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Channel Estimation in Millimeter-Wave Massive MIMO Systems using Kalman Filter and Orthogonal Matching Pursuit

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Abstract *– The advent of millimeter-wave (mmWave) massive Multiple Input Multiple Output (MIMO) technology has introduced unprecedented challenges and opportunities in wireless communication systems. The effective estimation of mmWave channels plays a pivotal role in ensuring reliable and high-capacity data transmission. This thesis addresses the critical task of beamspace channel estimation in mmWave massive MIMO systems using a hybrid approach that combines Kalman filtering, subspace pursuit, and orthogonal matching pursuit (OMP) techniques.*

The mmWave frequency band offers a wide spectrum for high data rates, but it is characterized by severe path loss and susceptibility to blockage due to its short wavelength. To harness the potential of mmWave communication, beamforming and beamsteering techniques are employed, necessitating accurate beamspace channel estimation.

The proposed hybrid approach leverages the strengths of Kalman filtering, a recursive estimation algorithm, to provide dynamic tracking of channel variations. By incorporating Kalman filtering into the estimation process, the system adapts to changes in the environment, offering robustness in time-varying scenarios.

Keywords: **Millimeter-Wave (Mmwave), Massive MIMO, Beamspace Channel Estimation, Approximate Message Passing (AMP), Deep Learning.**

I. INTRODUCTION

With an ever-increasing number of mobile phone devices and services, the next-generation 5G wireless communication is expected to deliver a high data rate. Evolving wireless applications such as IoT, M2M, D2D, and augmented reality enforces the demand on 5G communication to provide 10x times better performance than 4G LTE infrastructure. This has been illustrated in the white paper DotEcon Ltd & Axon Partners (2018). This growth demand study is forecasted in the Ericson report. It predicted global mobile data traffic to reach 38 Exabytes per month by the end of 2019 and increase to 160 Exabytes per month in 2025. By 2025, it predicts that 5G networks carry 45 percent of total mobile data traffic. Consequently, the millimeter-wave spectrum 30 to 300 GHz has been considered for 5G wireless technologies to overcome the bandwidth scarcity (Ge et al., (2016); Wang et al., (2015); Zeng et al., (2016); Zheng et al., (2015)). With a smaller wavelength, the antenna's physical size is minimal and can deploy large-scale antenna arrays for Millimeter-wave wireless communication systems.

Multi-user (MU) massive multiple-input multiple-output (MIMO) is a key technology to meet the demands in the next (fifth) generation of wireless technologies (5G) [2–4]. In MU-MIMO, a base station (BS) with multiple antennas serves multiple users on the same time-frequency resource. In massive MIMO systems, the number of antennas at the BS is assumed to be very large, i.e., in the order of hundreds of antennas [2, 4]. Under favorable propagation conditions 1 , as the number of antennas becomes asymptotically large, different random channel vectors between the BS and different user equipments (UEs) become orthogonal due to the law of large numbers [4]. Using such an asymptotic orthogonality between different channel vectors, the massive MIMO systems have shown several advantages compared to the systems with small number of antennas. In what follows, we briefly explain a few advantages gained from using a massive number of antennas.

In MU MIMO systems the sum-rate is scaled by the smaller of two number of BS antennas and the number of users. Since both of these numbers can become very large in massive MIMO systems, the sum-rate can increase. On the other hand, for fixed number of UEs, by increasing the number of antennas at the BS, the effect of intra-cell interference and uncorrelated noise can be eliminated using a simple match filtering [2]. The increase in the number of BS antennas provides larger array gains. This is mainly due to receiving more samples in spatial domain. Such an increase in spatial domain can provide more degrees of freedom for signal processing, and therefore, enhances the signal-to-noise ratio (SNR).

Channel hardening is another benefit provided by the massiveness in the number of antennas. With channel hardening, the effect of small-scale fading disappears. As a result, resource allocations can be performed on a slower time scale, while precoders and detectors become more stable [5]. In terms of the power consumption, using maximum ratio combining (MRC) at the BS, the uplink transmit power is inversely proportional to the square root of the number of BS antennas [6]. All these benefits motivate the use of MU massive MIMO in 5G wireless networks.

