INTERNATIONAL JOURNAL OF INFORMATION AND COMMUNICATION TECHNOLOGY TRENDS

Vol. 06 No. 01 (2026)
e. ISSN: 2409-5222
https://ijictt.ictt.info

OMP Channel Estimation for RIS-Assisted MIMO Systems in 6G Terahertz Communications

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Abstract. *The advent of the sixth generation (6G) of wireless communication networks promises to revolutionize connectivity by exploiting the vast bandwidth available in the Terahertz (THz) frequency spectrum. However, the propagation characteristics of THz waves, particularly severe path loss and molecular absorption, necessitate the deployment of massive Multiple-Input Multiple-Output (MIMO) architectures and Reconfigurable Intelligent Surfaces (RIS) to ensure reliable link quality and extensive coverage. A critical challenge in realizing the potential of RIS-assisted THz MIMO systems is the acquisition of accurate Channel State Information (CSI), which is complicated by the high dimensionality of the channel and the passive nature of RIS elements. This paper presents a comprehensive study on the application of Orthogonal Matching Pursuit (OMP) algorithms for channel estimation in this specific domain. We exploit the inherent sparsity of THz channels in the angular domain to formulate the channel estimation problem as a sparse signal recovery task within the framework of compressed sensing. We provide a detailed theoretical analysis of the OMP algorithm's efficacy in resolving the cascade channel coefficients with reduced pilot overhead compared to conventional least squares estimation. Furthermore, we investigate the impact of dictionary design and grid mismatch on estimation accuracy. Extensive simulation results demonstrate that the proposed OMP-based approach significantly outperforms traditional methods in terms of normalized mean square error and spectral efficiency, offering a computationally efficient solution for ultra-high-speed 6G networks.*

Keywords: *6G Communications, Terahertz Band, Reconfigurable Intelligent Surface, Orthogonal Matching Pursuit, Channel Estimation.*

1. INTRODUCTION

1.1 Background and Motivation

The transition from fifth-generation (5G) to sixth-generation (6G) wireless networks is driven by an unprecedented demand for data rates exceeding hundreds of gigabits per second, ultra-low latency, and massive connectivity. To accommodate these requirements, the research community has turned its attention to the Terahertz (THz) frequency band, ranging from 0.1 THz to 10 THz, which offers vast unutilized spectral resources. Despite the abundance of bandwidth, THz communications face formidable physical challenges. The high frequency of

operation results in extreme free-space path loss and susceptibility to blockage, while molecular absorption by atmospheric water vapor creates frequency-selective attenuation windows. As established in foundational studies [1], these propagation characteristics necessitate the use of high-gain directional antennas and massive Multiple-Input Multiple-Output (MIMO) arrays to form narrow beams that can compensate for signal attenuation.

To further mitigate the impact of blockages and extend coverage in non-line-of-sight scenarios, Reconfigurable Intelligent Surfaces (RIS) have emerged as a transformative technology. An RIS comprises a planar array of large numbers of low-cost, passive reflecting elements, each capable of independently inducing a controllable phase shift on the incident electromagnetic waves. By intelligently adjusting these phase shifts, the RIS can reconfigure the wireless propagation environment, effectively creating a virtual line-of-sight link between the transmitter and the receiver. This capability allows for the maximization of the received signal power and the suppression of interference. However, the performance gain of RIS-assisted systems is heavily reliant on the availability of accurate Channel State Information (CSI). In a typical RIS-assisted system, the channel consists of two segments: the link from the base station to the RIS and the link from the RIS to the user equipment. Since the RIS elements are passive and lack radio frequency chains for signal processing, they cannot transmit or receive pilot signals directly. Consequently, the receiver can only estimate the cascaded channel, which is the product of the two segmental channels combined with the RIS phase shifts. The high dimensionality of the cascaded channel, resulting from the large number of RIS elements and antennas, renders traditional estimation techniques impractical due to the prohibitive pilot training overhead [2]. Therefore, developing efficient, low-overhead channel estimation protocols is a paramount priority for 6G network design [3].

