Original Research Article

Research on Channel Estimation and Compensation Techniques in 5G Wireless Communication Systems Based on Millimeter Wave Frequency Band

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Abstract: The utilization of the millimeter wave (mmWave) frequency band has accelerated the development of 5G wireless communication systems. Although mmWave offers abundant bandwidth resources and faster data rates, channel estimation and compensation techniques face significant challenges in high-mobility scenarios and complex urban environments. This paper focuses on the proposal and enhancement of channel estimation and compensation technologies within mmWave-based 5G systems. We have developed a novel channel estimation algorithm that integrates compressed sensing and machine learning techniques. This approach not only significantly improves the accuracy of channel estimation but also effectively reduces implementation complexity. Experimental results demonstrate that the proposed method delivers superior performance across various channel conditions, achieving approximately a 30% reduction in error rate compared to traditional methods.

Keywords: Millimeter wave; 5G wireless communication; Channel estimation; Channel compensation; Compressive sensing

With the rapid expansion of 5G technology worldwide, wireless communication systems in the millimeter - wave frequency band have shown great potential in increasing network capacity and speed. However, due to path loss and scattering phenomena during propagation, millimeter - wave signals experience rapid channel fading and multipath effects, which pose severe challenges to channel estimation and compensation. Channel estimation is a key step in improving the performance of wireless communication systems, and its accuracy directly affects the accuracy of subsequent data detection. Channel compensation, on the other hand, is used to correct the adverse effects of channel fading, thereby enhancing the quality of the received signal. Therefore, developing efficient channel estimation and compensation methods is crucial for millimeter - wave wireless communication systems. This paper proposes a new method for channel estimation and compensation that integrates compressed sensing and machine learning to enhance the robustness and performance of 5G millimeter - wave systems.

1. Channel Estimation Technology Process

1.1. Introduction of Compressed Sensing Framework

The introduction of compressed sensing theory in the field of modern signal processing, especially in channel estimation of millimeter - wave communication systems, has become a revolutionary technical approach. This theory is based on the sparsity principle of signals and can efficiently reconstruct sparse signals at a rate far below the Nyquist rate. Millimeter - wave signals exhibit significant sparsity in the spatial domain, that is, within a given spatiotemporal resolution, non - zero items or significant signal energy are concentrated in a few locations, making it not only possible but also advantageous to reconstruct signals through sparse representation methods[1].

In millimeter - wave communication systems, traditional channel estimation is affected by the high frequency of signals and the complex and variable multipath effects. It requires a large amount of pilot overhead and faces a trade - off between computational complexity and accuracy. The core of compressed sensing theory lies in the fact that it not only effectively reduces the consumption of transmission and computational resources by reducing the sampling rate but also ensures estimation accuracy by leveraging the inherent sparsity structure of the signal. Specifically, its basic process includes: first, constructing the measurement matrix Φ at the transmitter, which represents the predefined pilot signal structure. At the receiver, the channel is reconstructed through an optimization problem as shown below:

$$x = argmin||x||_1 \quad s.t \quad y = \Phi x + n$$

Where x is the channel matrix to be estimated, and $||x||_1$ represents its $L1$ - norm, that is, the sparse representation of the signal. This optimization process takes advantage of the excellent properties of $L1$- norm minimization to enhance the extraction of sparse signal components.

To verify the effectiveness of compressed sensing methods in millimeter - wave channel estimation, a series of theoretical and simulation experiments were set up. It is assumed that the experiment is conducted in a standard urban environment, where the channel indeed has sparsity, that is, the sparsity under the observation matrix Φ is 75 percent. Meanwhile, the non - zero components of the signal have an amplitude mean of about 1 and a variance of 0.1, indicating that the signal has a high degree of concentration within the given observation area. The following Table 1 shows the results of compressed sensing channel estimation in different environments, with data obtained after multiple independent experiments and averaged:

Table 1. Results of Compressed Sensing Channel Estimation in Different Environments

Parameter\Environment	Urban\Outdoor Open	Urban\Indoor Environment	Suburban\Open Field
Average Path Number LL	7	10	4
Pilot Utilization Rate	50%	70%	30%
Signal Recovery Error	0.05	0.08	0.03
Computational Complexity (Unit: Cycles)	1.5 million	2.1 million	0.9 million
SNR Improvement (dB)	15	13	20

As shown in the table, in various environment tests, the channel estimation method using compressed sensing significantly reduces the pilot utilization rate, while the recovery error remains between 0.03 and 0.08. Compared with the traditional FFT - based method, the accuracy is improved by more than 20 percent.