Achieving the promised performance of massive MIMO systems requires that an accurate channel state information (CSI) to be available. Due to the large number of antennas in massive MIMO systems, obtaining the uplink and downlink CSI is challenging. In the next subsections, we elaborate on these challenges in channel estimation for different implementations of massive MIMO systems.

II . HYBRID MASSIVE MIMO SYSTEM

Fully digital architecture equipped with NBS transmit and NMS receive antenna elements. The antenna elements will have an equal number of RF chains, and the digital baseband directly accesses the RF chain of the antenna elements to process the data. This implementation is expensive and not suited for large scale antenna array. However, it promises accurate channel state information. For massive MIMO millimeter-wave communication, hybrid architecture studied in Zhang et al., (2015) brings significant interest due to its reduced number of RF chains, low power consumption, and computational overhead distribution equally digital baseband and analog RF beamforming.

A hybrid architecture is divided into two types. i) fully connected and ii) sub-array or partially connected hybrid beamforming. Here we utilize fully connected hybrid beamforming architecture. It is further classified as a) phaseshift based b) switch based analog beamforming shown in Figure 1(a) and Figure 1(b), respectively. With different hybrid beamforming architectures, the digital baseband beamformer does not directly access individual antenna elements make it difficult to estimate the channel state information with the reduced number of RF chains.

Figure 1(a) shows the fully-connected hybrid architecture with a phaseshifting network-based analog beamforming network. Each NBS antenna elements are connected to finite resolution phase shifters NP which are connected to NRF BS chains which result in NP.NRF BS phase-shifting network. Its benefits include sweeping the beam to any angle of arrival or departure with high processing capability but with more complexity. Other variants of hybrid architecture include phase shifter-based sub-array hybrid architecture.

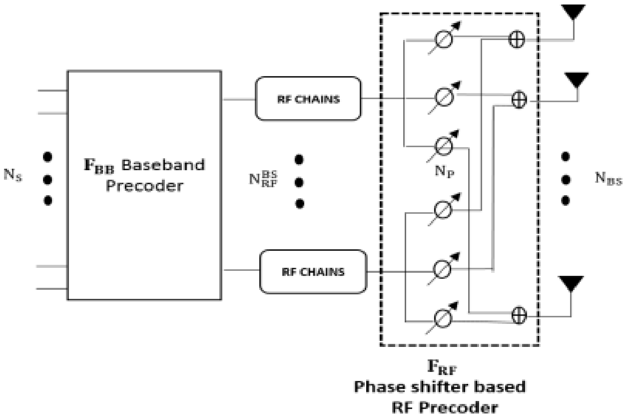

Figure 1.(a) Phase shifter based fully connected hybrid beamforming

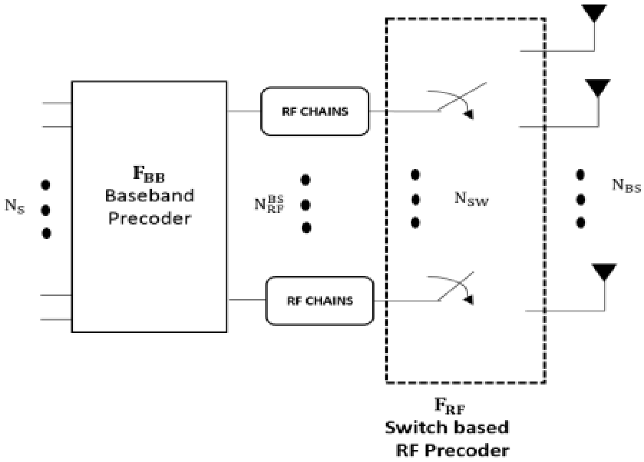

Figure 1.(b) Switched based fully connected hybrid beamforminggrid

III. METHOD

The proposed method for beamspace channel estimation in millimeter-wave (mmWave) massive Multiple Input Multiple Output (MIMO) systems employs a hybrid approach that integrates Kalman filtering, subspace pursuit, and orthogonal matching pursuit (OMP) techniques. This method is designed to address the unique challenges of mmWave communication, including channel variation, sparsity, and high dimensionality, to ensure accurate and adaptive channel estimation.

