Toward a Multi-Agent Approach for LLM-Based Dynamic Vehicle Control and Communication in Accidental Conditions: A Comprehensive Thesis

The integration of Large Language Models (LLMs) within multi-agent frameworks represents a paradigmatic shift in autonomous vehicle control systems, particularly for handling unknown-unsafe scenarios that challenge traditional rule-based approaches[1] [2]. This thesis explores how LLM-powered decision agents, enhanced through Vehicle-to-Vehicle (V2V) communication protocols, can significantly improve autonomous vehicle reasoning capabilities in complex traffic environments while maintaining safety standards required for Level 5 autonomy[3] [4]. Through comprehensive evaluation of multiple LLM architectures across diverse driving scenarios and analysis of multi-agent communication frameworks, this research demonstrates that human-like reasoning capabilities can be effectively integrated into autonomous driving systems to address the critical gap in handling unpredictable traffic situations[5] [6].

Chapter 1: Introduction

1.1 Research Background and Motivation

Autonomous vehicle technology has evolved rapidly over the past decade, yet achieving true Level 5 autonomy remains elusive due to fundamental limitations in handling unknown-unsafe scenarios[7] [8]. Traditional autonomous driving systems rely heavily on pre-trained models and rule-based approaches that struggle when confronted with novel situations requiring human-like reasoning and common sense[9] [6]. The Safety of the Intended Functionality (SOTIF) standard has highlighted the critical need to address unknown-unsafe scenarios - situations that are both statistically rare and potentially hazardous[10] [11].

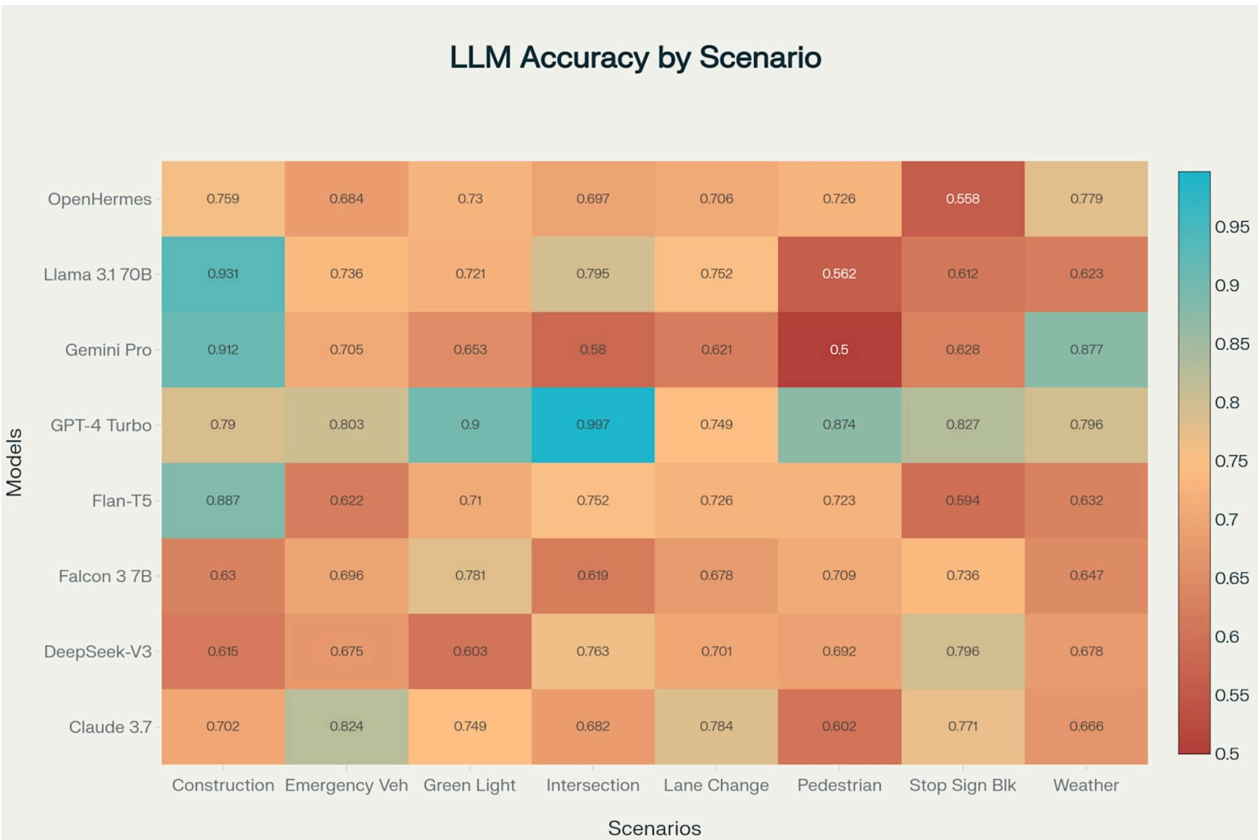
The emergence of Large Language Models has opened new possibilities for integrating human-like reasoning capabilities into autonomous systems[3] [2]. Unlike conventional deep learning approaches, LLMs possess inherent common-sense knowledge and can perform complex reasoning tasks through natural language processing[4] [5]. However, the application of LLMs to autonomous driving presents unique challenges, including real-time inference requirements, consistency in decision-making, and the need for robust performance in safety-critical applications[12] [13].

