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Sparse Bayesian Learning (SBL) Based Channel Estimation for Millimeter-Wave Hybrid Massive MIMO System

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Abstract: Reduced system complexity yields advantages that extend to enforcement obligations as well. The task of acquiring precise channel information for hybrid precoding in millimeter-wave (mmWave) systems is challenging for a multitude of reasons. Among the methods employed are analog precoding, a large number of antennas, and a pre-beamforming state with a low signal-to-noise ratio. To address this issue, an innovative channel estimation method is necessary. A massive MIMO channel estimation technique is suggested by the authors for hybrid millimeter-wave wireless networks. This scheme utilizes SBL and capitalizes on the spatial sparsity of wireless channels resulting from focused propagation. Spherical sparsity and response matrices for quantized directional cosines at the transmitting and receiving antenna arrays are distinctive characteristics of the enormous MIMO channel. A Sparse Bayesian Learning (SBL) channel estimation method utilizing Expectation Maximization (EM) is engineered. Using the NYUSIM millimeter channel simulator, the actual mmWave channel model is estimated so that the submitted techniques can be validated. In comparison to least-squares and orthogonal matching pursuit (OMP) techniques, SBL-based approaches for channel estimation demonstrate superior performance, as demonstrated by the simulation outcomes.

Keywords *: Millimeter-wave (mmWave), Sparse Bayesian Learning (SBL), Channel estimation, Massive MIMO, Sparse Channel.*

1. Introduction

Priority is given to power consumption and spectrum efficiency in wireless communication systems [1]. The fifth generation (5G) differs significantly from earlier communication systems due to its low-latency and high-speed qualities. The development of network densification, physical layer, and other technologies makes these attributes possible [2–5]. However, spectrum scarcity hinders communication network development. Technology mmWave satisfies the bandwidth requirements of 5G services and provides more spectrum resources for wireless communication networks [6, 7]. Due to the shorter wavelength of mmWave, big antenna arrays may fit in smaller spaces. Thus, mmWave systems can improve signal gain and spectral efficiency using huge MIMO transceivers. Future wireless communications will likely use mmWave massive MIMO, which uses gigahertz-level bandwidth and vast antenna arrays to give faster data speeds and wider coverage [8-10]. Purchasing distinct radio frequency circuits for every antenna leads to increased expenditures on hardware and electricity. Hybrid beamforming compensates for large mmWave route losses, improving connection dependability. Traditional MIMO transceiver architectures cannot provide enough gain for efficient signal detection in mmWave due to signal propagation route losses. Thus, both sending and receiving antennas must be strengthened to boost the received signal. Thus, 5G wireless communication networks are expected to use huge MIMO transceivers [11-13]. 5G networks rely on mmWave communication. The mmWave communication system uses hybrid precoding to balance energy consumption and system performance [14]. The most cost-effective analogue beamforming and best digital precoding are balanced by hybrid precoding [15]. To build the precoder and combiner at transmitters and receivers, mmWave systems need channel state. The accuracy of estimates for existing mmWave MIMO channels affects baseband and RF precoders and combiners [16, 17]. Effective methods for accurate channel estimation are crucial because mmWave communication requires precise channel knowledge in order to achieve significant gains associated with it. Compared to a microwave massive MIMO system, a mmWave hybrid massive MIMO system may need additional antennas at both the transmit and receive ends due to its shorter wavelength. Due to the several "virtual array" channel types commonly employed for massive MIMO in mmWave [18] and the particular hardware limitations forced by hybrid architecture, Channel estimation at mmWave frequencies is different from that at lower frequencies. This urges for development of new methods for channel estimation. Spatial sparsity can, however, be efficiently employed to predict channel coefficients linked to important spatial paths because of the strongly directed nature of mmWave channel propagation [19]. Therefore, strategies for recovering sparse signals [20,

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21] can be utilized to produce accurate channel predictions for channels which are spatially sparse. Preceding beamforming in mmWave massive MIMO systems is a difficult task due to the substantial quantity of antennas and the inadequate signal-to-noise ratio (SNR) [22]. Traditional approaches to channel estimation, including least squares (LS), have been found to be inadequate. As a result of the high directionality of mmWave wireless propagation, a recent study identified a large MIMO channel that is spatially sparse. Sparse channel estimation methods have been developed for this.

