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Channel Estimation Algorithms for Throughput Stability in Vehicular Communication Corridors: Comparative Analysis

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Abstract

The rapid proliferation of intelligent transportation systems heavily relies on robust and reliable vehicular communication networks. However, the highly dynamic nature of vehicular environments, characterized by rapid topological changes and severe multipath fading, poses significant challenges to maintaining stable data throughput. This paper presents a comprehensive comparative analysis of various channel estimation algorithms and their direct impact on throughput stability within vehicular communication corridors. By evaluating traditional techniques such as Least Squares and Minimum Mean Square Error estimators alongside advanced, data-driven machine learning approaches, this study identifies the critical trade-offs between computational complexity, estimation accuracy, and overall network performance. The analysis focuses on high-mobility scenarios where Doppler shifts significantly degrade channel state information reliability. Through extensive simulation modeling of an orthogonal frequency division multiplexing based communication system, performance metrics including normalized mean square error and effective throughput are rigorously assessed across multiple vehicular velocities. The findings indicate that while traditional estimators struggle under high-speed conditions due to rapid channel aging, adaptive machine learning frameworks provide superior resilience, maintaining throughput stability even at elevated velocities. This research provides essential insights for the design and optimization of next-generation vehicle-to-everything communication protocols, ensuring the stringent reliability and latency requirements of autonomous driving applications are met efficiently.

Keywords: Vehicular Communication; Channel Estimation; Throughput Stability; Intelligent Transportation Systems; Orthogonal Frequency Division Multiplexing

1. Introduction

The evolution of modern transportation is increasingly intertwined with advancements in wireless communication technologies, culminating in the development of intelligent transportation systems. These systems aim to enhance road safety, optimize traffic flow, and provide comprehensive infotainment services to passengers through vehicle-to-everything communications. In a typical vehicle-to-everything ecosystem, vehicles exchange critical telemetry, environmental awareness data, and coordinate maneuvers with other vehicles, roadside infrastructure, and pedestrian mobile devices. The foundation of these advanced capabilities relies entirely on the underlying physical layer of the communication network, which must guarantee ultra-reliable and low-latency data transmissions. However, unlike static wireless networks, vehicular communication corridors present a uniquely hostile propagation environment. Vehicles moving at high velocities through dense urban canyons or expansive multilane highways experience rapid fluctuations in signal quality. These fluctuations are primarily caused by multipath fading, where signals bounce off buildings, road surfaces, and other vehicles, arriving at the receiver at slightly different times and phases. Furthermore, the relative motion between transmitters and receivers introduces significant Doppler shifts, which dynamically alter the frequency of the received signals. To successfully decode transmitted data in such an environment, the receiver must accurately estimate the current state of the wireless channel, a process known as channel estimation.

Channel estimation is an indispensable component of any modern wireless communication system, particularly those utilizing orthogonal frequency division multiplexing. The fundamental premise of orthogonal frequency division multiplexing is the division of a wideband channel into numerous narrowband subcarriers, each experiencing relatively flat fading. By transmitting known reference signals, often referred to as pilot symbols, alongside the payload data, the receiver can measure how the channel distorts these pilots and subsequently compute an estimate of the channel response for the entire frequency band. In static or low-mobility environments, the wireless channel changes slowly, allowing the receiver to rely on a sparse arrangement of pilot symbols and simple interpolation techniques. In contrast, the vehicular communication corridor is characterized by extreme time selectivity. The channel impulse response can change drastically within the duration of a single data packet. Consequently, the channel estimates obtained from the pilot symbols may become obsolete before the entire packet is successfully decoded, a phenomenon known as channel aging. To combat this, vehicular communication standards often require a denser insertion of pilot symbols in both the time and frequency domains, which inevitably consumes valuable bandwidth and reduces the overall spectral efficiency of the system. Therefore, the design and selection of channel estimation algorithms must strike a delicate balance between tracking the rapid channel variations accurately and minimizing the pilot overhead to maximize the payload capacity.