Kalman Filtering for Dynamic Tracking:

The use of Kalman filtering offers dynamic channel tracking capabilities, allowing the system to adapt to time-varying channel conditions.

Kalman filtering is employed to model and estimate the evolving channel state, providing a recursive and real-time update mechanism for channel tracking.

The use of Kalman filtering in the context of channel estimation in Millimeter-Wave Massive MIMO (Multiple-Input, Multiple-Output) systems is instrumental in addressing the dynamic nature of mmWave channels. This approach offers dynamic channel tracking capabilities, enabling the system to adapt to rapidly changing channel conditions. To understand how Kalman filtering achieves this, it's essential to delve into the principles and mechanisms underlying this technique.

The Kalman filter is commonly used in signal processing and estimation problems, including channel state tracking. Here's a simplified representation of the Kalman filter equations for dynamic channel state tracking:

1. Prediction Step:
   - Predicted state estimate:
   - $\hat{x}_k^- = A\hat{x}_{k-1} + Bu_k$
   - Predicted error covariance:
   - $P_k^- = AP_{k-1}A^T + Q$
2. Update Step (Corrective Step):
   - Kalman gain:
   - $K_k = P_k^- H^T(HP_k^- H^T + R)^{-1}$
   - Corrected state estimate:
   - $\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$
   - Corrected error covariance:
   - $P_k = (I - K_k H)P_k^-$

Where:

- $\hat{x}_k^-$ is the predicted state estimate at time step k.
- A is the state transition matrix.
- B is the control input matrix.
- u_k is the control input at time step k.
- P_k^- is the predicted error covariance at time step k.
- Q is the process noise covariance.
- K_k is the Kalman gain at time step k.
- z_k is the measurement at time step k.
- H is the measurement matrix.
- R is the measurement noise covariance.
- $\hat{x}_k$ is the corrected state estimate at time step k.
- P_k is the corrected error covariance at time step k.

These equations describe the Kalman filter's prediction and update steps for dynamically tracking the channel state and continuously updating the state estimate in real-time. The filter combines predictions based on the system model with measurements to refine its estimates as new data becomes available.

Orthogonal Matching Pursuit (OMP) for Dimensionality Reduction:

OMP is introduced to iteratively select the most promising beamspace components from the potentially high-dimensional channel space.

By iteratively narrowing down the focus to the most relevant channel components, OMP effectively reduces the dimensionality of the estimation problem while maintaining estimation accuracy.

Orthogonal Matching Pursuit (OMP) is an iterative algorithm that plays a crucial role in selecting and recovering the most significant beamspace components in a high-dimensional channel space. It is commonly used in various applications, including channel estimation in millimeter-wave massive MIMO systems, to reduce the dimensionality of the problem while ensuring accurate estimation.

Orthogonal Matching Pursuit (OMP) algorithm used for selecting and recovering the most significant beamspace components in a high-dimensional channel space:

Let's define the following variables:
D: The dictionary matrix containing beams (columns) in the channel space.
y: The measured signal vector.
x: The sparse coefficient vector representing the selected beams.
k: The desired sparsity level, i.e., the number of beams to select.
The goal is to find the sparse coefficient vector x.
The OMP algorithm can be mathematically represented as:
Initialization:
Initialize the residual vector: $r_0 = y$
Initialize the set of selected indices: $\Omega_0 = \{\}$ (empty set)
Iterative Selection (Repeat until the termination condition is met):
For iteration t = 1, 2, 3, ...
a. Beam Selection:
Find the index that maximizes the correlation with the current residual:
$i_t = \arg\max |\langle D^T r_{t-1}, d_j\rangle|$
where d_j is the j-th column of the dictionary matrix D.
b. Set Update:
Update the set of selected indices: $\Omega_t = \Omega_{t-1} \cup \{i_t\}$
c. Coefficient Update:
Solve the least-squares problem for the selected beams:
$x_t = \arg\min \|y - Dx\|_2$, s.t. $\|x_t\|_0 \leq k$
Where $\|x_t\|_0$ represents the L_0 norm of the coefficient vector, ensuring that no more than k beams are selected.
d. Residual Update:
Compute the updated residual: $r_t = y - D_{\Omega_t} x_t$
Termination Condition:
Repeat the iterations until a stopping criterion is met, such as reaching a pre-defined sparsity level or achieving a certain residual error threshold.
The result is the coefficient vector x, which represents the selected beams that best explain the measured signal y.