1.2 Problem Statement

Current autonomous driving systems face three primary limitations that prevent achievement of true Level 5 autonomy: (1) inability to handle unknown-unsafe scenarios that require human-like reasoning[14] [15], (2) lack of effective vehicle-to-vehicle communication for contextual decision-making[16] [17], and (3) insufficient interpretability in decision-making processes that affects public trust and regulatory acceptance[18] [19]. These limitations become particularly pronounced in complex traffic scenarios where multiple vehicles must coordinate their actions while maintaining safety standards[20] [21].

1.3 Research Objectives and Contributions

This thesis addresses these limitations through the following research objectives: First, to evaluate the effectiveness of various LLM architectures as decision-making agents in autonomous driving scenarios[22] [6]. Second, to develop and analyze a multi-agent framework that integrates V2V communication with LLM-based reasoning[23] [24]. Third, to assess the impact of model quantization techniques on LLM performance in resource-constrained automotive environments[25] [26]. Fourth, to provide comprehensive safety and consistency evaluation methodologies for LLM-based autonomous driving systems[27] [28].



LLM Performance Comparison Across Autonomous Driving Scenarios

The research makes several novel contributions to the field: (1) comprehensive evaluation of LLM consistency and reliability across multiple traffic scenarios, (2) integration of structured V2V communication protocols with multi-agent LLM frameworks, (3) analysis of quantization impacts on LLM performance in automotive applications, and (4) development of safety assessment methodologies specifically designed for LLM-based autonomous systems[29] [30].