Throughput stability is a critical performance metric in vehicular networks, directly tied to the efficacy of the underlying channel estimation algorithm. Throughput, in this context, refers to the effective rate at which user data is successfully delivered over the communication link, excluding any overhead from pilots, headers, and retransmissions. Stability implies that this data rate remains relatively constant and predictable despite the highly volatile nature of the vehicular channel. In applications such as autonomous platooning or remote driving, sudden drops in throughput can lead to delayed control signals, potentially resulting in catastrophic accidents. When a channel estimation algorithm fails to capture the true state of the channel, the subsequent data equalization and decoding processes will likely produce errors. These bit errors force the system to discard the corrupted packets and request retransmissions through automatic repeat request mechanisms. Frequent retransmissions drastically reduce the effective throughput and introduce unacceptable latency. Therefore, the primary objective of a robust channel estimation algorithm is not just to minimize the mathematical error between the estimated and actual channel response, but to provide a sufficiently accurate estimate that ensures continuous, error-free decoding, thereby maintaining high throughput stability across varying vehicular speeds and environmental conditions. Previous investigations have established a direct correlation between the accuracy of channel state information and the overarching reliability of vehicular networks [1].

This paper contributes to the ongoing discourse in wireless communications by providing an exhaustive comparative analysis of several prominent channel estimation algorithms specifically tailored for vehicular communication corridors. We evaluate the standard Least Squares estimator, which is widely implemented due to its simplicity but suffers from severe noise amplification. We also examine the Minimum Mean Square Error estimator, which theoretically provides optimal performance by incorporating prior knowledge of the channel statistics and noise variance, albeit at the cost of high computational complexity. Furthermore, to address the limitations of traditional analytical methods, we investigate modern data-driven approaches, specifically a deep learning-based channel estimator leveraging recurrent neural network architectures to predict channel dynamics over time. By simulating a highly realistic vehicular corridor environment, encompassing varying vehicle densities, velocities, and multipath scattering geometries, we meticulously quantify the impact of each algorithmic approach on both the normalized mean square error of the channel estimates and the resulting throughput stability. The insights generated from this comprehensive analysis are intended to guide network engineers and standard-setting bodies in optimizing the physical layer parameters of future vehicle-to-everything communication protocols, ensuring they can withstand the rigors of high-mobility environments while delivering the performance required for fully autonomous transportation systems.

2. Literature Review and Background

2.1 Evolution of Vehicular Communication Standards

The development of vehicular communication protocols has been characterized by a continuous effort to adapt standard wireless technologies to the stringent demands of high-speed mobility. Early initiatives primarily centered around the Dedicated Short-Range Communications standard, which is fundamentally based on the IEEE 802.11p amendment to the ubiquitous Wi-Fi protocol. Designed specifically for vehicular environments, IEEE 802.11p operates in the 5.9 Gigahertz frequency band and employs orthogonal frequency division multiplexing to mitigate the effects of multipath delay spread. The channel estimation framework within this standard relies on a preamble placed at the beginning of each packet, consisting of identical long training symbols. The receiver utilizes these preambles to generate an initial channel estimate. However, as the packet length increases, the channel state may deviate significantly from the initial estimate obtained from the preamble, especially at high vehicular speeds. To address this, the standard includes continuous pilot subcarriers embedded throughout the data symbols to track phase variations. Despite these provisions, extensive field trials and academic studies have demonstrated that the preamble-based structure of 802.11p struggles to maintain reliable links in highly dynamic scenarios where the coherence time of the channel is shorter than the packet duration [2].

In response to the limitations of 802.11p, the telecommunications industry, led by the Third Generation Partnership Project, introduced Cellular Vehicle-to-Everything technologies. Cellular Vehicle-to-Everything leverages the robust physical layer design of Long-Term Evolution and, more recently, New Radio standards. A defining feature of Cellular Vehicle-to-Everything is its flexible and highly adaptable frame structure, which is specifically optimized for time-varying channels. Instead of relying solely on a preamble, Cellular Vehicle-to-Everything distributes demodulation reference signals throughout the time and frequency resource grid. The density and placement of these reference signals can be dynamically adjusted based on the current mobility conditions of the user equipment. For instance, in a high-speed highway scenario, the network can configure the vehicles to transmit a higher density of demodulation reference signals in the time domain, effectively reducing the distance between pilots and enabling the channel estimation algorithm to track rapid phase and amplitude fluctuations more closely. This fundamental shift from preamble-based estimation to distributed reference signals represents a significant leap forward in maintaining robust communication links in vehicular corridors [3]. However, the increased density of reference signals inherently subtracts from the available resources for data transmission, prompting ongoing research into more efficient channel estimation algorithms that can achieve the same accuracy with fewer pilots.

