z_m;\psi) + \text{const}$$
$$= \frac{N}{2}\ln\psi - \frac{1}{2}\psi \sum_{m=1}^{M}(|y_m - \hat{z}_m|^2 + \mu_m^z) \tag{22}$$

The updated approximation parameter for ψ can be determined by equating the derivative, as referenced in equation (22), to the fundamental condition of zeros. This process leads to the derivation of a new formula that encapsulates the solution for ψ.

$$\psi^{n+1} = \frac{M}{\sum_{m=1}^{M}(|y_m - \hat{z}_m|^2)} \tag{23}$$

The EM-TGM-AMP algorithm is employed to analyze the channel performance of CS-based massive MIMO-OFDM. This algorithm is utilized to assess the efficiency and effectiveness of the channel in this particular system. This algorithm is specifically designed to evaluate the performance of the communication channel, taking into account the massive MIMO-OFDM system.

Algorithm III: EM-TGM-AMP

The initial expressions $\psi^{(0)}, v^{(0)}$ are selected.

1. Start the mean and variance parameters of $q(x)$, and set the iteration number *t* for GAMP iterations to zero.
   Repeat until $t \geq t_{max}$
2. Determine the estimated distribution $\hat{p}(x|y;q)$ and $\hat{p}_{Z|Y}(z_m|y;q^n)$
3. Apply the estimated probabilities $\hat{p}(x|y;q)$, to revise the posterior variables $\hat{q}^n(\lambda^n, \omega^n, \theta^n, \phi^n)$
4. Calculate the noise variance ψ ^(n+1) based on the provided data $\hat{v}^{n+1}$

$t = t + 1.$

Return to step 2.

The parameter v, which represents the boundary, should be taken into consideration. There is an alternative way to determine the average of the parameter in the posterior distribution of *q(x)*.

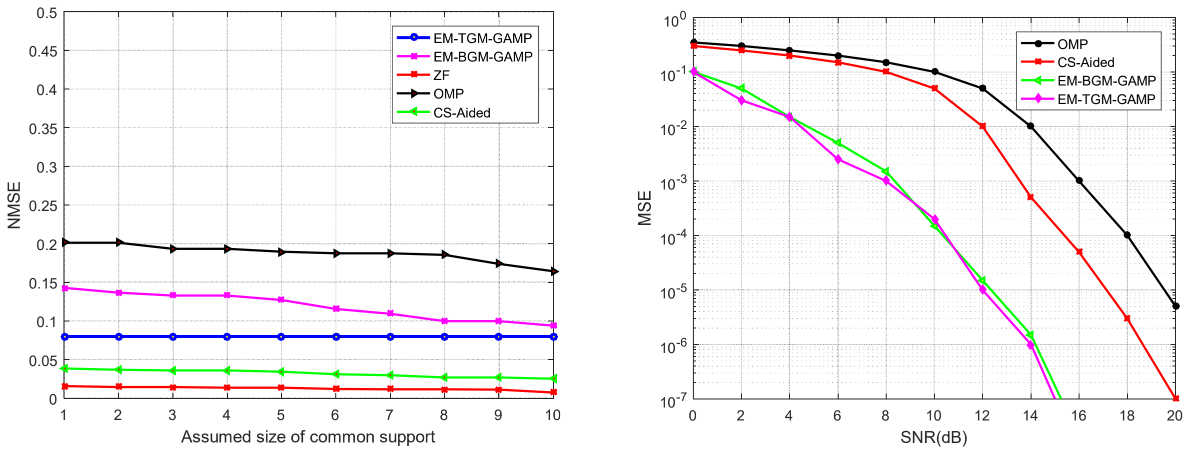
$$v^{n+1} = v^{n} + \Delta_{v} \tag{24}$$

Expand the boundary point v for that appropriately smaller step-size Δ_v where Δ_v Step-size of boundary points is: Based on our observations, it is anticipated that the signal x will show a significant rise in response to this situation.

Results and Discussions

The contrast between the newly introduced truncated Gaussian mixture EM-GAMP and Gaussian Bernoulli EM-GAMP algorithms and conventional techniques such as OMP and CS-Aided methods underscores the significance of investigating different approaches in the realm of sparse signal recovery. While OMP and CS-Aided techniques have been widely used in the past, the introduction of probabilistic models and mixture distributions in the EM-GAMP algorithms represents a significant advancement in signal processing. By evaluating the performance of these algorithms in various scenarios, researchers can gain a deeper understanding of their capabilities and limitations, ultimately leading to further advancements in sparse signal recovery techniques.

The comparison of several NMSE performance algorithms with a known error value of k_s^e is shown in Figure 1. When incorporating past support information into estimation methods, poor performance may arise with unbalanced parameters. The evaluation of faulty channel coefficients with compressed sensing (CS) minimizes mismatches. Furthermore, if this procedure is used to choose erroneous coefficients, the clipping step can stop the erroneous coefficients from having an influence. Furthermore, the constant support information can be kept for both proposed and CS-Aided procedures. Furthermore the Figure 1 shows how the performance of NMSE versus SNR varies depending on the pilot tone performance in various schemes with varying SNR. Because CS algorithms are inherently sensitive to noise levels, estimate methods used with CS, including the ones under consideration, produce excellent results in the SNR range. Furthermore, the pre-coding schemes CS-Aided, and OMP have low error rates. Outperforming OMP in SNR (13-20 dB) with better error rates than OMP in simulation results (Figure 2), the proposed systems demonstrate exceptional performance. The basic greedy algorithm is commonly known as OMP.



(a) (b)

Fig.1. (a) Performance Comparison of NMSE and mismatched parameter using M = 128, k = 64, and SNR = 20 dB. (b) Performance comparison of MSE and SNR recovery with proposed methods.

GM-based CS techniques enhance training signals, improving performance. Comparative evaluations demonstrate their effectiveness in assessing channel estimate quality. These methods provide a simple way to enhance performance in the primary task of training signals.

Conclusion

By utilizing Gaussian mixture learning and compressed sensing, this study calculates the channel effectiveness in a massive MIMO downlink system based on OFDM. The combination of GAMP with EM iterative methods reduces computational complexity through the use of a structured pilot strategy. Pilot overhead decreases with ongoing CS-Aided support. EM-TGM-GAMP, EM-BGM-GAMP, and CS-Aided improve channel performance. In compressed sensing, the truncated GM method outperforms GB, and OMP methods. These advancements enhance communication efficiency and signal processing in various applications.

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