Consequently, the spatial grid methodology incorporates OMP into the method for estimating time-domain channels in mmWave systems with a single carrier (SC) [23]. By arbitrarily selecting columns from the dictionary matrix in a greedy fashion that correspond to the spatially active channel components, this strategy seeks to reduce approximation errors. But the method's sensitivity is introduced by its reliance on the particular dictionary matrix and halting criterion, which results in convergence mistakes and reduced performance with small deviations. Furthermore, the intrinsic group sparsity of the mmWave frequency-selective MIMO channel is not incorporated into the model, and the potential effects of comparable noise on the analogous system are not accounted for. A Sparse Bayesian estimation strategy is described in [24] as an alternate method. This technique is utilized to compute the posteriors produced when an indicator function is applied to the support of a beamspace sparse channel vector. Nevertheless, due to the fact that its efficacy is contingent on an exact understanding of the power profile linked to the formation of each cluster, its application is limited in circumstances where such prior knowledge is not attainable. Furthermore, it is possible that these techniques failed to produce the most sparse solution possible; if they converge to suboptimal local solutions, this may result in structural defects [25]. In beamspace channel estimation for mmWave system using 3D lens antenna array architecture is studied [26]. Here, an image reconstruction method called SCAMPI is used for channel estimation. To further improve its performance, it is embedded with the EM learning method to learn the Gaussian-Mixture (GM) probability parameters. For estimating second-order statistical variables of the time-selective channel and mmWave channel statistics under time-varying conditions, scientists devised an OMP diagonal-search technique [27] based on compressive covariance sensing. The fact that only non-coherent detection can be done with the generated estimates is a significant drawback of such statistics-based estimation systems. By using a practical user mobility model, the authors construct a rule for temporal variation [28] for each mobile user's physical direction in relation to the base station. This rule was applied to anticipate whether the time-selective channel would be supported as well to track the beamspace channel vector. However, the estimation accuracy of this method was greatly dependent on how accurately the temporal variation rule is utilized. An improvement was observed in the performance of channel estimation in a massive MIMO orthogonal frequency division multiplexing (OFDM) system designed to support multiple users at mmWave and provide frequency selective channels through the integration of approximation message passing (AMP) and closest neighbor pattern learning. A three-dimensional clustered structure in the delay domain of Angle of Arrival (AOA)-Angle of Departure (AOD) in conjunction with adaptive learning forms the foundation of the presented technique [29].

A significant contribution involves the development of an original frequency domain method for a mmWave MIMO-OFDM system [30]. By reimplementing the OMP algorithm, this method attempts to calculate the MIMO channel for every subcarrier. Because each sub-carrier uses a single RF combiner and precoder, there are difficulties in constructing hybrid combiners/precoders for OFDM transmission, which could result in inefficiencies [32]. Furthermore, for systems with large bandwidths, the application of linear-power amplifiers becomes difficult and expensive. To reduce the peak-to-average power ratio (PAPR) in mmWave transmissions, a SC is often implemented [33]. Hence, in order to rectify the deficiencies of existing techniques, there is an immediate requirement for a channel estimation strategy that is both more resilient and effective, with a specific focus on frequency-selective single-carrier mmWave MIMO channels. The subsequent section presents a concise overview of the contributions that were put forth in the paper.

The efficacy of signal recovery has been demonstrated to be enhanced through the resolution of several inherent issues that plague conventional sparse estimating methods, as demonstrated by the recently introduced SBL framework [31]. This approach has demonstrated efficacy in the estimation of OFDM channels [34] and the visualization of MIMO radar targets, yielding considerably improved outcomes. For the estimation of mmWave-based hybrid massive MIMO channels, this investigation presents a novel SBL method based on (EM), expanding on the successful outcomes of SBL in previous estimation frameworks. In contrast to OMP, the suggested approach removes user parameters, guaranteeing the achievement of the sparsest parameter estimates feasible. Next, an adjusted version of the proposed SBL method is created, which includes strict thresholding of evaluated hyperparameter values, leading to additional gains in estimating precision. Modern techniques such as OMP and Least Squares (LS) are contrasted with the efficacy of the proposed method in the concluding presentation of the simulation findings.

Notation:

The subsequent symbols shall be employed throughout this documentation: Column vectors are denoted by boldfaced lowercase characters, whereas matrices are represented by uppercase characters. In matrix A, A_(i.) indicates the ith row and A_(.j) the jth column. Concatenating the columns of matrix A results in the formation of its vector representation, denoted as vec, which consists of a single column. The symbol I_N is used to signify a N×N identity matrix(A). vec^(-1)(a) is the matrix that is produced after the inverse vectorization process. The value of diag denotes a diagonal matrix consisting of the principal members a_(1), a_2,..., a_N. The corresponding superscripts for the inverse, conjugate, Hermitian, and transposition operations are as follows: (.)^(-1), (.)^*, (.)^H, and (.)^T. The 2_. symbol represents the l_2 norm. The symbol ⊗ denotes the Kronecker product of matrices, whereas Tr() represents the matrix trace operator. E{.} stands for the statistical expectation.

The following constitutes the paper's structure: The subsequent section introduces an expanded system paradigm. The authors commence the discourse in Section III by providing an overview of the massive MIMO channel paradigm for millimeter waves. The LS and Genie-assisted channel estimation techniques are subsequently examined. In Section IV, the OMP channel estimation method and the sparse mmWave channel model are described in detail. In Section V, the paper estimates the properties of massive MIMO channels operating at millimeter waves utilizing the SBL technique. Section VII serves as the article's conclusion. In Section VI, the outcomes and performance evaluation of the simulation are examined in depth.