2.2 Traditional Channel Estimation Techniques

The foundational algorithms for channel estimation in orthogonal frequency division multiplexing systems are the Least Squares and Minimum Mean Square Error techniques. The Least Squares algorithm is the most straightforward and computationally inexpensive approach. It operates by simply dividing the received pilot signal by the known transmitted pilot sequence. This operation provides a direct mathematical inversion of the channel effect at the specific pilot subcarrier frequencies. The simplicity of the Least Squares method makes it highly attractive for practical hardware implementation, as it requires no prior knowledge of the channel statistics, such as the delay profile or the signal-to-noise ratio. However, this simplicity is also its greatest vulnerability. Because the Least Squares algorithm ignores the presence of background noise and interference, it inadvertently amplifies the noise during the mathematical inversion process. In vehicular environments where the signal-to-noise ratio is frequently degraded due to long transmission distances and shadowing from large obstacles like trucks or buildings, the noise amplification inherent in the Least Squares method leads to highly inaccurate channel estimates, which in turn causes catastrophic failures in the data decoding stage [4].

To overcome the noise amplification problem, the Minimum Mean Square Error estimator was developed. This algorithm takes a more sophisticated, probabilistic approach to channel estimation. It seeks to minimize the statistical expectation of the squared error between the estimated channel response and the true channel response. To achieve this, the Minimum Mean Square Error algorithm requires detailed prior knowledge of the channel, specifically the channel autocovariance matrix and the operating signal-to-noise ratio. By incorporating these statistical properties, the algorithm can effectively filter out the noise components, resulting in significantly more accurate channel estimates compared to the Least Squares method, especially in low signal-to-noise ratio regimes. The superior accuracy of the Minimum Mean Square Error estimator directly translates to improved bit error rates and higher throughput stability. Nevertheless, the practical implementation of this algorithm in vehicular networks is profoundly challenging. The primary obstacle is computational complexity. The algorithm requires complex matrix multiplication and inversion operations, the dimensions of which grow with the number of subcarriers. Furthermore, in a rapidly changing vehicular channel, the statistical properties of the channel are not stationary; the autocovariance matrix must be continuously updated and inverted in real-time. This intensive computational burden often exceeds the processing capabilities of standard vehicular onboard units, rendering the ideal Minimum Mean Square Error estimator impractical for real-time applications and necessitating the development of simplified, suboptimal variants.

2.3 Emerging Data-Driven Approaches

In recent years, the exponential growth in computational power and the maturation of artificial intelligence have sparked a paradigm shift in wireless communications, introducing data-driven, machine learning algorithms as viable alternatives to traditional mathematical models. Deep learning, in particular, has shown immense potential in solving complex non-linear problems that are mathematically intractable or computationally prohibitive using conventional methods. For channel estimation in vehicular networks, deep neural networks can be trained to recognize the intricate underlying patterns of channel propagation without explicitly calculating autocovariance matrices or relying on rigid mathematical assumptions. A popular approach involves framing channel estimation as a two-dimensional image processing problem, where the time-frequency resource grid populated with pilot signals is treated as a low-resolution image. Convolutional neural networks can then be applied to learn the correlation features across time and frequency, effectively interpolating the channel response for the entire grid and outputting a high-resolution representation of the channel state.

