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SVM-Based Signal Detection for Low-Resolution Quantized Systems

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I. Introduction

The rapid evolution of wireless communication has led to the advent of next-generation networks, driven by the need for ultra-reliable low-latency communications (URLLC), and massive machine type communications (mMTC). With the future sixth-generation (6G), researchers are trying to move beyond millimeter wave (mmWave) into subTHz bands, [1] to enable the Ultra Massive MIMO (UM-MIMO) systems. Though these emerging technologies have significantly enhanced spectral efficiency and network capacity, they present challenges in power consumption due to the larger number of antennas, each equipped with dedicated analog-to-digital converters (ADCs). The power consumption of ADCs grows exponentially with resolution and linearly with sampling rate [2], resulting in unsustainable power demands. For instance, a system with 256 RF chains can consume over 250 W in ADC power alone, which is impractical for energy-constrained environments.

To mitigate this challenge, low-resolution ADCs have emerged, while significantly reducing power consumption by limiting the number of quantization bits [3]. However, this low-resolution ADCs introduces nonlinear distortions, severely impacting receiver performance. Traditional signal processing techniques, which assume a linear input-output relationship, struggle to mitigate these distortions, necessitating novel approaches for effective detection and estimation.

To this end, a maximum likelihood (ML) detector was derived [4] for the phase quantization in low-resolution ADC-based single-input single-output (SISO) systems, but it requires channel state information (CSI). Therefore, we are trying to apply Artificial intelligence (AI) to estimate the transmitted signal at the receiver without channel knowledge. Here, we applied support vector machine(SVM) based approach to detect the quantized signals at the receiver in a SISO system with n-bit ADC. It gives nearly optimum results when comparing to the ML detector in [4]. Also in the ML detector, an error in CSI causes a severe performance degradation in the system. Our method overcomes this issue by eliminating the need for CSI while achieving nearly optimal results. This work lays the foundation for AI-driven detection in complex systems like gigantic MIMO, where deriving an ML detector is infeasible and achieving accurate CSI through channel estimation is also impractical due to the presence of over two thousand antennas.

II. Literature Review

Recent advancements in artificial intelligence (AI) and deep learning (DL) have presented a transformative opportunity for next-generation wireless receivers. Deep learning models have demonstrated remarkable capabilities in channel estimation, equalization, and signal detection, making them a viable solution for energy-efficient wireless systems [5]. Unlike conventional model-based methods, deep learning leverages data-driven techniques to learn complex input-output mappings, effectively mitigating the distortions caused by low-resolution quantization. Recently, data-driven optimal detection techniques for massive MIMO systems with one-bit ADCs have been explored [6]. However, this approach has not been applied to phase quantization-based n-bit ADCs.

III. System Setup

A. Channel Model and Signal Modulation

We consider a point-to-point flat-fading wireless channel, where the received signal is given by:

$$Y = \sqrt{\mathsf{SNR}}HX + W, \tag{1}$$

where $X \in \mathcal{C} \subset \mathbb{C}$ is the transmitted signal, $\mathcal{C}$ is the constellation set of information signals. We assume that that $\mathcal{C} = \left\{ e^{j\pi\left(\frac{2\alpha+1}{M}-1\right)} \right\}_{\alpha=0}^{M-1}$ and M is a power of 2 for M-PSK constellation, SNR is the ratio of the transmitted signal energy to the additive white Gaussian noise (AWGN) spectral density, $H \in \mathbb{C}$ is the unit power channel gain between the transmitter and the receiver, and W is the circularly-symmetric zero-mean unit-variance AWGN.

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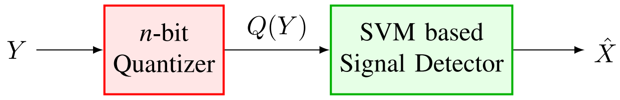

Fig. 1. General receiver architecture with low-resolution quantization.