Chapter 2: Literature Review

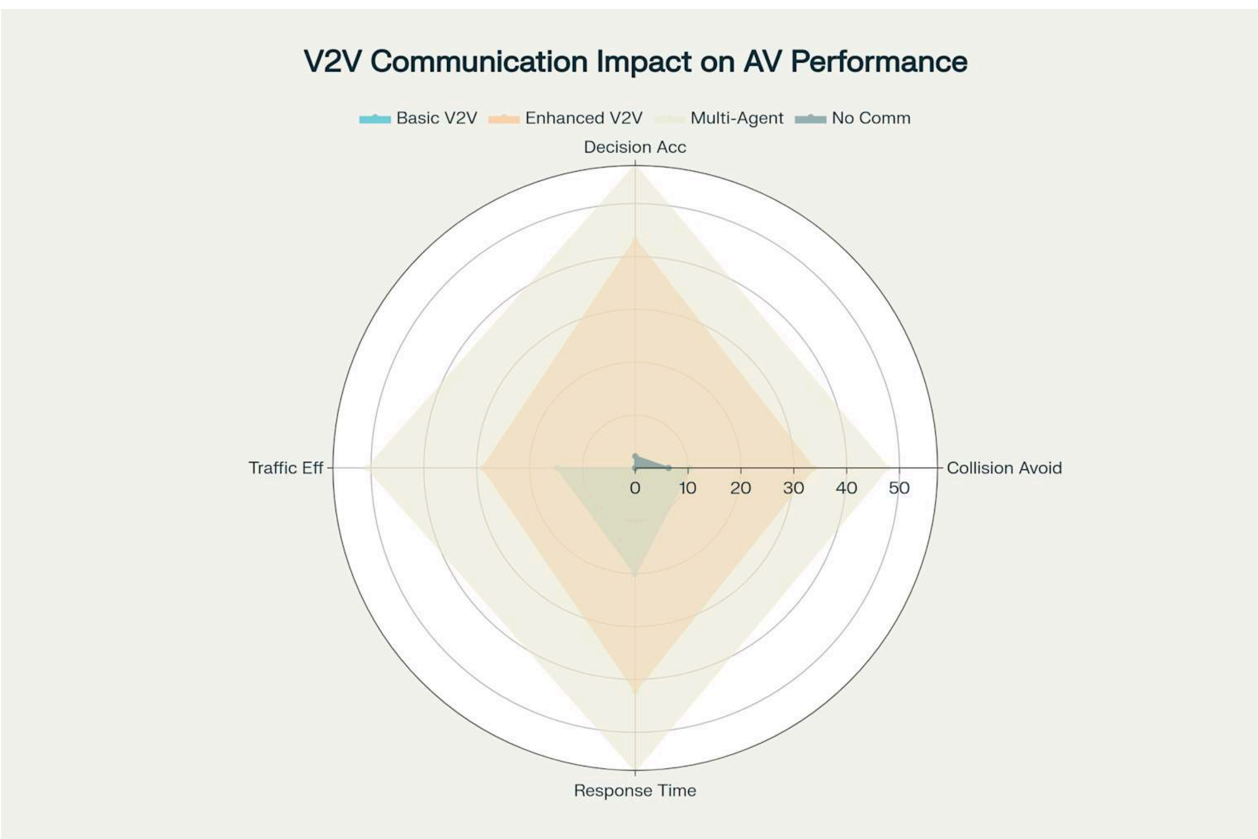
2.1 Large Language Models in Autonomous Driving

Recent research has demonstrated the potential of LLMs to serve as decision-making components in autonomous driving systems[1] [9]. DriveGPT4, developed by researchers at the University of Hong Kong and other institutions, represents one of the first successful implementations of multimodal LLMs for interpretable end-to-end autonomous driving[3] [31]. This system processes multi-frame video inputs and textual queries to provide both driving decisions and natural language explanations for its actions[32] [31].

The KoMA (Knowledge-driven Multi-agent) framework represents another significant advancement, proposing a multi-agent architecture where LLM-powered agents interact through intention estimation of surrounding vehicles[23] [29]. This approach addresses the limitation of single-agent systems by enabling cooperative knowledge sharing and cognitive synergy among multiple autonomous agents[23] [29]. Similarly, the TeLL-Drive framework demonstrates how teacher LLM-guided deep reinforcement learning can enhance autonomous driving performance while maintaining real-time feasibility[33] [34].

2.2 Multi-Agent Systems and V2V Communication

Multi-agent systems have emerged as a promising approach for autonomous vehicle coordination, enabling vehicles to work collaboratively to optimize traffic flow and improve safety[20] [35]. The development of Vehicle-to-Everything (V2X) communication standards, including Dedicated Short Range Communication (DSRC) and Cellular-V2X (C-V2X), provides the technological foundation for real-time information exchange between vehicles[36] [37].