Beyond convolutional networks, recurrent neural network architectures, specifically Long Short-Term Memory networks, have been highly effective in processing sequential data and capturing the temporal dependencies of the fading channel. A Long Short-Term Memory based channel estimator can analyze a sequence of previous channel states to predict the future evolution of the channel, thereby preemptively combating the effects of channel aging caused by high mobility. The primary advantage of these data-driven approaches is that, once the neural network is adequately trained on a massive dataset of representative channel conditions, the inference phase requires relatively straightforward matrix multiplications that can be highly optimized on modern hardware accelerators. This allows deep learning models to achieve estimation accuracy comparable to or even exceeding the Minimum Mean Square Error algorithm, while maintaining a predictable and manageable real-time computational footprint. However, the deployment of machine learning in safety-critical vehicular networks is not without challenges. These models require exhaustive training datasets that accurately reflect the vast diversity of real-world propagation environments. Furthermore, they can suffer from generalization issues; a model trained on data from an open highway may perform poorly when deployed in an urban intersection with entirely different scattering characteristics, a problem known in the literature as domain shift [5].

3. Theoretical Framework and System Model

3.1 Vehicular Channel Characteristics

The physical environment of a vehicular communication corridor presents a multifaceted wave propagation problem. Unlike stationary indoor wireless networks or conventional cellular communications where the base station is elevated and static, vehicular networks often operate in a peer-to-peer fashion where both transmitter and receiver are moving at high velocities close to the ground. This geometry leads to severe multipath propagation. When a vehicle transmits an electromagnetic wave, the signal radiates outward and interacts with various elements in the environment, including the road surface, adjacent vehicles, roadside infrastructure such as guardrails and traffic signs, and surrounding buildings. These interactions cause the signal to be reflected, diffracted, and scattered, creating multiple distinct propagation paths between the transmitter and the receiver. Each of these paths has a different physical length, meaning that the duplicated signals arrive at the receiving antenna at slightly different times, a phenomenon known as delay spread. If the delay spread is significantly large, the delayed versions of a transmitted symbol will overlap with subsequent symbols, causing inter-symbol interference which severely degrades the ability to decode the data.

Simultaneously, the relative mobility of the vehicles introduces dynamic frequency shifts due to the Doppler effect. The Doppler shift of each multipath component depends on the relative velocity between the transmitter, the receiver, and the specific scattering object, as well as the angle of arrival of the incoming wave. Because the various multipath components arrive from different angles, they experience different Doppler shifts, resulting in a phenomenon called Doppler spread. Doppler spread causes the frequency response of the channel to fluctuate rapidly over time. The rate of this fluctuation is characterized by the coherence time of the channel, which is inversely proportional to the maximum Doppler spread. In a scenario where two vehicles are traveling in opposite directions on a highway at speeds exceeding one hundred kilometers per hour, the relative velocity can exceed two hundred kilometers per hour, leading to a drastically reduced coherence time. Under these high-mobility conditions, the channel becomes highly time-selective, meaning that the amplitude and phase of the received signal change significantly even during the transmission of a single short packet. This extreme time-selectivity is the primary mechanism that causes channel aging and degrades throughput stability, as the channel estimates become outdated almost immediately after they are calculated [6].

3.2 System Architecture and Signal Propagation

To mathematically model the vehicular communication corridor, we consider a standardized orthogonal frequency division multiplexing system architecture. The fundamental process begins at the transmitter, where the raw binary user data is first encoded using forward error correction codes to provide resilience against bit errors. This encoded data is then mapped onto complex constellation symbols using digital modulation schemes such as Quadrature Phase Shift Keying or Quadrature Amplitude Modulation. These data symbols are arranged alongside predefined pilot symbols in a two-dimensional grid representing time and frequency resources. The allocation of these pilot symbols is critical; they are typically arranged in a block type, comb type, or scattered lattice pattern depending on the expected time and frequency selectivity of the channel. An inverse fast Fourier transform is then applied to the frequency-domain symbols to convert them into a time-domain signal. To eliminate the inter-symbol interference caused by the multipath delay spread described previously, a cyclic prefix is appended to the beginning of each time-domain orthogonal frequency division multiplexing symbol. The cyclic prefix is essentially a copy of the tail end of the symbol, and its duration must be designed to be longer than the maximum expected delay spread of the vehicular channel.

