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A Review of Low-Bits Quantization Techniques in Massive MIMO Systems

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Abstract. Massive Multiple-Input Multiple-Output (Massive MIMO) serves as a foundational enabling technology for 5G and future communication systems, markedly boosting spectral and energy efficiency through the deployment of large-scale antenna arrays. However, the scaling-up of antenna arrays has led to a substantial increase in system power consumption and hardware costs, with high-precision analog-to-digital converters (ADCs) emerging as the dominant power consumption bottleneck in the radio frequency chain. To alleviate system complexity and power consumption, low-resolution ADCs (1–3 bits) have attracted extensive research interest in recent years. Such schemes can substantially curtail hardware costs and energy consumption while retaining satisfactory system performance. Nevertheless, the introduction of severe nonlinear distortion due to low-precision quantization disrupts the linear Gaussian model assumption upon which traditional receiver algorithms rely, resulting in compromised channel estimation and signal detection performance. Quantization errors demonstrate non-Gaussian and input-dependent characteristics, leading to the degradation of amplitude information and thus constraining the applicability of technologies such as high-order modulation and high-precision sensing. This paper presents a systematic review of low-precision quantization techniques for Massive MIMO. It first investigates the impacts of low-bit quantization on system models and signal statistical properties. Subsequently, it elaborates on transceiver architectures and key design challenges pertaining to low-precision ADCs/DACs. The paper highlights signal processing and algorithmic strategies to overcome quantization distortion, including Bussgang decomposition linearization methods, statistical inference techniques such as approximate message passing (AMP), model-driven deep learning frameworks, and Σ–Δ quantization architectures endowed with noise-shaping capabilities. Finally, it discusses the challenges and future directions of this technology in emerging scenarios, including terahertz communications, intelligent reflecting surfaces, and integrated sensing and communication. This paper seeks to provide researchers with a systematic technical overview, clarifying the intrinsic connections and trade-offs among different methods, and offering valuable insights for the realization of high-energy-efficiency and low-cost Massive MIMO systems.

Keywords: Massive MIMO, 5G, Communication system, ADC

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1. Introduction

Massive Multiple-Input Multiple-Output (Massive MIMO) technology serves as a fundamental pillar of future wireless systems [1]. By harnessing spatial multiplexing to boost spectral and energy efficiency [2], it is set to assume a crucial role in 6G. Nevertheless, the deployment of large-scale antenna arrays substantially increases hardware costs and power consumption. To tackle these issues, low-resolution ADCs have drawn significant interest. Prominent solutions include 1-bit quantization based on Bussgang decomposition [3] and spatial oversampling through Sigma–Delta modulation [4-6]. The latter makes use of dense arrays to implement spatial noise shaping, enabling high-resolution reception with a considerably reduced complexity. This paper presents a systematic review of these quantization technologies, synthesizing recent advancements and future challenges. By analyzing the trade-offs among performance, energy efficiency, and cost, this research aims to offer a comprehensive view to stimulate further innovations in practical Massive MIMO systems. the field.

2. The impact of Massive MIMO systems and low-bit quantization

2.1. Massive MIMO systems

Massive MIMO technology amplifies the inherent merits of traditional MIMO systems by deploying large-scale antenna arrays (typically encompassing hundreds of antennas) at the base station, thereby facilitating concurrent communication with multiple user terminals within the same time-frequency resources [7].

The canonical TDD cellular system model for Massive MIMO is formulated as follows: a base station equipped with $(\mathrm{M} \gg \mathrm{K})$ antennas serve (K) single-antenna user equipment (UE) devices occupying the same time-frequency resource block.