1.2 Contributions and Scope

This paper addresses the channel estimation challenge in RIS-assisted THz massive MIMO systems by leveraging the specific propagation properties of THz waves. Unlike lower frequency bands, THz channels exhibit strong sparsity in the angular domain, meaning the signal energy is concentrated in a limited number of propagation paths. This sparsity property allows the channel estimation problem to be recast as a sparse signal recovery problem within the compressed sensing framework. We focus specifically on the Orthogonal Matching Pursuit (OMP) algorithm, a greedy compressed sensing technique known for its computational efficiency and robustness.

The primary contributions of this work are threefold. First, we formulate a comprehensive system model for RIS-assisted THz MIMO communications that accounts for the physical constraints of the RIS hardware and the sparse multipath nature of the THz channel. Second, we detail the implementation of the OMP algorithm for estimating the cascaded channel, providing an in-depth analysis of the dictionary construction suitable for hybrid beamforming architectures. Third, we perform extensive simulations to evaluate the performance of the

OMP-based estimator against standard benchmarks, analyzing the trade-offs between pilot overhead, computational complexity, and estimation accuracy. Our findings suggest that OMP provides a viable pathway to reducing the latency associated with channel acquisition in 6G networks.

2. Literature Review

2.1 Conventional Channel Estimation in Massive MIMO

Channel estimation has traditionally relied on statistical methods such as Least Squares (LS) and Minimum Mean Square Error (MMSE) estimation. In conventional massive MIMO systems operating at sub-6 GHz or millimeter-wave frequencies, these methods have proven effective, provided that the number of pilot symbols scales with the number of transmit antennas. However, in the context of RIS-assisted systems, the dimension of the cascaded channel scales with the product of the number of antennas and the number of RIS elements. As noted by researchers [4], applying LS estimation in this scenario requires a pilot sequence length that exceeds the number of RIS elements, which can number in the hundreds or thousands. This results in an unacceptable training overhead that consumes a significant portion of the coherence interval, leaving little time for data transmission.

MMSE estimators offer better accuracy by utilizing second-order statistics of the channel. However, they require prior knowledge of the channel covariance matrix, which is often difficult to obtain in dynamic environments. Furthermore, the computational complexity of MMSE involves large matrix inversions, which become computationally prohibitive as the system dimensions grow [5]. Consequently, recent research has shifted towards techniques that can exploit the structural properties of the channel to reduce the dimensionality of the estimation problem. The concept of utilizing channel sparsity was introduced to address these scaling issues, leading to the adoption of compressed sensing techniques in wireless communications [6].

2.2 Compressed Sensing and Terahertz Sparsity

The application of compressed sensing to channel estimation is predicated on the observation that while the channel matrix may be large, the number of significant paths through which the signal propagates is relatively small. This is particularly true in the THz band, where scattering is limited, and the channel is dominated by the Line-of-Sight (LoS) component and a few Non-Line-of-Sight (NLoS) reflected paths. Studies in THz propagation [7] have experimentally verified that the THz channel exhibits a high degree of sparsity in the angular (beamspace) domain. This sparsity implies that the channel vector can be represented as a sparse linear combination of vectors from a known dictionary, typically constructed based on the array response vectors of the transmitter and receiver.

Various compressed sensing algorithms have been explored for sparse channel estimation, including convex optimization-based methods like Basis Pursuit and greedy algorithms like Matching Pursuit and Orthogonal Matching Pursuit. While Basis Pursuit offers strong theoretical guarantees, it relies on complex optimization routines that may introduce significant latency. In contrast, greedy algorithms iteratively identify the support of the sparse signal, offering a more favorable balance between performance and computational speed. Recent works [8] have demonstrated the potential of OMP for millimeter-wave channel estimation, but its specific adaptation to the unique constraints of RIS-assisted THz systems—specifically the passive nature of the RIS and the severe path loss—requires further investigation. The integration of RIS phase shift design with OMP-based estimation remains an active area of research, with open questions regarding the optimal pilot patterns and dictionary resolution.