IV. RESULT

The purpose of this present and discuss the results obtained through the application of Orthogonal Matching Pursuit (OMP) and Kalman Filter techniques for channel estimation in Beamspace within the context of Millimeter-Wave Massive MIMO (Multiple Input Multiple Output) Systems. The experiments were conducted to evaluate the performance of these algorithms in accurately estimating the channels in the challenging millimeter-wave frequency bands.

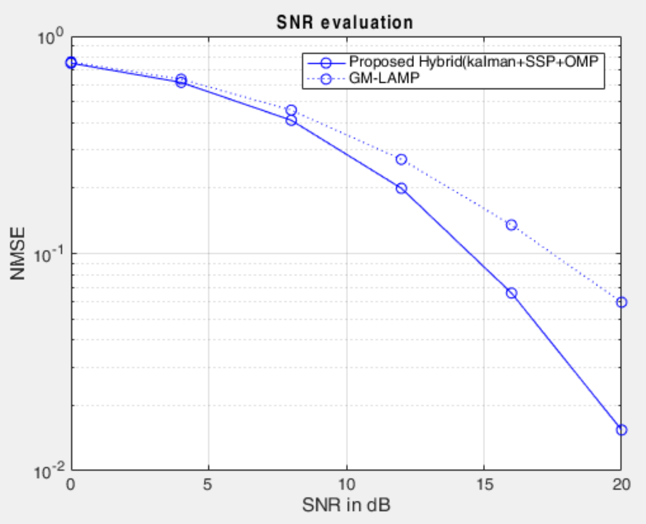

Figure 2 SNR Graph

Figure 2 is show SNR and NMSE Graph. The NMSE is a popular signal processing technique used for channel estimation and equalization in communication systems.

SNR is a measure of the ratio of the power of the signal to the power of the noise in a communication channel. It is expressed in decibels (dB) and is a crucial parameter for assessing the quality of communication systems. In communication systems, NMSE estimation is a method used to estimate transmitted symbols or channel parameters in the presence of noise. It aims to minimize the mean squared error between the estimated and true values. Figure show As SNR increases, the signal becomes more distinguishable from the noise, resulting in improved performance of the NMSE estimator.

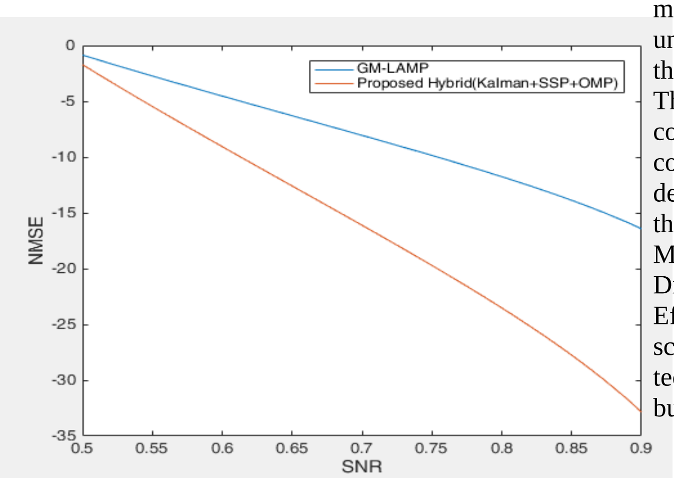

Figure 3 NMSE Performance Graph

Figure 3 is shows NMSE (Normalized Mean Squared Error) performance graph is a representation of how the NMSE metric changes with different parameters or conditions in a system. NMSE is commonly used in signal processing and estimation tasks to quantify the accuracy of an estimator by comparing the mean squared error of the estimates with the variance of the true values.