The uplink received signal model is formulated as:

$$\mathrm{y_u} = \sqrt{\rho_{\mathrm{ul}}} \sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{h_k x_k} + \mathrm{n} \tag{1}$$

The downlink received signal at the user terminal is expressed as:

$$\mathrm{y_k} = \sqrt{\rho_{\mathrm{dl}}} \mathrm{h_k^T} \sum_{\mathrm{i}=1}^{\mathrm{K}} \mathrm{w_i s_i} + \mathrm{n_k} \tag{2}$$

The channel vector is modeled as $\left(\mathrm{h_k} = \sqrt{\beta_{\mathrm{k}}}\mathrm{g_k}\right)$ where $(\mathrm{g_k} \sim \mathscr{CN}(0, \mathrm{I_M}))$; the channel state information (CSI) is acquired via uplink orthogonal pilot sequences, with pilot contamination induced by cross-cell pilot reuse. Signal detection and precoding can adopt linear processing schemes such as MRC/MRF, ZF, and OAMP. When $(\mathrm{M} \to \infty)$, the system demonstrates favorable propagation characteristics such as channel hardening, and linear processing algorithms attain near-optimal performance. Recent research has extended the application scenarios of Massive MIMO to encompass hybrid beamforming, low-precision ADC, and cell-free distributed cooperation [8]. However, these technologies—particularly in the context of large-scale antenna arrays—typically confront the challenge of a drastic surge in system power consumption and hardware costs. Among them, high-resolution ADC, as the main energy-consuming unit in the RF link, have emerged as a critical bottleneck. Therefore, the adoption of low-precision ADCs is recognized as a viable solution to achieve a trade-off between performance and energy efficiency.

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2.2. The specific impact of low-bits ADC on signal quantization

The nonlinearity of low-bit ADCs introduces input-dependent, non-Gaussian noise, causing systematic bias in standard linear estimation and detection. To mitigate this, linearization via Bussgang decomposition or noise whitening through dithering and oversampling can be employed. Although low-bit quantization limits spectral efficiency by discarding amplitude information, it offers significant hardware benefits. Notably, 1-bit ADCs eliminate the need for automatic gain control and require only a single comparator, substantially reducing power consumption and cost. Consequently, designing quantization-aware transceivers is crucial. By integrating quantization-aware detection at the receiver and pre-distortion at the transmitter, systems can effectively balance performance and complexity despite constrained quantization precision.

3. Low-bit ADC/DAC receiver and transmitter architecture

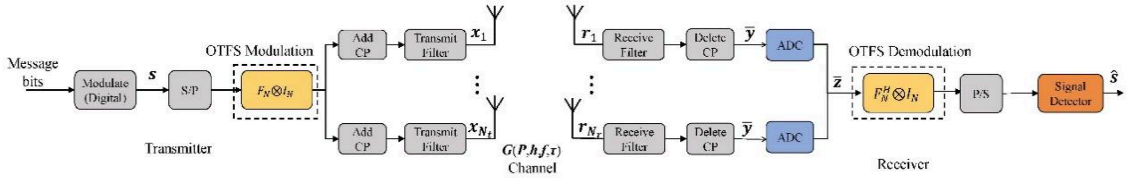

Figure 1. Framework of quantized OTFS system

Figure 1: illustrates a complete wireless communication link architecture employing low-precision data converters. The OTFS modulation block can be substituted with any other modulation scheme (e.g., OFDM, SC-FDMA, GFDM) without altering the overall transceiver architecture. At the transmitter, the source bit stream is first mapped to symbols via digital modulation, followed by serial-to-parallel conversion. The modulated signal is then appended with a cyclic prefix and passed through a transmission filter. Finally, it is converted to an analog signal by a low-precision DAC and radiated via an antenna array. The signal subsequently propagates through a wireless channel encompassing effects such as multipath and Doppler. At the receiver, the received signal is first filtered and the cyclic prefix is removed. It is then sampled and quantized by a low-precision ADC, which introduces nonlinear quantization distortion. The receiver subsequently performs OTFS demodulation corresponding to the modulation at the transmitter (as shown $\mathrm{F}_{\mathrm{N}}^{\mathrm{H}} \otimes \mathrm{I}_{\mathrm{N}}$ in the figure), and this module can be replaced by a demodulator matched to the transmitted modulation. Finally, the signal detector makes symbol decisions based on the quantized signal to recover an estimate value of the original bit stream.