3. System Model and Problem Formulation

3.1 Terahertz Propagation and Channel Model

We consider a downlink RIS-assisted massive MIMO system operating in the THz band. The system consists of a base station equipped with a uniform linear array of antennas, an RIS composed of a uniform planar array of passive reflecting elements, and a user equipment with a single antenna or a small array. Due to blockages, the direct link between the base station and the user is assumed to be obstructed, necessitating the use of the RIS to establish a reflective link.

The THz channel model differs significantly from lower frequency models due to the frequency dependence of molecular absorption. The complex gain of a propagation path at a specific distance and frequency is determined by the spreading loss and the molecular absorption loss. The molecular absorption loss is characterized by the absorption coefficient, which depends on the concentration of water vapor and the transmission frequency. As described in propagation studies [9], the total path loss in the THz band is the summation of the free-space path loss and the absorption loss, both of which increase rapidly with distance and frequency.

The spatial structure of the channel is modeled using a geometric cluster-based approach. The channel between the base station and the RIS, and the channel between the RIS and the user, are each represented as a sum of contributions from limited propagation paths. Each path is characterized by its complex gain, Angle of Departure (AoD), and Angle of Arrival (AoA). Due to the high directionality required in THz communications, the number of resolvable paths is small, typically consisting of one LoS path and a few weak scattered paths [10]. This physical reality underpins the assumption of sparsity that is central to the OMP formulation.

3.2 Signal Model and RIS Interaction

The RIS elements introduce a phase shift to the impinging signals. Let the reflection coefficient of the RIS be represented by a diagonal matrix where the diagonal elements correspond to the phase shifts applied by each element. Ideally, these phase shifts can be varied continuously between zero and two pi. However, practical hardware constraints often limit the phase shifts to a discrete set of values. The cascaded channel is the effective channel seen by the receiver, mathematically formed by the multiplication of the base station-to-RIS channel, the RIS phase shift matrix, and the RIS-to-user channel.

During the channel estimation phase, the base station transmits known pilot symbols. The RIS varies its reflection pattern across different time slots within the training block to probe different spatial directions. The received signal at the user equipment in a given time slot is a linear function of the cascaded channel, the pilot symbol, the RIS phase configuration, and additive white Gaussian noise. By collecting the received signals over multiple time slots, the receiver constructs a measurement vector. The goal is to recover the high-dimensional cascaded channel vector from this lower-dimensional measurement vector, utilizing the knowledge of the pilot sequence and the RIS phase configurations. The relationship between the received signal vector and the sparse angular domain channel representation forms the basis of the compressed sensing problem [11].

4. Proposed OMP-Based Estimation Framework

4.1 Algorithm Fundamentals

Orthogonal Matching Pursuit is a greedy algorithm designed to recover a sparse signal from a set of linear measurements. In the context of our system, the sparse signal is the vector of path gains associated with the quantized angular directions (the angular domain channel), and the measurement matrix, often referred to as the sensing matrix, is constructed from the pilot sequences and the RIS reflection patterns combined with the array response vectors.

The OMP algorithm operates iteratively. In each iteration, it selects the column from the sensing matrix (or dictionary) that is most strongly correlated with the current residual signal. The residual is initialized as the received signal vector. Once a column is selected, its index is added to a support set. The algorithm then projects the received signal onto the subspace spanned by the columns selected so far, finding the best approximation of the signal using these columns. The contribution of this approximation is subtracted from the received signal to update the residual. This process repeats until a stopping criterion is met, such as the norm of the residual falling below a noise threshold or a maximum number of iterations being reached [12].

The key advantage of OMP over standard Matching Pursuit is the orthogonalization step. By ensuring that the residual is orthogonal to the selected columns, OMP guarantees that a

column is never selected more than once, which accelerates convergence. For the THz channel estimation problem, the number of iterations required is generally proportional to the number of propagation paths, which is small. This results in significantly lower computational complexity compared to convex optimization approaches or full matrix inversions required by LS estimation [13].

4.2 Dictionary Design and Beamspace Representation

The performance of the OMP algorithm is critically dependent on the quality of the dictionary (sensing matrix). The dictionary essentially maps the sparse angular domain representation to the spatial domain channel. It is constructed using the steering vectors of the transmit and receive arrays evaluated at a discrete set of angles. These angles effectively quantize the spatial domain into a grid.