2. System Model

Consider a mmWave hybrid massive MIMO system capable of simultaneously processing N_s≤N_RF data streams for a single user. This system is comprised of N_RF≈min(N_T, N_R) RF circuits, N_R receiving antennas, and N_T transmitting antennas. In Figure 1, the configuration of a hybrid massive MIMO system is illustrated. A matrix-based precoder (F_RF∈C^(N_(T×N_RF)) is used in the analogue RF domain in conjunction with a set of baseband digital MIMO precoders (F_BB∈C^(N_(RF×N_s)), where F= 〖F_RF F_BB〗 ∈C^(N_T×N_s)) is the hybrid precoder. Let us consider an L-size delay tap channel between the transmitter and receiver in a frequency-selective mmWave massive MIMO system. H_d∈C^(N_(R×N_T)), where d = 0, 1,..., L – 1 indicates the tap index, can be used to express the channel. The received signal vector for the system under description at time instant n, r[n]∈C^(N_R×1), is as follows:

$$r[n] = \sqrt{\rho}\sum_{d-0}^{L-1} \mathbf{H}_d\, \mathbf{Fs}[n-d] + v[n] \qquad (1)$$

The received signal strength is expressed as ρ, where the symbol vector to be transmitted is represented by s[n]∈C^(N_s×1), and the complex Additive White Gaussian Noise (AWGN) vector with zero mean and a covariance matrix of σ^2 I_(N_R) is represented by v[n]∈C^(N_R×1)~CN(0,σ^2 I_(N_R)).

To obtain a N_sdimensional output signal, the receiver uses a hybrid combiner

W= 〖W_RF W〗 _BB∈C^(N_R×N_s).

$$y[n] = \sqrt{\rho}\sum_{d-0}^{L-1} \mathbf{W}^H\, \mathbf{H}_d \mathbf{Fs}[n-d] + \mathbf{W}^H\, v[n] \qquad (2)$$

The RF and baseband combiner are represented by the matrices W_RF∈C^(N_(R ×N_RF)) and W_BB∈C^(N_(RF ×N_s)), respectively. In spite of the fact that $\mathbf{F}_{RF}$ and $\mathbf{W}_{RF}$ are implemented by analog phase shifters, the norm of each of their parts must be the same.

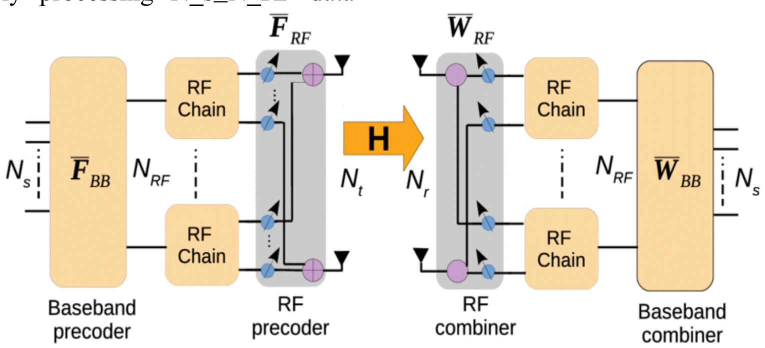

Fig 1. Hybrid signal processing for mmWave massive MIMO [23]

3. Channel Model For Mmwave Massive Mimo

A. *Genie-assisted Channel estimate*

For mmWave massive MIMO, the channel model H is represented as

$$H=\sum_{l=1}^{L} \alpha_l\, \boldsymbol{a}_R(\theta_l^r)\, \boldsymbol{a}_T^H(\theta_l^t) \qquad (3)$$

The channel model might be made even simpler by

$$H = \underbrace{[\,a_R(\theta_1^r) \quad a_R(\theta_2^r) \dots a_R(\theta_L^r)\,]}_{\bar{\mathbf{A}}_R} \times \underbrace{\begin{bmatrix} \alpha_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \alpha_L \end{bmatrix}}_{\Omega} \times \underbrace{\begin{bmatrix} a_T^H(\theta_1^t) \\ a_T^H(\theta_2^t) \\ \vdots \\ a_T^H(\theta_L^t) \end{bmatrix}}_{\bar{\mathbf{A}}_T^H}$$

(4)

We can obtain genie assisted channel estimate as

$$H= \sum_{l=1}^{L} \alpha_l\, \boldsymbol{a}_R(\theta_l^r)\, \boldsymbol{a}_T^H(\theta_l^t) = \bar{\mathbf{A}}_R \boldsymbol{\Omega} \bar{\mathbf{A}}_T^H \quad (5)$$

$$\bar{\mathbf{h}} = \mathrm{vec}\,(H) = \sum_{l=1}^{L} \mathbf{a}_T^*(\theta_l^t) \otimes \mathbf{a}_R(\theta_l^r)\alpha_l \quad (6)$$

$$\bar{\mathbf{h}} = \boldsymbol{\Psi}\bar{\boldsymbol{\alpha}} \quad (7)$$

Ψ= [$\mathbf{a}_T^*(\theta_1^t) \otimes \mathbf{a}_R(\theta_1^r)$………… $\mathbf{a}_T^*(\theta_L^t) \otimes \mathbf{a}_R(\theta_L^r)$] and the channel gain vector ¯α is indicated by

$$\bar{\boldsymbol{\alpha}} = \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_L \end{bmatrix}$$