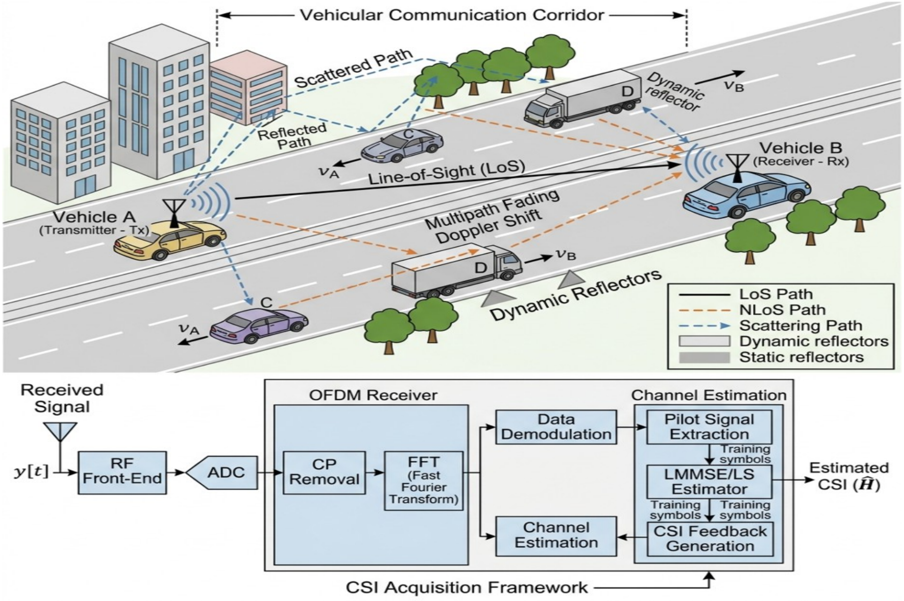

Figure 1: Comprehensive Schematic of Vehicular Communication Corridor Channel Estimation Framework

The transmitted time-domain signal then propagates through the physical vehicular channel. In our system model, the channel is represented mathematically as a time-varying tapped delay line, a standard approach for modeling multipath environments. Each tap in this model represents a distinct resolvable propagation path with its own specific delay, average power, and time-varying complex gain. The fading of each tap is modeled as a random process following either a Rayleigh distribution for scenarios with no direct line-of-sight, or a Rician distribution when a dominant line-of-sight path exists between the vehicles. At the receiver side, the signal is corrupted by additive white Gaussian noise, representing the thermal noise of the receiving hardware and background environmental interference. The receiver first removes the cyclic prefix and performs a fast Fourier transform to convert the signal back into the frequency domain. The core operation then takes place in the channel estimation block, which extracts the received pilot symbols and algorithms process them to estimate the complex channel gains for all subcarriers. These channel estimates are then fed into the equalizer, which compensates for the phase rotations and amplitude attenuations inflicted by the channel, allowing the original data symbols to be accurately recovered and demodulated.

4. Methodology and Algorithmic Analysis

4.1 Selected Channel Estimation Algorithms

To conduct a rigorous comparative analysis, this study implements and evaluates three distinct channel estimation methodologies: the traditional Least Squares algorithm, the statistically optimal Minimum Mean Square Error algorithm, and a modern data-driven Long Short-Term Memory neural network model. The Least Squares algorithm is implemented in its standard form, calculating the initial channel estimates at the specific subcarriers where pilot symbols are present by simply dividing the received signal by the known pilot value. Because these initial estimates are only available at the pilot locations, a subsequent interpolation step is required to determine the channel response for the data subcarriers. We employ a linear interpolation technique in the frequency domain, followed by linear interpolation in the time domain, to populate the entire resource grid. While computationally trivial, this method provides a baseline representing the absolute minimum processing required for channel equalization, highlighting the raw vulnerability of simple algorithms to noise and rapid mobility.