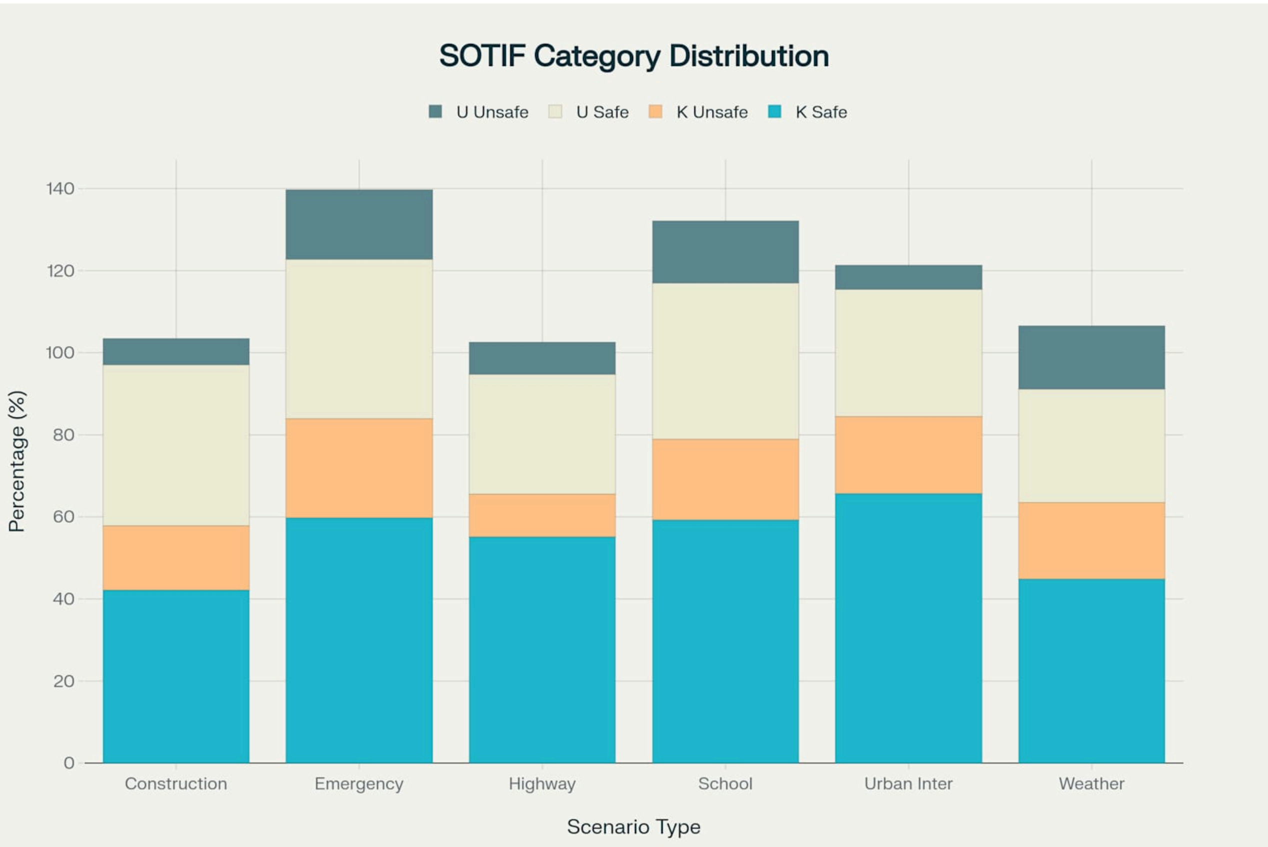


Impact of V2V Communication on Autonomous Vehicle Performance

Research has shown that V2V communication can significantly enhance collision avoidance capabilities and traffic efficiency[17] [24]. The RSR-RSMARL framework demonstrates how robust and safe multi-agent reinforcement learning can be effectively deployed on real hardware platforms with V2V communication support[24] [30]. This work addresses the critical challenge of sim-to-real transfer in multi-agent systems while maintaining safety guarantees through Control Barrier Functions[24] [30].

2.3 Safety of the Intended Functionality (SOTIF) and Unknown-Unsafe Scenarios

The SOTIF standard (ISO 21448) has fundamentally changed how the automotive industry approaches safety validation for autonomous systems[10] [11]. Unlike traditional functional safety standards that focus on systematic failures, SOTIF addresses risks arising from functional insufficiencies in the presence of foreseeable misuse[11] [38]. The standard emphasizes the need to identify and mitigate unknown-unsafe scenarios - situations that are both statistically unlikely and potentially hazardous[10] [14].