For $\sqrt{P}\boldsymbol{I}_{N_T}Beam$ being the pilot matrix, the signal received is represented by its matrix **Y** as

$$\sqrt{P}\mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{H} \mathbf{F}_{RF} \mathbf{F}_{BB} \boldsymbol{I}_{N_T} Beam + \tilde{\mathbf{N}} \quad (8)$$

$$y = \mathrm{vec}\,(Y) = \bar{\mathbf{Q}}\bar{\boldsymbol{\alpha}} + \tilde{\mathbf{n}} \quad (9)$$

$$\bar{\mathbf{Q}} = \left(\sqrt{P}\, \underbrace{\mathbf{F}_{BB}^T \mathbf{F}_{RF}^T \otimes \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H}_{\tilde{\mathbf{Q}}} \right) \boldsymbol{\Psi} \quad (10)$$

Consequently, y= Q¯α¯+n˜ can be represented as the model for Genie-assisted channel estimation, and the anticipated channel gain vector is then provided as

$$\hat{\boldsymbol{\alpha}} = \left(\bar{\mathbf{Q}}^H \bar{\mathbf{Q}}\right)^{-1} \bar{\mathbf{Q}}^H \mathbf{y} \quad (11)$$

B. Least Square (Ls) Based Estimation Of Channel

According to (8) **Y** is the matrix of received signal

$$\mathbf{Y} = \sqrt{P}\mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{H} \mathbf{F}_{RF} \mathbf{F}_{BB} \boldsymbol{I}_{N_T} Beam + \tilde{\mathbf{N}}$$

After vectorization, the aforementioned equation might be expressed as

$$y = \mathrm{vec}\,(Y) = \left(\sqrt{P}\, \underbrace{\mathbf{F}_{BB}^T \mathbf{F}_{RF}^T \otimes \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H}_{\tilde{\mathbf{Q}}} \right) \mathrm{vec}(H) + \tilde{\mathbf{n}} \quad (12)$$

$$\bar{\mathbf{h}} = \mathrm{vec}(H) \quad (13)$$

Finally, the predicted channel vector $\bar{\mathbf{h}}$ using LS estimate is given as

$$\hat{\mathbf{h}} = \left((\sqrt{\boldsymbol{P}}\tilde{\mathbf{Q}})^H \sqrt{\boldsymbol{P}}\tilde{\mathbf{Q}}\right)^{-1} (\sqrt{\boldsymbol{P}}\tilde{\mathbf{Q}})^H \mathbf{y} \quad (14)$$

4. Model For Estimating Sparse Channels Using Omp

A. Sparse Channel Model

In comparison to sub-6 GHz variants, MmWave exhibits less diffraction because of a smaller Fresnel zone and fewer multipath components as a result of higher penetration losses. Massive MIMO is integrated with mmWave, leading to greater channel sparsity. mmWave channel model could be described as follows:

$$H = \sum_{l=1}^{L} \alpha_l\, \mathbf{a}_R(\theta_l^r)\, \mathbf{a}_T^H(\theta_l^t) \mathbf{A}_R =$$

$$[\mathbf{a}_R(\theta_1) \quad \mathbf{a}_R(\theta_2) \ \dots \ \mathbf{a}_R(\theta_G)] \times \begin{bmatrix} h_{11} & \dots & h_{1G} \\ \vdots & \ddots & \vdots \\ h_{G1} & \dots & h_{GG} \end{bmatrix} \begin{bmatrix} \mathbf{a}_T^H(\theta_1) \\ \mathbf{a}_T^H(\theta_2) \\ \vdots \\ \mathbf{a}_T^H(\theta_G) \end{bmatrix}$$

(15)

The number of dispersion or multipath components is denoted by L. The reaction of the antenna array is denoted by the vectors a_T and a_R, which represent the angle of arrival (Θ_l^r) and angle of departure (Θ _l^t), respectively. The complex gain associated with the lth path is denoted by α_l. The matrices of the dictionary that contain the answers of the received and transmitted arrays are designated A_T and A_R, correspondingly. The set denoting an angular grid is denoted as θ_i ∈ Φ = {θ_(1 ,) θ_2,…,θ_G }

In beamspace channel can be represented as $\mathbf{H} = \mathbf{A}_R\, \mathbf{H}_b \mathbf{A}_T^H$

Because there are a lot of zeros in the beamspace channel matrix (H_b), it is sparse in nature.

B. Channel Estimation Based on OMP

The channel estimate problem, also known as compressive sensing, can be expressed as min‖h_b ‖_0. Being a non-convex problem, it is difficult to use direct methods to solve it. The technique known as OMP is a promising method for estimating and improving sparse signal.