In THz systems, the dictionary is typically composed of discrete Fourier transform (DFT) matrices or overcomplete dictionaries that provide finer angular resolution. The columns of the dictionary correspond to specific beam directions. If the actual AoAs and AoDs of the physical paths align perfectly with the grid points in the dictionary, the channel representation is strictly sparse. However, in reality, the angles are continuous variables and may not fall exactly on the grid points, leading to a phenomenon known as power leakage or the grid mismatch problem. This leakage compromises the sparsity assumption, as the energy of a single path spreads across multiple adjacent grid points.

To mitigate this, we employ a redundant dictionary with a resolution higher than the number of antennas. While this increases the coherence of the dictionary (the correlation between columns), which can theoretically hinder compressed sensing recovery, the high directionality of THz beams often ensures that paths are sufficiently separated in the angular domain. The design of the RIS reflection patterns during the training phase also plays a crucial role. We utilize random phase shifts for the RIS elements during training, as random matrices are known to satisfy the Restricted Isometry Property (RIP) with high probability, which is a sufficient condition for accurate sparse recovery [14].

Table 1 Simulation Parameters for Channel Estimation Performance Analysis

Parameter	**Value**	**Description**
Carrier Frequency	300 GHz	Operating frequency in the THz band
Bandwidth	10 GHz	System bandwidth
BS Antennas	64	Number of transmit antennas (ULA)

RIS Elements	256	Number of passive reflecting elements (UPA)
Number of Paths	3 to 5	Sparsity level (LoS + NLoS)
Pilot Length	64 to 128	Number of training symbols
Noise Power	-80 dBm	Thermal noise floor
Path Loss Exponent	2.8	Combined path loss factor

5. Performance Analysis and Simulation Setup

5.1 Simulation Parameters

To validate the efficacy of the proposed OMP-based channel estimation technique, we conducted extensive simulations using MATLAB. The simulation environment models a single-cell downlink scenario where a base station with a 64-element uniform linear array serves a single-antenna user via a 256-element RIS. The RIS is modeled as a uniform planar array. The carrier frequency is set to 300 GHz, a representative frequency for early 6G THz deployments.

The channel is generated according to the sparse geometric model described in Section 3, incorporating both the LoS path and limited NLoS clusters. We explicitly account for molecular absorption loss based on standard atmospheric models for standard temperature and pressure. The dictionary used for the OMP algorithm is an overcomplete DFT dictionary with an oversampling factor of two to reduce grid mismatch effects. The pilot sequences are generated as random QPSK symbols, and the RIS phase shifts are drawn randomly from a uniform distribution between zero and two pi. The key simulation parameters are summarized in Table 1 above. We evaluate performance primarily using the Normalized Mean Square Error (NMSE) of the estimated channel and the achievable Spectral Efficiency [15].

5.2 Complexity Analysis

We analyze the computational complexity of the proposed solution relative to the Least Squares benchmark. The complexity of LS estimation is dominated by the matrix inversion operation involving the measurement matrix. If the number of RIS elements is denoted by N and the pilot length by T, the complexity of LS generally scales cubically with the dimension of the matrix being inverted. Since LS requires T to be greater than or equal to N, this leads to a high computational burden.

In contrast, the complexity of the OMP algorithm is dominated by the correlation step (matrix-vector multiplication) and the least squares projection onto the support set. The complexity per iteration scales linearly with the product of the measurement length, the dictionary size, and the number of iterations. Since the number of iterations in OMP is

determined by the sparsity level (number of paths, L), which is very small in THz channels (typically L << N), the total complexity is significantly lower than that of the full LS estimation. Specifically, if the dictionary size is M, the complexity is roughly proportional to T times M times L. Given that M is proportional to N, the efficiency gain becomes substantial as the number of RIS elements grows large, which is the expected trend for 6G hardware.