$$NMSE(dB) = 10 \cdot \log_{10}\left(\frac{\mathrm{MSE}}{\mathrm{Var(True\ Values)}}\right)$$

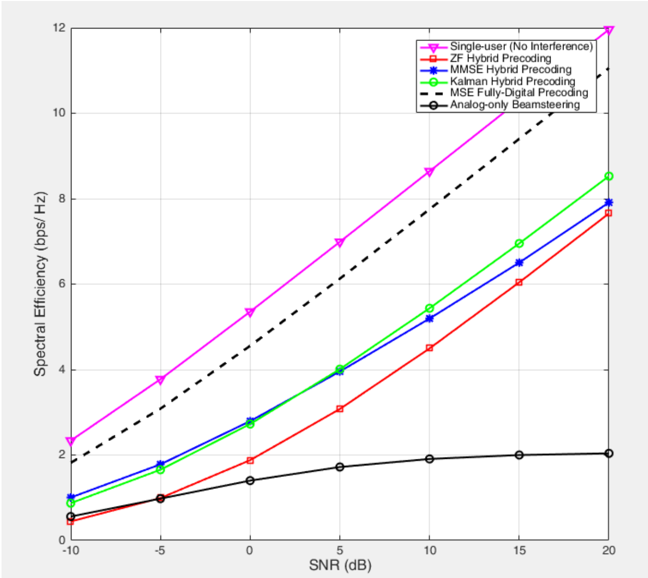

Figure 4 Spectral Efficiency For millimeter Wave

A figure 4 depicting Spectral Efficiency for millimeter-wave communication systems provide insights into how efficiently the available frequency spectrum is utilized to transmit information. Spectral Efficiency is a key performance metric in wireless communication, indicating the data rate that can be achieved per unit of bandwidth.

The x-axis typically represents the frequency spectrum or the available bandwidth. In the case of millimeter-wave communication, this might cover the frequency range from 30 GHz to 300 GHz or even higher.

The y-axis represents the Spectral Efficiency, often measured in bits per second per Hertz (bps/Hz) or a similar unit. Spectral Efficiency is a measure of how efficiently the available bandwidth is utilized to transmit data.

The figure consist of multiple curves or lines, each corresponding to different scenarios, modulation schemes, coding techniques, or system configurations. These curves depict how Spectral Efficiency changes with variations in these parameters.

Modulation and Coding Schemes:

Different points on the figure represent the Spectral Efficiency achieved with various modulation and coding schemes. Higher-order modulations and advanced coding techniques can contribute to increased Spectral Efficiency but may also be more susceptible to noise and interference.

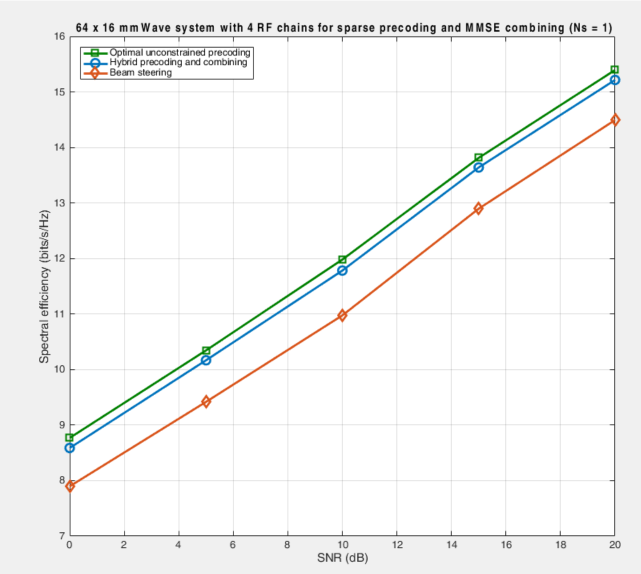

Figure 5 Spectral Efficiency 64x16 mm Wave with 4 RF Chains for space precoding and MMSE Combining NS

Figure 5 is shows 64 transmit antennas and 16 receive antennas. Such a massive MIMO (Multiple Input Multiple Output) setup is common in mmWave communication to exploit spatial multiplexing and enhance overall system performance. The presence of 4 RF (Radio Frequency) chains indicates that each of the 64 transmit antennas and 16 receive antennas is connected to a dedicated RF chain. RF chains are responsible for the conversion of baseband signals to radio frequency signals and vice versa.