If $\sqrt{P}\boldsymbol{I}_{N_T}Beam$ denotes pilot matrix, then received signal is represented by its matrix **Y** from (8) as

$$\mathbf{Y} = \sqrt{P}\mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{H} \mathbf{F}_{RF} \mathbf{F}_{BB} \boldsymbol{I}_{N_T} Beam + \tilde{\mathbf{N}} \quad (16)$$

Substitute $\mathbf{H} = \mathbf{A}_R\, \mathbf{H}_b \mathbf{A}_T^H$ and vectorise both sides

$$y = \mathrm{vec}\,(Y) = \mathbf{Q}\mathbf{h}_b + \tilde{\mathbf{n}} \quad (17)$$

$$\mathbf{h}_b = \mathrm{vec}(\mathbf{H}_b)\ ,\ \mathbf{Q} = \sqrt{P}\mathbf{F}_{BB}^T \mathbf{F}_{RF}^T \mathbf{A}_T^* \otimes \mathbf{W}_{BB}^H \mathbf{W}_{RF}^H \mathbf{A}_R \quad (18)$$

Vector h_b is sparse in nature and for this sparse vector estimation, the OMP approach is employed.

5. Estimation Of Spatially Sparse Mmwave Massive Mimo Channel Using Sparse Bayesian Learning (Sbl)

Utilising beamspace sparse channel vector, SBL $\mathbf{h}_b \in \mathbb{C}^{G^2\times 1}$ a Gaussian prior parameterization as

$$p(\mathbf{h}_b;\mathbf{\Gamma}) = \prod_{i=1}^{G^2} \frac{1}{\pi\gamma_i} e^{-\frac{|\mathrm{h}_b(i)|^2}{\gamma_i}} \quad (19)$$

In this case, Γ=diag(γ_1, γ_2,..., γ_(G^2)) denotes the hyperparameters, which indicate the variance related to the i^th element of the beamspace channel vector h_b for all 1≤i≤G^2. With the help of the previous assignment that was previously mentioned, it is clear that when γ_(i) gets closer to 0, so does the matching channel component h_b(i). As a result, estimating the hyperparameter vector γ=[γ_1, γ_2,..., γ_(G^2)] is equivalent to estimating h_b.

Learning parameter initialization:

$$\Gamma = \mathrm{Diag}\,(\gamma) = \begin{bmatrix} \gamma_1 & & \\ & \ddots & \\ & & \gamma_{G^2} \end{bmatrix}$$

Γ is a diagonal matrix of unknown hyperparameters (Learning Parameter) of size $G^2 \times G^2$ that needs to be estimated. This gamma (**Γ**)'s initial value can be any arbitrary.

Here, gamma (**Γ**) has been initialised as the identity matrix, as illustrated below..

$\hat{\mathbf{\Gamma}}^{(\mathbf{0})} = \mathrm{I}$

The SBL system treats the uncertain sparse beamspace channel vector h_b and applies a parameterized Gaussian prior, which is different from earlier approaches used for mmWave channel estimation. The prior p(h_b; Γ) that maximizes the effectiveness of the Bayesian analysis can be chosen to improve performance. The Expectation-Maximization (EM) framework is used in the SBL-based mmWave channel estimation technique to enable the iterative estimate of hyperparameters. Using the expectation (E step), the log-likelihood function L(├□┤| □ Б^((k))) is assessed in the k^th iteration as follows:

$$\mathrm{L}(\mathbf{\Gamma}|\hat{\mathbf{\Gamma}}^{(k)} = \mathrm{E}_{\mathbf{h}_b|\mathbf{y};\hat{\mathbf{\Gamma}}^{(k)}}\{\log p\,(\mathbf{y},\mathbf{h}_b;\mathbf{\Gamma})\} \quad (20)$$

Channel $\mathbf{h}_b$'s posteriori probability density function (PDF) is calculated as $p(\mathbf{h}_b|\mathbf{y};\hat{\mathbf{\Gamma}}^{(k)} \sim \mathcal{CN}\left(\boldsymbol{\mu}_{\mathbf{h}_b}^{(k)},\ \mathbf{\Sigma}_{\mathbf{h}_b}^{(k)}\right)$ having mean $\hat{\boldsymbol{\mu}}^{(k)} = \frac{\sqrt{P}}{\sigma_n^2}\hat{\mathbf{\Sigma}}^{(k)}\overline{\mathbf{Q}}^H \mathbf{y} \in \mathbb{C}^{G^2\times 1}$ and varience $\hat{\mathbf{\Sigma}}^{(k)} \in \mathbb{C}^{G^2\times G^2}$ given by

$$\hat{\mathbf{\Sigma}}^{(k)} = \left(\frac{\sqrt{P}}{\sigma_n^2}\overline{\mathbf{Q}}^H\overline{\mathbf{Q}} + \left(\hat{\mathbf{\Gamma}}^{(k)}\right)^{-1}\right)^{-1} \quad (21)$$

$$= \hat{\mathbf{\Gamma}}^{(k)} - P\hat{\mathbf{\Gamma}}^{(k)}\,\overline{\mathbf{Q}}^H\hat{\mathbf{\Sigma}}_y^{-1}\overline{\mathbf{Q}}\,\hat{\mathbf{\Gamma}}^{(k)} \quad (22)$$