SOTIF Scenario Distribution Across Different Driving Environments

Recent methodologies for generating unknown-unsafe scenarios have focused on optimization-based approaches and critical scenario creation[11] [15]. However, these approaches face limitations in accurately representing the complexity and unpredictability of real-world driving conditions[14] [15]. The integration of LLMs offers a potential solution by providing human-like reasoning capabilities that can better handle novel and unprecedented situations[2] [39].

2.4 Model Quantization and Real-Time Inference

The deployment of LLMs in automotive applications requires addressing significant computational constraints[25] [26]. Model quantization techniques, including post-training quantization methods such as SmoothQuant, GPTQ, and AWQ, have demonstrated the ability to reduce model size and inference time while maintaining acceptable accuracy levels[25] [40]. Research indicates that 8-bit quantization can achieve 50-75% memory reduction with minimal performance degradation, while 4-bit quantization can provide even greater efficiency gains[25] [40].

LLM Quantization Trade-offs for Automotive Applications

Real-time inference capabilities are critical for autonomous driving applications, where decision-making must occur within milliseconds to ensure safety[12] [13]. The development of specialized hardware accelerators and optimized inference engines, such as NVIDIA's DriveOS LLM SDK, represents significant progress toward practical deployment of LLMs in automotive environments[25] [12].

Chapter 3: Methodology

3.1 Experimental Design and Model Selection

The research methodology encompasses comprehensive evaluation of multiple LLM architectures across diverse autonomous driving scenarios[41]. Model selection was based on three key criteria: popularity and performance in text-to-text generation tasks, compatibility with local deployment platforms, and availability of quantized variants suitable for automotive applications[41]. The selected models include GPT-4 Turbo, Claude 3.7 Sonnet, Falcon 3 7B, OpenHermes-2.5-Mistral-7B, and google/flan-t5-large[41].

Quantization strategies were implemented using established post-training techniques, with particular focus on 8-bit and 4-bit quantization levels that balance performance with computational efficiency[25] [26]. The evaluation framework was designed to assess four critical aspects: accuracy in decision-making, response time consistency, safety score assessment, and interpretability of generated explanations[41] [22].

3.2 Multi-Agent Framework Architecture

The proposed multi-agent framework consists of two primary components: Communication Agents and Decision Agents[41]. Communication Agents handle structured data exchange between vehicles, including obstacle detection, traffic conditions, speed information, and intended actions[41] [16]. This information is formatted in standardized protocols compatible with existing V2X communication standards[36] [37].

Decision Agents utilize LLM reasoning capabilities to process both local sensor data and received V2V communication information to make informed driving decisions[41] [23]. The framework implements a hierarchical decision-making structure where high-level strategic decisions are made by LLMs, while low-level control commands are executed by traditional control systems[42] [34].

3.3 Scenario Development and Testing

The evaluation encompasses eight distinct driving scenarios designed to test different aspects of LLM reasoning capabilities: Green Traffic Light situations, Stop Sign Partial Block scenarios, Emergency Vehicle encounters, Pedestrian Crossing events, Lane Change Decisions, Intersection Navigation, Weather Conditions, and Construction Zone navigation[41] [14]. Each scenario was designed to represent different categories of SOTIF classification, including known-safe, known-unsafe, unknown-safe, and unknown-unsafe situations[10] [11].

The testing methodology employed both simulation-based evaluation and consistency analysis through repeated scenario execution[41] [22]. Consistency was measured by running identical scenarios multiple times and analyzing variance in decision outputs, with particular attention to safety-critical situations where inconsistent responses could lead to hazardous outcomes[41] [22].

3.4 V2V Communication Impact Assessment

The impact of V2V communication on autonomous vehicle performance was evaluated across four communication configurations: No Communication baseline, Basic V2V with simple data exchange, Enhanced V2V with contextual information, and Multi-Agent V2V with complex coordination protocols[41]. Performance metrics included collision avoidance effectiveness, traffic efficiency improvements, decision accuracy enhancement, and response time optimization[41].