B. Receiver Architecture

As shown in Fig. 1, the receiver employs a low-resolution ADC with phase quantization. The quantizer $Q(\cdot)$ maps Y to one of 2^n phase-based regions, eliminating the need for automatic gain control, where n is the number of bits used in the ADC. Unlike previous work, our design integrates an SVM-based signal detector that predicts X solely using $Q(Y) \in [0 : 2^n - 1]$ without explicit channel knowledge.

IV. Proposed Architecture

This section details our SVM based model-free framework which provides near-optimal results within low-resolution quantization environments, dispensing with the necessity for explicit channel state information(CSI). Unlike traditional maximum likelihood(ML) approaches, our solution is a fully data-driven methodology.

The proposed method classifies the received quantized signal $Q(Y)$ into one of the M possible transmitted signals;

$$X_\alpha = e^{\jmath\pi\left(\frac{2\alpha+1}{M}-1\right)} \quad \text{for} \quad \alpha = 0, 1, \ldots, M-1.$$

As the transmitted symbol depends only on α, the proposed architecture is designed to predict α by observing $Q(Y)$.

In our method, we use One-Versus-One (OvO) method to tackle an M-class classification problem. Essentially, this involves training a separate classifier for every possible pair of classes, leading to a total of $\frac{M(M-1)}{2}$ classifiers. Each classifier focuses on distinguishing just two specific classes. The decision for each classifier is made through a function containing learnable parameters, which are optimized during the training phase (TP) to ensure the most accurate predictions.

During the TP, the model tries to minimize the complexity of the decision boundary (to avoid overfitting) while also allowing some leeway for misclassifications, which is handled using slack variables. The transmitter transmits labeled data that the receiver also knows. The receiver then uses the received quantized data and corresponding labels to create a dataset to train the model.

When it comes to data transmission phase(DP) where the transmitter sends unknown data, each of the classifiers casts a vote for one of the classes, and the final predicted class, α is the one that receives the most votes. This voting scheme ensures that even if one classifier makes an incorrect decision, the collective perception of all the classifiers leads to a more reliable result, making the OvO method an effective and intuitive way to handle complex classification tasks.

V. Results and Discussion

In this section, as a case study, we present the Symbol Error Probability (SEP) results obtained using SVM-based signal detector, for QPSK modulation with n-bit quantization. Fig. 2 compares the SEP performance of the proposed method with the ML detector from [4] for QPSK and 16-PSK. The comparison is made for phase quantization levels of $n = \log_2 M$, $n = \log_2 M + 1$, and $n = \log_2 M + 2$. The ML detector in [4] is the optimum detection rule if the receiver has access to full channel knowledge. Hence, it serves as the universal lower bound on the SEP performance of our method. The performance gap remains below 1% across QPSK and the quantization levels we studied. Our SVM-based approach effectively mitigates the challenge introduced by accurate channel estimation in low-resolution ADC receivers.

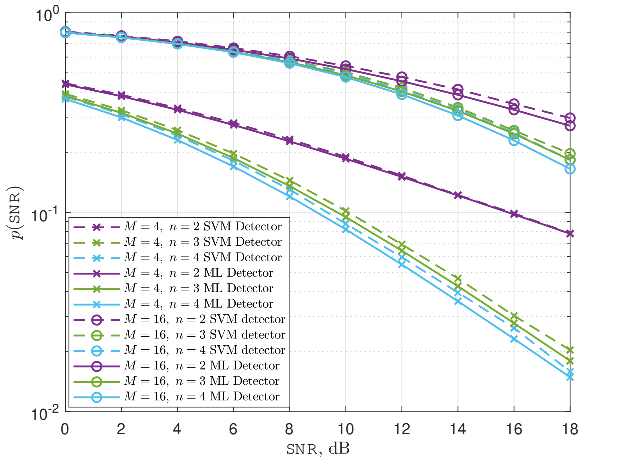

Fig. 2. Comparison of the SEP performances of proposed method and the optimum ML detector. The number of quantization bits is set to $n = \log_2 M$, $\log_2 M + 1$ and $\log_2 M + 2$ for QPSK and 16-PSK

VI. Conclusion

Our proposed method closely matches ML detection with a minimal performance gap less than 1%, while eliminating the need for CSI in low-resolution wireless systems.

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