Where $\hat{\mathbf{\Sigma}}_y = \sigma_n^2\mathbf{I} + P\overline{\mathbf{Q}}\hat{\mathbf{\Gamma}}^{(k)}\,\overline{\mathbf{Q}}^H \in \mathbb{C}^{\mathrm{N}_T^{Beam}\mathrm{N}_R^{Beam}\times\,\mathrm{N}_T^{Beam}\mathrm{N}_R^{Beam}}$

One can simplify equations 21 and 22 by using the Woodbury matrix identity. The estimate of the hyperparameter vectors γ Б^((k+1)) in the maximisation (M-step) is accomplished by maximising L(├□┤| Γ Б^((k))) with respect to γ in the following way:

$$\hat{\gamma}^{(k+1)} = \arg\max_{\hat{\gamma}} \mathbb{E}_{\mathbf{h}_b|\mathbf{y};\hat{\mathbf{\Gamma}}^{(k)}}\ \{\log p(\mathbf{y}|\mathbf{h}_b;\mathbf{\Gamma}) + \log \mathrm{p}(\mathbf{h}_b;\mathbf{\Gamma})\}$$

(23)

$$\equiv \arg\max_{\hat{\gamma}} \mathbb{E}_{\mathbf{h}_b|\mathbf{y};\hat{\mathbf{\Gamma}}^{(k)}}\ \log p(\mathbf{h}_b;\mathbf{\Gamma}) \quad (24)$$

$$= \arg\max_{\hat{\gamma}} \sum_{i=1}^{G^2} -\log(\pi\gamma_i) - \frac{\mathbb{E}_{\mathbf{h}_b|\mathbf{y};\hat{\mathbf{\Gamma}}^{(k)}}\{|\mathrm{h}_b\,(i)|^2\}}{\gamma_i} \quad (25)$$

Because the first term in (23) may be condensed as log⁡p (├y┤| h_b;□)≡-‖y-√P Q ̅h_b ‖^2/σ^2, the optimisation problem in (24) is equivalent to the one in (23) because it is independent of the hyperparameter vector γ. The resulting maximisation problem is decoupled with regard to each Ά_(i), as shown in (25). This enables it to be tackled in the k^th iteration of the EM approach, yielding γ Б^((k+1)), in the manner described below:

$$\hat{\gamma}^{(k+1)} = \mathbb{E}_{\mathbf{h}_b|\mathbf{y};\hat{\mathbf{\Gamma}}^{(k)}}\{|\mathrm{h}_b\,(i)|^2\} \quad (26)$$

$$= \hat{\mathbf{\Sigma}}^{(k)}(i,i) + \left|\hat{\boldsymbol{\mu}}^{(k)}(i)\right|^2 \quad (27)$$

In this case, the i-th elements of the mean vector and the a posteriori covariance matrix are denoted by the symbols μ Б^((k))(i) and Σ ^((k))(i, i), respectively. After K_EM iterations, the beamspace channel vector estimate using SBL is represented as 〖h ̂_b=μ ̂〗^((K_EM)). As a result, the following formula may be used to estimate the mmWave huge MIMO channel matrix Ĥ_SBL based on SBL:

$$\hat{\mathbf{H}}_{\mathrm{SBL}} = \mathbf{A}_R(\Phi_R)\mathrm{vec}^{-1}(\hat{\mathbf{h}}_b)\mathbf{A}_T^H(\Phi_T) \quad (28)$$

Although the majority of the estimated hyperparameters associated with the final beamspace sparse channel vector h_b tend to be near zero, the proposed mmWave MIMO channel estimation technique utilizing SBL can be enhanced by thresholding or applying an appropriate threshold γ_th to the hyperparameter estimates. Applying the thresholded SBL technique yields the subsequent outcome for the channel vector h ̂_b in beamspace: Initialization of channel components to zero occurs when their hyperparameters in the beamspace are less than Ό_th.

$$\hat{\mathbf{h}}_b(i) = \begin{cases} \hat{\boldsymbol{\mu}}^{(K_{EM})}(i) & \hat{\gamma}_i^{(K_{EM}+1)} > \gamma_{th} \\ 0 & \text{otherwise} \end{cases} \quad (29)$$

6. Simulation Results

This section shows how different channel estimate techniques work in a huge MIMO system model that operates in the mmWave spectrum. The evaluation focuses specifically on the performance prediction of the massive MIMO channel under quasi-static conditions at the millimeter wave (mmWave) using the proposed SBL algorithms. The efficiency of the suggested SBL-based techniques is then compared to the existing OMP-based mmWave channel estimation approach. According to the model, there are 32 antennas on each transmitter and receiver and BS contains eight RF chains. Dictionary matrices of size 32-grid are used to determine the departure angles between 0 and 180. OMP is initialised with a threshold value of 1. The channel is considered to have a sparsity level of 5. The current OMP-based technique's halting conditions are described in so that residual error E across subsequent iterations is $E^{(t+1)} - E^{(t)} < \frac{1}{\sigma_n^2}$