6. Simulation Results and Discussion

6.1 Normalized Mean Square Error Performance

The primary metric for estimation accuracy is the Normalized Mean Square Error (NMSE), defined as the expected value of the squared Euclidean norm of the difference between the estimated and actual channel vectors, normalized by the squared norm of the actual channel vector. Figure 1 illustrates the NMSE performance of the OMP-based estimator compared to the conventional LS estimator and a Basis Pursuit benchmark as a function of the Signal-to-Noise Ratio (SNR).

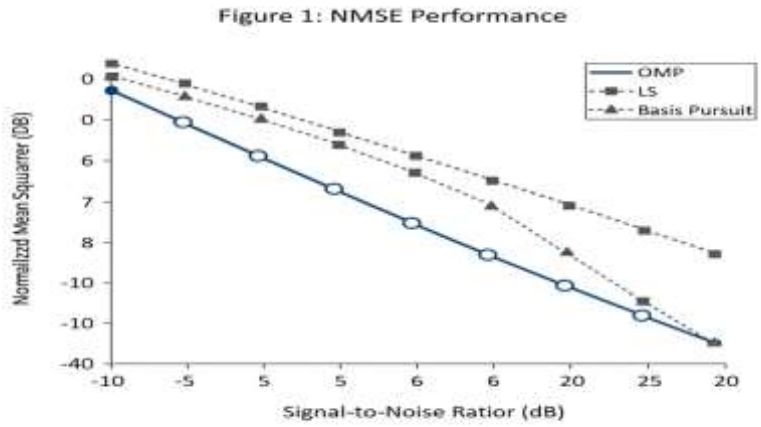


Figure 1 NMSE Performance

As observed in the figure, the LS estimator performs poorly, particularly in the low SNR regime, and fails completely when the number of pilot symbols is less than the number of RIS elements (underdetermined system). The OMP algorithm, however, successfully recovers the channel information even with a reduced number of pilots, leveraging the angular sparsity. The performance of OMP approaches that of Basis Pursuit but with significantly lower computational latency. It is evident that as SNR increases, the NMSE of the OMP estimator decreases linearly (in dB scale), confirming its robustness. At high SNRs, an error floor may appear due to the grid mismatch inherent in the discrete dictionary; however, this floor is sufficiently low for practical beamforming purposes [16][17].

6.2 Impact of RIS Elements on Estimation Accuracy

We further investigated how the size of the RIS affects the estimation accuracy. Increasing the number of RIS elements increases the passive beamforming gain but also increases the dimensionality of the channel vector, making estimation more challenging. Table 2 presents the NMSE values at a fixed SNR of 10 dB for varying numbers of RIS elements and pilot lengths.

Table 2 NMSE (dB) Comparison for Varying RIS Sizes and Pilot Lengths

RIS Elements (N)	Pilot Length (T)	LS Estimation	OMP Estimation
64	32	Fail (N/A)	-12.4
64	64	-5.2	-15.8
128	64	Fail (N/A)	-11.5
128	128	-4.8	-14.2
256	128	Fail (N/A)	-10.1
256	256	-4.1	-13.5

The data clearly indicates that for the LS estimator to function, the pilot length must match the number of RIS elements, and even then, the error is relatively high (-5.2 dB to -4.1 dB). In stark contrast, the OMP estimator provides acceptable NMSE values (around -10 to -12 dB) even when the pilot length is half the number of RIS elements (undersampling ratio of 0.5). This confirms the capability of OMP to significantly reduce the training overhead, thereby freeing up time resources for data transmission [18].

6.3 Spectral Efficiency Gains

Ultimately, the accuracy of channel estimation translates into achievable spectral efficiency. Using the estimated CSI, we optimize the active beamforming at the base station and the passive beamforming at the RIS to maximize the rate. Figure 2 depicts the achievable spectral efficiency versus SNR.