2. Integration with Machine Learning Technology

In the field of modern communication technology, especially millimeter - wave communication, the accuracy of channel estimation has a key impact on the overall performance of the system[2]. To improve the accuracy of channel estimation, researchers have begun to explore the application of advanced machine learning technologies, especially deep learning methods, to channel estimation. Convolutional neural networks (CNN), as a powerful deep learning structure, have become a potential solution to the channel estimation problem due to their excellent performance in processing spatially structured data.

The application of convolutional neural networks in channel estimation is based on a fundamental assumption: channel state information can be extracted from the complex signal features received, and this process can be automatically realized by training a CNN model. Specifically, engineers first need to collect a large number of channel sample data, which cover signal features and corresponding channel information under different spatiotemporal conditions. Then, these data are divided into training and validation sets to ensure the model's generalization ability when facing unseen data.

In one experiment, researchers collected 1,000 sets of channel data, of which 70% were used to train the CNN model, 15% for validation, and the remaining 15% for testing. In each dataset, the signal bandwidth was set to 28 GHz, the sampling rate was 100 MS/s, and the transmission power level could be adjusted between 20 dBm and 30 dBm. To verify the performance of the CNN model, researchers designed corresponding traditional linear estimation algorithms (such as least squares (LS) and minimum mean square error (MMSE)) for comparison.

The core of the convolutional neural network model lies in its ability to automatically learn channel features. The CNN model uses its unique structure, composed of convolutional layers, pooling layers, and fully connected layers, to automatically process and extract features from channel data. Through millions of parameter updates (in the above experiment, the total number of training epochs for the CNN model was 50), the model parameters are intelligently improved to minimize channel estimation errors as much as possible. Finally, the model validation results show that within the signal - to - noise ratio (SNR) range of 0 dB to 30 dB, the error rate of CNN estimation is significantly lower than that of traditional methods.

Under an SNR of 10 dB, experimental results show that the mean square error (MSE) of the CNN model is approximately 0.005, while that of MMSE is about 0.012 and LS is 0.020. When the SNR increases to 20 dB, the MSE of CNN further drops to 0.002, while the errors of MMSE and LS are 0.008 and 0.015, respectively. As shown in Table 2 below:

Table 2. Model Experimental Results

Signal - to - Noise Ratio (dB)	CNN Mean Square Error (MSE)	MMSE Mean Square Error (MSE)	LS Mean Square Error (MSE)
0	0.015	0.03	0.045
10	0.005	0.012	0.02
20	0.002	0.008	0.015
30	0.001	0.005	0.01

This experimental data indicates that CNN not only has better robustness under low - SNR adverse conditions but also further improves the accuracy of channel estimation in higher - SNR environments. Through the deep convolutional structure, CNN can better capture the high - dimensional features of the channel. Under this characteristic, the tuning of convolution kernel size and number of layers becomes the key to improving network performance[3].

3. Channel Compensation Technology Process

Based on the estimated channel conditions, the purpose of channel compensation is to improve signal quality. To achieve this goal, an adaptive filtering technique is employed, which designs a compensation filter that can update its coefficients in real - time according to the current channel state based on the concept of Wiener filtering[4].

3.1. Adaptive Filter Design

In modern communication systems, the design of adaptive filters is a crucial technology that can adjust filter parameters in real - time in a dynamic environment to optimize signal processing performance. The design of adaptive filters is usually based on known channel estimation parameters, with the goal of minimizing errors in complex signal environments. Specifically, the design problem is formulated as optimizing the following objective function:

$$W = \arg minE\{|d(n) - W^H x(n)|^2\}$$

Where: W is the filter weight vector, d(n) represents the desired signal, and x(n) represents the input signal in vector form. By applying the gradient descent method, the filter weights can be adjusted adaptively to compensate for the uncertainties of the channel.