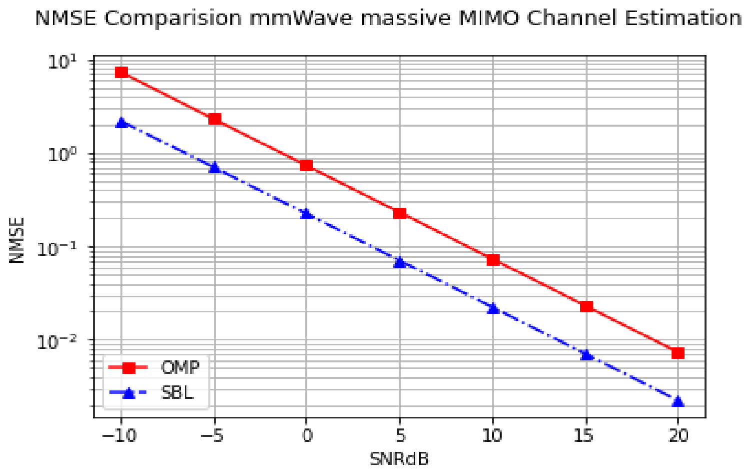

Fig 2. *NMSE vs SNR using setup* $N_T = N_R = 32$

$L = 5$, $N_{RF} = 8$, *N_Beam*=32, $G = 32$,

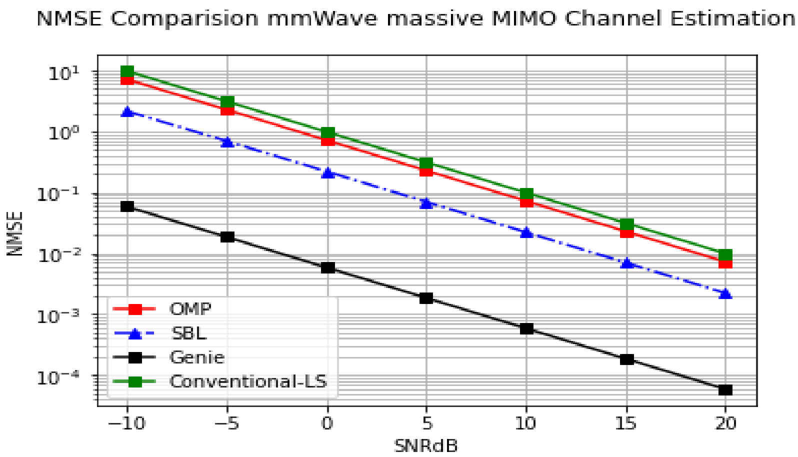

Fig 3. mmWave *channel estimate error with*

$N_T = N_R = 32$, $L = 5$, $N_{RF} = 8$, N_*Beam*=32, $G = 32$,

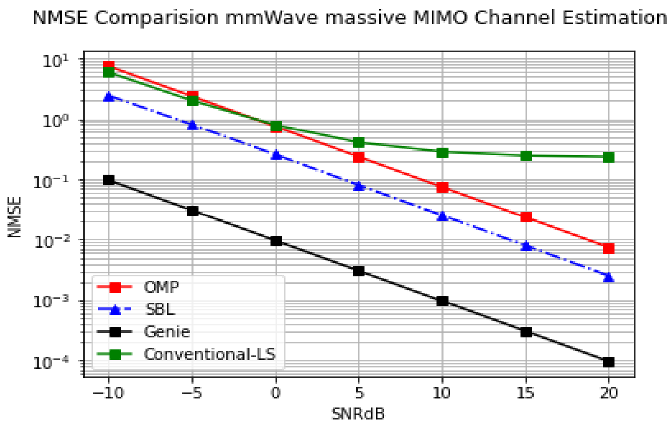

Fig 4. mmWave *channel estimate error with*

$N_T = N_R = 32$, $L = 5$, $N_{RF} = 8$, N_*Beam*=24, $G = 32$,

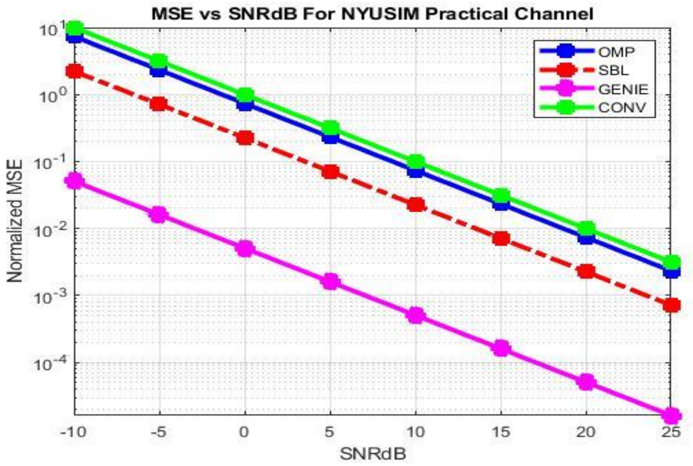

Fig 5. *mmWave channel estimate error with*

$N_T = N_R = 32$, $L = 5$, $N_{RF} = 8$, N_*Beam*=32, $G = 32$,

The SBL-based method sets the initial values of the hyperparameters to γ_i^((0))= 1 ∀ 1≤i≤G^2, and K_EM = 50 indicates how many iterations there are in the EM algorithm. Utilizing the mean squared error of each component, the efficacy of the current mmWave channel estimation technique centered on the proposed SBL and the OMP algorithm is assessed, which is given by the formula 1/(N_T N_R) E{‖H-Hˆ‖_F^2}. As benchmarks, genie-assisted estimators are used, assuming full knowledge of the spatial profile of the channel.