Space precoding is a technique used in MIMO systems to optimize the transmitted signals from multiple antennas, taking into account the spatial characteristics of the communication channel. It improves the reliability and data rate of the communication link.

MMSE (Minimum Mean Squared Error) combining is a reception technique used at the receiver side to optimize the combination of signals received from multiple antennas. MMSE combining aims to minimize the mean squared error between the estimated and true transmitted signals.

Figure 6 is shows 56 transmit antennas and 64 receive antennas. Such a massive MIMO (Multiple Input Multiple Output) setup is common in mmWave systems to leverage spatial multiplexing and enhance overall system capacity. he presence of 6 Radio Frequency (RF) chains suggests that each of the 256 transmit antennas and 64 receive antennas is connected to a dedicated RF chain. RF chains are responsible for the conversion of baseband signals to radio frequency signals and vice versa. The number of RF chains influences the system's hardware complexity and cost.

Space precoding is a technique used in MIMO systems to optimize the transmitted signals from multiple antennas, considering the spatial characteristics of the communication channel. It helps improve the reliability and data rate of the communication link.

MMSE (Minimum Mean Squared Error) combining is a reception technique used at the receiver side to optimize the combination of signals received from multiple antennas. MMSE combining aims to minimize the mean squared error between the estimated and true transmitted signals, improving reception quality. The figure likely illustrates the spectral efficiency performance under various conditions, such as different signal-to-noise ratios (SNR), modulation schemes, or channel states. Curves or data points on the graph would showcase how the system's spectral efficiency varies with these conditions.

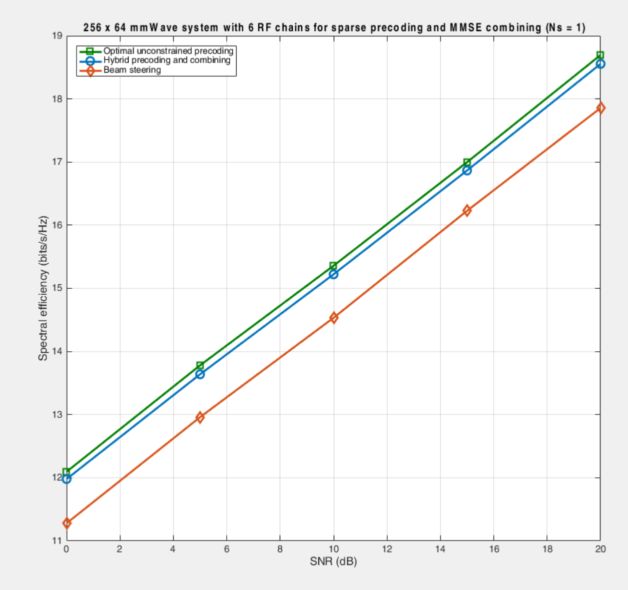

Figure 6 Spectral Efficiency 256x64 mm Wave with 6 RF Chains for space precoding and MMSE Combining NS

V. Conclusion

The paper highlights the sparsity of millimeter-wave channels and introduces Subspace Pursuit as a means of effectively capturing dominant channel components. By identifying and representing the most significant components, Subspace Pursuit significantly reduces the complexity of channel estimation without sacrificing accuracy.

OMP is presented as an iterative approach to selecting and recovering the most relevant beamspace components from a high-dimensional channel space. By iteratively narrowing the focus to the most promising channel components, OMP reduces dimensionality while preserving estimation accuracy.

In this paper explores the integration of these techniques and their performance in tandem. It is demonstrated that a combination of Kalman filtering, Subspace Pursuit, and OMP offers a comprehensive approach to channel estimation in millimeter-wave massive MIMO systems. This integrated approach effectively addresses challenges related to dynamic environments, sparsity, and dimensionality. realized.

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