As previously mentioned, the severe distortion and nonlinearity induced by ultra-low precision (1-2 bit) quantization pose fundamental challenges to traditional receiver architectures predicated on the assumption of infinite precision. The research focus must shift toward innovative methodologies that explicitly account for quantization effects, with particular emphasis on quantization-aware signal detection, while concurrently considering aspects such as channel estimation. This chapter will systematically elaborate on the core algorithms and signal processing techniques developed to alleviate quantization distortion, with a primary focus on signal detection.

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4. Algorithms and signal processing techniques for overcoming quantization distortion

With the relentless advancement of Massive MIMO, millimeter-wave, and terahertz communications, the power consumption and hardware complexity of receiver front-ends have become prominent bottlenecks in system deployment. The adoption of low-resolution ADC/DAC (typically 1–3 bits) can significantly reduce system energy consumption and hardware overheads; however, the introduced quantization nonlinearity reduces system energy consumption and hardware overheads, leading to substantial performance degradation of classical detection algorithms (e.g., least squares (LS) and minimum mean square error (MMSE)).

To address these challenges, a variety of innovative signal detection methods have been proposed. Key technical approaches include: equivalent linear system-based modeling approaches (e.g., AQNM [9] and Bussgang decomposition [10]); statistical inference-based approaches that attain near-optimal estimation via probabilistic modeling (e.g., AMP/GAMP/VAMP [11,12] and variational Bayesian frameworks); learning-driven paradigms that exploit data-driven mechanisms to learn quantization-induced nonlinear mappings (e.g., OAMP-Net [13] and deep neural networks); and non-uniform quantization architectures capable of suppressing distortion via noise shaping (exemplified by spatial Sigma-Delta [14]). Notably, concepts including sparse reconstruction for channel estimation, variational inference, and model-driven learning have been deeply integrated with signal detection, propelling the evolution of detection algorithms from isolated module-wise processing toward joint optimization and intelligent system-level modeling.

4.1. Signal detection

Low-bit quantization imposes considerable challenges on signal detection, with relevant research evolving from linear detection toward probabilistic inference and deep learning-enabled approaches. Although sharing methodological commonalities with channel estimation, detection tasks exhibit distinct characteristics regarding objectives, prior information utilization, and evaluation metrics.

Linear detection approaches based on AQNM [9] or Bussgang [10] models (e.g., MRC, ZF, LMMSE) feature simplicity and computational efficiency, functioning as theoretical baselines. However, their performance is constrained by linearity assumptions, which restricts their capacity to attain near-optimal performance. To overcome these limitations, a range of near-optimal detection approaches have been proposed. GAMP/OAMP/GOAMP detection [11,12] formulates symbol detection as an output estimation problem, guaranteeing convergence via state evolution, sharing core principles with AMP-class algorithms for channel estimation. The SD-VB detection algorithm [15], operating under the spatial ΣΔ architecture [14], efficaciously suppresses quantization noise through variational Bayesian inference, attaining near-maximum likelihood (ML) performance in 1–2-bit scenarios. This method adapts the variational Bayesian framework from channel estimation [16,17], with specific optimization for detection tasks. Additionally, RIS-assisted low-bit MIMO detection [18] jointly estimates the RIS reflection matrix and channel under the VAMP framework, exemplifying a collaborative design paradigm between detection and estimation.

In the domain of deep learning and model-driven detection, DetNet and OAMP-Net [13] unroll iterations of traditional detection algorithms into neural network layers, striking a balance between convergence speed with interpretability, drawing inspiration from Learned-GAMP for channel estimation. Subsequent studies have further integrated attention and sparse connection mechanisms (Self-Attention OAMP/ScNet-OAMP), enhancing robustness against quantization mismatch and channel variations. The 2025 NeuroDetect model [19] validates the feasibility of end-to-end data-driven detection in low-bit phase modulation systems, attaining near-ML performance without

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relying on explicit channel models—thus representing a novel direction for the independent advancement of detection algorithms.