Figure 2 displays the suggested and available approaches. By using the robustness of the SBL framework, the SBL-based method presented in this research recovers the beamspace sparse channel vector h_b, achieving a considerable 6dB improvement over the OMP-based method. Because OMP is sensitive to the dictionary matrix Q and depends on the parameter vector h_b's sparsity level, its performance is usually insufficient. A major shortcoming of the current OMP technique is that even small changes to the halting criterion or dictionary matrix limitations result in convergence problems. Consequently, its efficacy is comparatively weaker than that of approaches predicated on SBL. A comparison of the Normalized Mean Squared Error (NMSE) among various channel estimation methods is illustrated in Figure 3. The Genie-assisted channel estimate, the standard LS channel estimation, the proposed SBL, and the present OMP are some of the techniques utilized in this context. Assuming that we know the angles of departure and arrival, all we need to do for Genie-based channel estimation is estimate various multipath gains $(\alpha_1, \alpha_2, \dots, \alpha_L)$ therefore, it will always be better and yield the least NMSE. In this case, we only require L pilot symbols if there are L multipaths. Therefore, this Genie-assisted channel estimate serves as a benchmark. However, in real-world situation, knowing the angles of departure and arrival in advance is impossible, therefore we must estimaFte the gain of dominating pathways as well as their AoD and AoA. The enhanced performance of the channel estimation technique based on SBL is clearly illustrated in Figure 3, in comparison to the current approaches utilizing LS (least-square) and OMP. The traditional Least-Square (LS) channel estimation method's reliance on a pilot signal count equal to or higher than what the transmitting antennas require is a major drawback (N_Beam ≥ N_t). This can result in pilot overhead problems and the waste of resources, such as power and spectrum. Achieving this criterion is exceedingly challenging in an enormous MIMO system operating at mmWave due to the considerable quantity of transmit antennas. For mmWave massive MIMO, the suggested SBL-based channel estimate technique performs better and requires less prototype signals than the current OMP-based and traditional Least-Square (LS) methods. Channel estimating techniques based on sparse-bayesian learning perform admirably with real-world channels. The NYUSIM mmWave Channel Simulator is used to achieve the practical channel realisation. Even for the actual (practical) channel model, Figure 5 shows that the suggested SBL-based channel estimate approach performs better than the conventional OMP-based channel estimation method.

7. Conclusion

When compared to sub-6 GHz frequencies, massive MIMO operating at mmWave frequencies shows unique characteristics such as decreased multipath components and less diffraction because to a smaller Fresnel zone. Higher penetration losses and less dispersion are the reasons for this drop. In order to minimize system complexity while attaining the necessary array gain and multiplexing metrics for mmWave systems, a hybrid precoding method is necessary. Precise channel knowledge is necessary for designing precoders and combiners for hybrid precoding. Effective channel estimate techniques are therefore essential, since mmWave channel estimation is not feasible with conventional techniques such as LS/MMSE. This impracticality arises from the necessity for a considerable quantity of mmWave large MIMO systems, which may equal or even surpass the quantity of transmitting antennas. For mmWave massive MIMO, the suggested SBL-based channel estimate technique performs better and requires less prototype signals than the current

OMP-based and traditional LS methods. The primary components of the beamspace sparse channel vector are estimated and used in this technique. By contrast to the presently employed cutting-edge methods, namely LS-based sparse mmWave channel estimation and OMP, the proposed SBL methodology guarantees the retrieval of maximally sparse solutions. Because of its EM-based structure, which does not require a regularisation parameter, it is suited for practical implementation despite its minimal complexity. On the other hand, OMP depends on a hedonistic selection of dictionary matrix columns, which causes structural faults as a result of convergence towards less-than-ideal solutions. The stopping criteria also affects OMP's performance. The study shows the applicability of the SBL-based channel estimate scheme in practise by utilising the NYUSIM millimetre channel simulator for actual channel realisation. The results of the simulation demonstrate a significant improvement over the current OMP approach of about 6dB in Normalised Mean Squared Error (NMSE). Prospective studies could expand the suggested SBL-based methods to spatially and temporally linked mmWave multiplexing (mmWave MIMO) channels and investigate their suitability for estimating time- and frequency-selective mmWave MIMO channels.

Credit Authorship Contribution Statement

Shailender: Methodology, Conceptualization of Original draft, data curation, software. Shelej Khera: Conceptualization, Supervision, Data curation, Funding acquisition. Sajjan Singh: Supervision, Writing-review & editing, Software, Proofreading.

Conflict Of Interest

There is no conflict of interest.

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Data Availability

This study's data is available upon reasonable request.

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