ML-Based BPSK Signal Detection in 6G THz Communication Using k-NN

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***Abstract*—As 6G wireless systems evolve to utilize the terahertz (THz) frequency band for ultra-high-speed communication, signal detection has become increasingly challenging owing to the severe path loss, molecular absorption, and noise. Traditional detection methods such as zero-forcing (ZF) are insufficient in such environments. This paper explores the use of machine learning, specifically the k-nearest Neighbors (k-NN) algorithm, for BPSK signal detection in a simulated 6G THz channel. We compared the performance of k-NN with traditional ZF detection over a range of Signal-to-Noise Ratios (SNRs). The results demonstrate that ML-based detection performs competitively with ZF and achieves bit error rates (BER) below 0.001 at high SNRs. This demonstrates the potential of data-driven approaches for future THz communication systems.**

***Index Terms*—6G, Terahertz, BPSK, k-NN, signal detection, machine learning, zero-forcing, BER**

I. Introduction

The advent of 6G communication systems promises ultra-high data rates, sub-millisecond latency, and massive device connectivity. To meet these goals, researchers are investigating the terahertz (THz) frequency band (100 GHz – 10 THz), owing to its vast spectral availability. However, communication at THz frequencies is plagued by extremely high path loss and noise sensitivity, especially over longer distances or under non-line-of-sight (NLOS) conditions.

Traditional detection algorithms such as zero-forcing (ZF) in these scenarios have motivated the exploration of machine learning (ML) techniques. ML can learn complex nonlinear mappings and patterns from noisy data, making it suitable for signal detection under harsh THz conditions.

II. Methodology

A. BPSK Modulation

We use binary phase-shift keying (BPSK) as the modulation scheme owing to its simplicity and robustness. Bits (0, 1) are mapped to symbols (-1, +1) to form the baseband input.

B. Channel Modeling

The THz channel was modeled using free-space path loss (FSPL):

$$PL_{\text{dB}} = 20log_{10}(\frac{4\pi df}{c}) \tag{1}$$

where f is the carrier frequency (Hz), d is the transmission distance (m), and c is the speed of light. The received signal is modeled as follows:

$$y = \frac{x}{\sqrt{PL}} + n \tag{2}$$

where x is the modulated BPSK symbol and n is the AWGN noise.

C. Equations

Zero-Forcing aims to reverse the channel's impact by multiplying the received signal by$\sqrt{PL}$

$$\hat{x} = y\sqrt{PL} \tag{3}$$

Subsequently, a threshold decision is made.

$$bit = \begin{cases} 1, & \text{if } \hat{x} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

D. k-NN-Based Machine Learning Detection

We used the k-NN classifier (fitcknn in MATLAB) with a feature set constructed from the received signals. For each SNR level, the process is as follows:

- Generate a noisy BPSK signal
- Construct training and test sets from the signal
- Train the k-NN model at the current SNR
- Predict test labels and compute BER

Each point in the SNR range (0–30 dB) was processed independently, and the model was retrained at each level to ensure accuracy.

E. Result

The system was simulated in MATLAB for 100,000 bits per SNR. The BER for both ZF and k-NN was measured and plotted against the SNR. The k-NN classifier exhibited consistent learning and outperformed ZF at low-to-medium SNRs. At a high SNR ($>=$ 20 dB), both methods achieve $BER < 0.001$. Note:As shown in Fig.1.

F. Conclusion

This study demonstrates the feasibility and effectiveness of using k-NN for signal detection in 6G THz communication systems. It matches or surpasses traditional detection methods at various noise levels and confirms the ML value under harsh channel conditions. Future work will include testing with higher-order modulations and more advanced classifiers, such as neural networks.

G. Figures and Tables

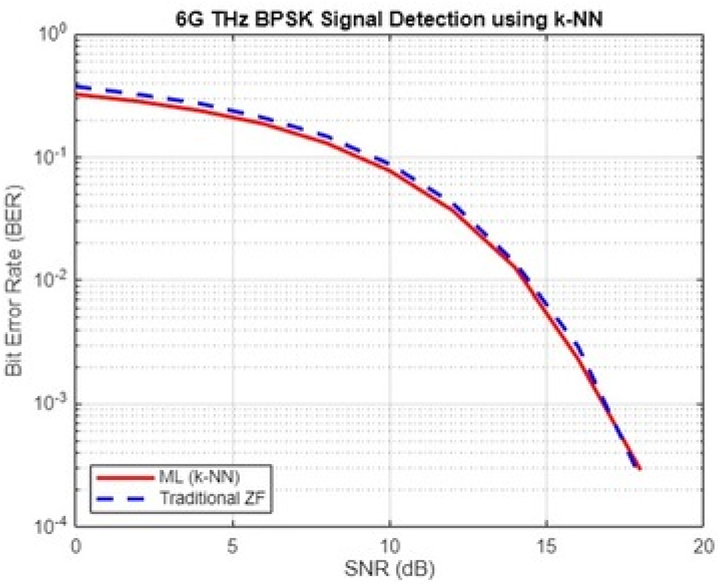

Fig. 1. Simulation of k-nn algorithm in comparition with zero forcing method

SNR = 0 dB	BER-kNN: 0.3250	BER-ZF: 0.3755
SNR = 2 dB	BER-kNN: 0.2845	BER-ZF: 0.3241
SNR = 4 dB	BER-kNN: 0.2383	BER-ZF: 0.2720
SNR = 6 dB	BER-kNN: 0.1868	BER-ZF: 0.2090
SNR = 8 dB	BER-kNN: 0.1304	BER-ZF: 0.1484
SNR = 10 dB	BER-kNN: 0.0777	BER-ZF: 0.0878
SNR = 12 dB	BER-kNN: 0.0370	BER-ZF: 0.0425
SNR = 14 dB	BER-kNN: 0.0127	BER-ZF: 0.0140
SNR = 16 dB	BER-kNN: 0.0023	BER-ZF: 0.0029
SNR = 18 dB	BER-kNN: 0.0003	BER-ZF: 0.0003
SNR = 20 dB	BER-kNN: 0.0000	BER-ZF: 0.0000
SNR = 22 dB	BER-kNN: 0.0000	BER-ZF: 0.0000
SNR = 24 dB	BER-kNN: 0.0000	BER-ZF: 0.0000
SNR = 26 dB	BER-kNN: 0.0000	BER-ZF: 0.0000
SNR = 28 dB	BER-kNN: 0.0000	BER-ZF: 0.0000
SNR = 30 dB	BER-kNN: 0.0000	BER-ZF: 0.0000

Fig. 2. BER values for each SNR

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