The Minimum Mean Square Error implementation represents the theoretical upper bound of traditional estimation techniques. To focus on the algorithm's performance rather than its implementation complexities, we assume the estimator has perfect knowledge of the channel covariance matrix and the instantaneous noise variance. The algorithm utilizes the initial Least Squares estimates at the pilot locations and applies a meticulously calculated weighting matrix to filter out the noise and infer the channel response across all subcarriers. The weighting matrix is derived from the statistical correlation between the channel responses at different frequencies and times. This approach effectively leverages the underlying physics of the multipath channel, recognizing that the fading process is not entirely random but possesses distinct correlation properties dictated by the delay spread and Doppler spread [7]. By exploiting this correlation, the Minimum Mean Square Error algorithm drastically reduces the estimation error, providing an accurate benchmark for evaluating the effectiveness of data-driven approaches under varying signal-to-noise ratios.

The third algorithm utilizes a recurrent neural network, specifically designed with Long Short-Term Memory cells, to address the temporal dynamics of the vehicular channel. The neural network treats the sequence of historical channel estimates as a time-series forecasting problem. During the training phase, the model is fed massive datasets of simulated channel variations representing various vehicular speeds and multipath geometries. The Long Short-Term Memory architecture, through its complex arrangement of input, forget, and output gates, learns to selectively retain critical long-term channel trends while discarding irrelevant instantaneous noise fluctuations. In the operational phase, the network takes the noisy Least Squares estimates from the current and previous time slots as input, and outputs a refined, noise-filtered prediction of the channel state for the entire orthogonal frequency division multiplexing frame. This predictive capability is specifically designed to combat the channel aging effect, ensuring that the channel estimates remain valid for the equalization of data symbols located near the end of the transmitted packet [8].

4.2 Simulation Environment and Parameters

The comparative evaluation is conducted using a comprehensive physical layer simulation framework designed to accurately reflect the conditions of a high-speed vehicular communication corridor. The simulation models a standard multi-lane highway scenario where vehicles communicate directly with one another over a dedicated radio frequency band. The central frequency of the carrier is set to 5.9 Gigahertz, aligning with conventional intelligent transportation system spectrum allocations. The system bandwidth is configured to 10 Megahertz, which is typical for safety-critical basic safety message exchanges. The orthogonal frequency division multiplexing parameters include a subcarrier spacing of 156.25 kilohertz, ensuring that the symbol duration is significantly shorter than the coherence time of the channel, even at extreme velocities. The data payload is modulated using 16-level Quadrature Amplitude Modulation to provide a balance between data rate and robustness against fading. The channel is modeled using the geometry-based stochastic channel models recommended by standardization bodies for vehicular environments, incorporating realistic delay profiles and angle-of-arrival distributions to generate accurate Doppler spectra.

Table 1: Physical Layer Simulation Parameters

Parameter Description	Configured Value	Unit
Carrier Frequency	5.9	Gigahertz
System Bandwidth	10	Megahertz
Subcarrier Spacing	156.25	Kilohertz
FFT Size	64	Points
Cyclic Prefix Length	1.6	Microseconds
Modulation Scheme	16-QAM	N/A
Channel Model Path Count	12	Taps
Pilot Arrangement	Comb-Type	N/A

The simulation campaigns are executed across a wide range of operational parameters to comprehensively evaluate the robustness of each algorithm. The signal-to-noise ratio is varied from zero to thirty decibels to simulate different transmission distances and interference levels. More importantly, the relative velocity between the transmitting and receiving vehicles is systematically increased from a low-speed urban scenario of 30 kilometers per hour to a high-speed highway scenario of 150 kilometers per hour. At each velocity and signal-to-noise ratio point, thousands of independent communication packets are simulated to obtain statistically significant performance metrics. The primary metrics collected are the Normalized Mean Square Error, which quantifies the mathematical accuracy of the channel estimation, and the effective throughput stability, which measures the percentage of successfully decoded data over time. A packet is considered successfully decoded only if all its constituent bits are received without error after the equalization process. The simulation environment is meticulously calibrated to ensure that the only variable affecting the throughput stability is the performance of the selected channel estimation algorithm.