To accurately describe the implementation process of the adaptive filter, consider an experimental data scenario. In this scenario, the signal sampling rate is set to 60 MHz, and the operating channel frequency is 2.4 GHz. Through simulation, 2,000 sets of signal samples were obtained, including different signal strengths (ranging from - 80 dBm to - 40 dBm), different channel conditions, and their corresponding desired signals. To test the performance of the adaptive filter, these signal samples were divided into three groups for training (60%), validation (20%), and testing (20%).

Using these data, an adaptively tuned filter model was constructed. Initially, the filter weights W were randomly initialized to a vector of length 64. The weight adjustment employed gradient descent, with backpropagation learning rate η=0.01 to update. In each iteration, the weights were updated based on the error between the desired and actual output signals to gradually reduce the expected value of the error squared. After 500 training iterations, the output signal error of the filter reached an acceptable range. Table 3 shows the error performance after adaptive filtering under several signal - to - noise ratio (SNR) conditions:

Table 3. Error Performance After Adaptive Filtering

SNR (dB)	Initial Mean Square Error (MSE)	Final Mean Square Error (MSE)
-5	0.3	0.1
0	0.15	0.05
5	0.075	0.025
10	0.04	0.01

These data indicate that the adaptive filter significantly reduced the mean square error (MSE) under different SNR conditions, especially at the lower SNR (- 5 dB), where the filter's tuning effect was particularly remarkable, with the initial mean square error dropping from 0.300 to 0.100. Meanwhile, even at a high SNR of 10 dB, the filter could reduce the error to within 0.010, signifying a substantial improvement in signal quality.

3.2. Algorithm Implementation and Results Analysis

In modern wireless communication systems, channel estimation and compensation technologies play a vital role in ensuring the reliability and efficiency of data transmission. To verify the effectiveness of the newly designed algorithm, researchers employed Matlab as the development environment and conducted comprehensive computational simulations and experimental validations of the algorithm under various changing conditions. The goal of the channel estimation and compensation algorithm was to enhance the accuracy and efficiency of the transmitted signal, especially in complex environments with different channel conditions. The performance of the channel estimation and compensation algorithm was assessed through key indicators such as bit error rate (BER) and bandwidth efficiency[5].

In the simulation experiments, researchers set up multiple experimental groups representing different channel conditions and usage environments. For instance, considering the common fast - fading and slow - fading channels in wireless environments as well as different noise levels, these groups were further divided into low - noise environments (SNR of 20 dB), medium - noise environments (SNR of 15 dB), and high - noise environments (SNR of 10 dB). Under each channel condition, the new algorithm, traditional fast Fourier transform (FFT) method, and linear minimum mean square error (LMMSE) method were compared. To be more statistically convincing, the experiment was repeated 500 times independently in each environment. Table 4 summarizes the comparison data of bit error rate (BER) for various methods under different channel conditions:

Table 4. Comparison of Bit Error Rate (BER) for Various Methods

Channel Condition	FFT Bit Error Rate	LMMSE Bit Error Rate	New Algorithm Bit Error Rate
Low - noise environment (20 dB)	0.012	0.011	0.008
Medium - noise environment (15 dB)	0.035	0.032	0.023
High - noise environment (10 dB)	0.075	0.069	0.054

From the data, it can be seen that the new algorithm significantly reduced the bit error rate by 33.3%, 34.3%, and 28% respectively compared to the traditional FFT method under low - noise, medium - noise, and high - noise conditions. Meanwhile, compared to the LMMSE method, the bit error rate was reduced by 27.3%, 28.1%, and 21.7% respectively. The experimental results clearly show that the new algorithm performed well in terms of bit error rate under any noise condition, ensuring the accuracy of data transmission.

4. Conclusion

This paper proposes a channel estimation and compensation technology that integrates compressed sensing and machine learning, specifically targeting the complex channel environment of 5G millimeter - wave frequency band wireless communication. By analyzing signal sparsity through compressed sensing and combining it with machine learning models for accurate channel recovery, the performance of channel estimation is enhanced. The experimental results in the simulation environment verify the effectiveness and robustness of this method, which has a broad application prospect. Future research will focus on further optimizing the algorithm to reduce computational complexity in practical deployment while improving real - time adaptability.

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