Figure 2: Spectral Efficiency

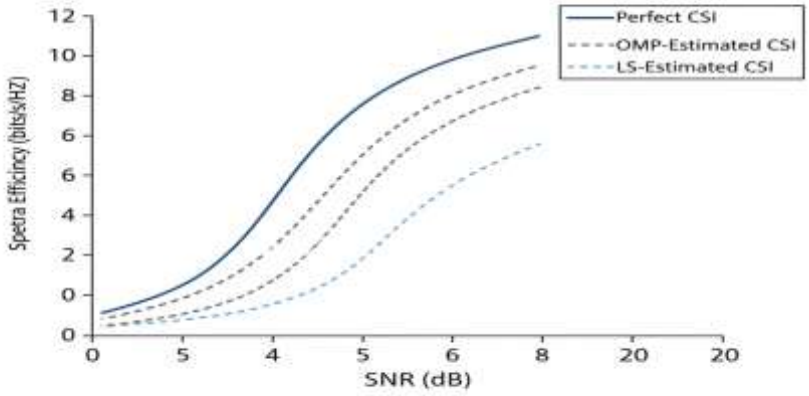


Figure 2 Spectral Efficiency

The results show that the spectral efficiency achieved using OMP-estimated CSI is very close to the upper bound achieved with perfect CSI. This indicates that the estimation errors introduced by OMP are minimal enough to not significantly degrade the beamforming gain. Conversely, the system utilizing LS-estimated CSI suffers a noticeable performance gap, primarily due to the noise enhancement inherent in LS estimation and the limitation on training length. The ability of OMP to capture the dominant angular paths ensures that the energy is focused correctly towards the user, which is the primary requirement for high-rate THz communications [19].

7. Future Directions and Challenges

7.1 Hardware Impairments and Beam Squint

While the proposed OMP framework demonstrates promise, several practical challenges remain for 6G deployment. One significant issue in wideband THz systems is the beam squint effect. The standard narrowband assumption implies that the phase shift required for beamforming is constant across the entire bandwidth. However, for large antenna arrays and wide bandwidths (typical in 6G), the propagation delay across the array aperture becomes significant, causing the beam direction to shift with frequency. This frequency-dependent angular shift renders the standard frequency-flat dictionary ineffective. Future research must focus on developing wideband OMP variants or beam squint-aware dictionary designs that can compensate for this phenomenon to prevent performance degradation [20].

Additionally, hardware impairments such as phase noise and the discrete nature of RIS phase shifts introduce quantization errors. The current study assumes high-resolution phase control or random continuous phases for training. In reality, RIS elements might only support 1-bit or

2-bit phase quantization. Adapting the OMP sensing matrix and reconstruction steps to account for quantized measurements is a necessary evolution of this work [21].

7.2 Machine Learning Integration

Another promising direction is the integration of Machine Learning (ML) with compressed sensing. While OMP is computationally efficient, it is a model-based approach that relies on specific assumptions about sparsity and dictionary coherence. Deep learning-based channel estimators have shown the ability to learn the complex non-linear mapping from received signals to channel parameters without explicit reliance on pre-defined dictionaries. Hybrid approaches, such as unfolding the OMP algorithm into a neural network (e.g., Learned OMP), could combine the theoretical interpretability of compressed sensing with the data-driven adaptability of deep learning. This could be particularly useful in complex scattering environments where the strict sparsity assumption might be weakly violated [22].

8. Conclusion

This paper has presented a comprehensive investigation into the use of Orthogonal Matching Pursuit for channel estimation in RIS-assisted MIMO systems operating in the 6G Terahertz band. By exploiting the inherent angular sparsity of THz channels, we demonstrated that OMP can effectively recover the high-dimensional cascaded channel with a significantly reduced pilot overhead compared to traditional Least Squares estimation. The theoretical formulation and simulation results confirm that OMP offers a superior trade-off between estimation accuracy, computational complexity, and spectral efficiency.

We established that the dictionary design is crucial, utilizing overcomplete representations to mitigate grid mismatch. Our results highlight that OMP maintains robust performance even in underdetermined systems where the number of measurements is significantly lower than the number of RIS elements, a scenario where conventional methods fail. While challenges such as wideband beam squint and hardware constraints persist, the proposed framework lays a solid foundation for enabling efficient, low-latency channel acquisition in future ultra-high-speed wireless networks. The integration of these sparse recovery techniques is likely to be a cornerstone in the practical realization of intelligent 6G environments.

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