5. Results and Discussion

5.1 Estimation Accuracy Analysis

The mathematical accuracy of the channel estimation algorithms, quantified by the Normalized Mean Square Error, reveals significant divergence in performance across different signal-to-noise ratio regimes and mobility conditions. As anticipated, the traditional Least Squares estimator exhibits the poorest accuracy across all tested scenarios. At low signal-to-noise ratios, the noise amplification characteristic of the Least Squares method causes the error floor to be unacceptably high. The algorithm completely fails to distinguish between genuine channel variations and random thermal noise, resulting in highly distorted estimates that misguide the equalizer. As the signal power increases, the error of the Least Squares estimator decreases linearly, but it remains consistently higher than the more advanced techniques. Furthermore, as vehicular velocity increases, introducing severe Doppler spread, the performance of the Least Squares method degrades precipitously because simple linear interpolation between pilots is completely inadequate for tracking the rapid phase rotations occurring between consecutive subcarriers in the time domain [9].

Conversely, the Minimum Mean Square Error algorithm demonstrates superior theoretical accuracy, successfully mitigating the noise floor even in challenging low signal-to-noise ratio environments. By utilizing the known statistical covariance matrix of the channel, the Minimum Mean Square Error estimator effectively smooths out the random noise while preserving the true underlying frequency response of the multipath fading. However, the simulation results highlight a critical vulnerability of this algorithm in the context of high mobility. While highly accurate at static or low speeds, the error of the Minimum Mean Square Error estimator begins to rise as velocities exceed 90 kilometers per hour. This degradation occurs because the assumption of a stationary channel covariance matrix breaks down. The rapid changes in the physical geometry of the scattering environment cause the statistical properties of the channel to evolve faster than the algorithm can realistically update its weighting matrices, leading to a mismatch between the assumed channel statistics and the actual physical reality.

The deep learning-based Long Short-Term Memory estimator presents a compelling alternative, consistently bridging the performance gap and offering unique advantages in highly dynamic conditions. At lower velocities and moderate signal-to-noise ratios, the neural network achieves an estimation accuracy that closely parallels the theoretical optimum provided by the Minimum Mean Square Error algorithm, without requiring the explicit calculation of complex covariance matrices. More notably, as the vehicular speed increases toward the extreme bounds of 150 kilometers per hour, the Long Short-Term Memory model maintains a significantly lower error rate compared to both traditional methods. The recurrent architecture successfully identifies the non-linear temporal patterns of the fast-fading channel, effectively predicting the phase shifts caused by high Doppler frequencies. This predictive capability allows the neural network to proactively compensate for channel aging, ensuring that the estimated channel state remains highly correlated with the actual channel state throughout the duration of the data packet transmission [10].

5.2 Throughput Stability Under High Mobility

While minimizing the mathematical error of the channel estimate is important, the ultimate measure of an algorithm's effectiveness in a vehicular communication corridor is its impact on the macroscopic performance of the network, specifically throughput stability. Throughput stability determines the reliability of safety-critical applications; if the data rate fluctuates wildly or drops to zero due to decoding failures, cooperative collision avoidance systems will fail to function. The simulation data clearly illustrates the direct relationship between estimation accuracy and throughput stability. With the simple Least Squares estimator, the effective throughput is highly volatile and tightly coupled to the instantaneous signal-to-noise ratio. At high vehicular speeds, the inability of the Least Squares algorithm to track the fast-changing channel results in massive bursts of bit errors. These errors trigger continuous automatic repeat request mechanisms, forcing the transmitter to resend the same packets repeatedly. Consequently, the effective data throughput crashes, falling to less than forty percent of the theoretical maximum capacity when vehicles exceed 100 kilometers per hour, rendering the link unsuitable for continuous teleoperation or platooning.