4.2. Comprehensive trends and development directions

Low-bit quantization communication systems are rapidly evolving towards joint optimization, intelligence, and multi-dimensional integration, giving rise to several prominent trends in the field of signal detection. Firstly, signal detection is no longer passively adapting to quantization effects but is now being jointly optimized with modules including channel estimation [20] and coding-modulation within the variational Bayesian or approximate message passing framework to enhance performance—exhibiting a detection-led joint design characteristic. Secondly, Bussgang decomposition and OAMP/AMP cascaded structures provide initial prior information via linearization, followed by optimizing detection accuracy through iterative inference—thus striking an effective balance between computational complexity and system performance. In terms of model architecture, interpretable deep learning detection approaches rooted in physically interpretable algorithms such as OAMP-Net and Learned-GAMP not only maintain detection performance but also retain model generalization capability. Spatio-temporal Sigma-Delta modulation and hybrid resolution architectures [21] deliver enhanced quantization inputs for detection algorithms via the integration of noise shaping and dynamic ADC allocation strategies—embodying a hardware-aware detection optimization paradigm. Lastly, the collaborative design of intelligent hardware jointly optimizes quantization, modulation, and detection modules while incorporating AI technologies to realize adaptive control of hardware-level quantizers, enhancing detection energy efficiency at the system level. This denotes a crucial development direction for system-level detection collaboration.

5. Future research challenges and directions

In the landscape of future-generation communication systems, the research on low-bit quantization persists in confronting a suite of critical challenges alongside promising opportunities:

In terahertz communication scenarios, the deployment of ultra-massive antenna arrays imposes formidable quantization challenges. Due to the extremely wide system bandwidth and sparse channel properties inherent to the THz frequency band, developing scalable low-bit quantization models and realizing commensurate low-power radio frequency front-ends remain unresolved critical issues that need to be addressed. Meanwhile, intelligent reflecting surfaces, as an emerging technology for boosting coverage and spectrum efficiency, exhibit strong coupling between quantization errors and RIS phase adjustment when aiding low-precision quantization systems. Future research should prioritize joint optimization algorithms for beamforming and quantization parameters to alleviate performance degradation induced by such coupling.

In integrated sensing and communication (ISAC) systems, the impact of low-bit quantization is more intricate. Although low-precision ADCs contribute to reducing the power consumption of communication receivers, they inflict more severe degradation on the amplitude and phase accuracy of radar sensing signals—potentially resulting in compromised performance in target detection and parameter estimation. Therefore, designing quantization strategies that strike a trade-off between communication throughput and sensing precision is pivotal for achieving high-efficiency and low-power operation of ISAC systems.

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6. Conclusion

This paper presents a systematic review of low-bit quantization technologies for massive MIMO systems. Extensive research validates that advanced signal processing methodologies, encompassing Bussgang decomposition, approximate message passing, model-driven deep learning, and spatial Sigma-Delta modulation, can efficaciously alleviate nonlinear distortion and quantization noise induced by low-precision ADCs/DACs. These approaches substantially curtail system power consumption and hardware overheads while preserving satisfactory communication performance. Theoretically, through comparative analysis and integration of core concepts and inherent trade-offs across diverse technical pathways, this study offers a systematic perspective for establishing a unified analytical and design framework. Practically, the elaborated quantization-aware transceiver architectures and algorithms carry profound implications for advancing the energy-efficient and cost-effective deployment of massive MIMO in future networks such as 6G and terahertz communications. However, this paper predominantly concentrates on algorithmic and architectural dimensions, with inadequate analysis of specific factors in hardware implementation factors—potentially compromising the generalizability of its conclusions under extreme operating scenarios. Future research could concentrate on hardware-algorithm co-design and explore the deep integration of low-bit quantization with emerging paradigms like intelligent reflecting surfaces and integrated sensing and communication. In conclusion, this study offers novel insights into the understanding and advancement of massive MIMO quantization technologies, underscoring that cross-layer optimization and intelligent design are pivotal for unlocking the system's potential in approaching the Shannon limit.

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