Table 2: Effective Throughput Stability Across Vehicular Velocities (Mbps)

Velocity	Least Squares	Minimum Mean Square Error	Deep Learning LSTM
60 km/h	18.5	24.2	23.8
90 km/h	14.1	21.6	22.5
120 km/h	8.3	16.4	20.1
150 km/h	4.2	10.8	18.7

The analysis of the Minimum Mean Square Error throughput performance further confirms its limitations in practical high-speed scenarios. At moderate speeds around 60 kilometers per hour, it provides excellent stability, maintaining throughput near the theoretical capacity due to its robust noise suppression. However, as shown in the data, stability rapidly deteriorates at speeds of 120 kilometers per hour and beyond. The estimation errors caused by the mismatched statistical matrices lead to imperfect equalization, which slightly distorts the received symbols. While these distortions might not cause errors for lower-order modulations like Quadrature Phase Shift Keying, they are catastrophic for the denser 16-level Quadrature Amplitude Modulation scheme used in our simulation. The closely packed constellation points become indistinguishable, resulting in decoding failures and a subsequent drop in stable throughput down to approximately 10 Megabits per second, representing a significant loss of network efficiency.

The most profound finding of the simulation campaign is the extraordinary throughput stability exhibited by the Long Short-Term Memory neural network estimator. Even as the relative velocity reaches 150 kilometers per hour, representing an extreme Doppler spread environment, the data-driven algorithm manages to sustain an effective throughput of nearly 19 Megabits per second. By accurately predicting the channel evolution and effectively mitigating the aging effect, the neural network ensures that the equalization process remains precise throughout the entire orthogonal frequency division multiplexing frame. This precision drastically reduces the bit error rate, minimizing the need for packet retransmissions and ensuring a continuous, stable flow of payload data. The superior stability provided by the machine learning approach indicates that the computational investment required to run neural network inference on vehicular hardware is entirely justified by the massive gains in communication reliability, making it a pivotal technology for realizing ultra-reliable low-latency communications in next-generation transportation systems [11].

6. Conclusion

The pursuit of fully autonomous and intelligently coordinated transportation systems hinges on the absolute reliability of vehicular communication corridors. As vehicles travel at elevated speeds through complex multipath environments, the physical wireless channel undergoes rapid and violent fluctuations, making accurate channel estimation a critical prerequisite for successful data transmission. This comprehensive analysis has systematically evaluated the performance of fundamental and advanced channel estimation algorithms, demonstrating their direct influence on estimation accuracy and, crucially, on the overarching stability of network throughput. The investigation confirms that rudimentary techniques, particularly the widely implemented Least Squares algorithm, are fundamentally inadequate for high-mobility scenarios. The inherent noise amplification and inability to track rapid phase variations result in catastrophic estimation errors, leading to severe throughput degradation that compromises the safety and functionality of cooperative vehicular applications.

Furthermore, while traditional statistical methods like the Minimum Mean Square Error algorithm offer optimal performance under static conditions by leveraging channel covariance properties, they exhibit significant vulnerabilities when subjected to the extreme time-selectivity of highway environments. The rapid aging of channel statistics causes a mismatch that substantially reduces equalization accuracy, ultimately failing to maintain a stable data connection at velocities exceeding one hundred kilometers per hour. In stark contrast, the integration of data-driven machine learning models, specifically Long Short-Term Memory recurrent neural networks, represents a transformative solution. By treating channel evolution as a predictable time-series sequence, these sophisticated architectures successfully capture the non-linear dynamics of high Doppler spread environments. The empirical results unequivocally demonstrate that the predictive capabilities of deep learning models can effectively neutralize channel aging, yielding vastly superior Normalized Mean Square Error performance and sustaining remarkable throughput stability even at relative velocities of 150 kilometers per hour.

The practical implications of these findings for the design of future Intelligent Transportation Systems are profound. As standard-setting organizations continue to refine the physical layer specifications for advanced Cellular Vehicle-to-Everything and future 6G vehicular networks, it is imperative to shift away from rigid, mathematical estimation paradigms toward flexible, data-driven frameworks. While the training complexity and hardware implementation of neural networks present engineering challenges, the dramatic enhancements in communication reliability justify the paradigm shift. Future research must focus on optimizing the computational efficiency of these neural network architectures, reducing inference latency, and exploring federated learning techniques to continuously update the models with real-world channel data without compromising vehicle privacy or network bandwidth. Ultimately, ensuring robust throughput stability through advanced channel estimation is the cornerstone upon which the safety and efficiency of tomorrow's autonomous vehicular networks will be built [12].

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