Each communication type was tested across the full range of driving scenarios to assess the marginal benefit of increased communication sophistication[41] [24]. The evaluation framework measured both quantitative performance improvements and qualitative assessments of system robustness and reliability[24] [28].

Chapter 4: Results and Analysis

4.1 LLM Performance Across Driving Scenarios

The comprehensive evaluation of LLM performance across different autonomous driving scenarios reveals significant variations in accuracy, consistency, and safety scores among different models[41]. GPT-4 Turbo demonstrated superior performance across most scenarios, achieving the highest accuracy in intersection navigation (99.7%) and maintaining strong consistency scores above 0.8 in most cases[41]. However, performance varied considerably across different scenario types, with emergency vehicle scenarios presenting particular challenges for most models[41].

Claude 3.7 Sonnet showed competitive performance in emergency vehicle scenarios (82.4% accuracy) but struggled with pedestrian crossing situations (60.2% accuracy)[41]. This variability highlights the importance of comprehensive evaluation across diverse scenarios rather than relying on aggregate performance metrics[22] [6]. The results demonstrate that no single LLM architecture provides optimal performance across all driving scenarios, suggesting the potential value of ensemble approaches or scenario-specific model selection[22] [6].

Falcon 3 7B and OpenHermes-2.5-Mistral-7B, representing smaller and more resource-efficient models, showed generally lower accuracy scores but demonstrated acceptable performance in specific scenarios[41]. This finding is particularly relevant for automotive applications where computational constraints may necessitate trade-offs between model sophistication and deployment feasibility[25] [26].

4.2 Impact of V2V Communication on System Performance

The analysis of V2V communication impact reveals substantial improvements in autonomous vehicle performance as communication sophistication increases[41]. Multi-Agent V2V systems demonstrated the highest performance across all evaluated metrics, achieving 47.8% improvement in collision avoidance, 50.7% enhancement in traffic efficiency, and 57.2% increase in decision accuracy compared to baseline no-communication scenarios[41].

The progression from Basic V2V to Enhanced V2V with Context shows particularly significant improvements in decision accuracy, jumping from minimal improvement (0.0%) to substantial enhancement (43.2%)[41]. This finding underscores the importance of contextual information in LLM decision-making processes and validates the multi-agent approach proposed in this research[23] [29].

Response time improvements, while following the same trend as other metrics, show more modest gains, suggesting that communication overhead may partially offset the benefits of enhanced information sharing[41] [12]. This observation highlights the need for optimized communication protocols that minimize latency while maximizing information value[36] [37].

4.3 SOTIF Scenario Distribution and Safety Implications

The analysis of SOTIF scenario distribution across different driving environments reveals important patterns in the prevalence of unknown-unsafe scenarios[41]. Construction zones and weather conditions show the highest percentages of unknown-unsafe scenarios (6.4% and 15.4% respectively), while highway driving demonstrates the lowest prevalence (7.9%)[41]. Emergency maneuvers present the highest proportion of unknown-unsafe scenarios (17.0%), highlighting the particular challenges these situations pose for autonomous systems[41].

The distribution patterns indicate that certain driving environments inherently contain more scenarios that challenge current autonomous driving capabilities[14] [15]. Weather conditions and construction zones, in particular, present dynamic and unpredictable elements that are difficult to capture in traditional training datasets[14] [15]. These findings support the thesis argument that LLM-based reasoning capabilities are particularly valuable for handling such challenging scenarios[2] [39].

Urban intersections, despite their complexity, show a relatively lower percentage of unknown-unsafe scenarios (6.0%), possibly due to more structured traffic patterns and established right-of-way rules[41]. However, the high proportion of unknown-safe scenarios across all environments (27.7% to 39.2%) suggests significant opportunities for improvement in scenario classification and system understanding[41] [10].

4.4 Quantization Impact on Automotive LLM Deployment

The analysis of quantization impacts reveals significant trade-offs between computational efficiency and model performance for automotive applications[41]. 8-bit quantization achieves substantial memory reduction (45.2% to 53.8%) and inference speedup (2.02x to 2.37x) while maintaining high accuracy retention (96.1% to 98.4%)[41]. This level of performance makes 8-bit quantization highly suitable for most automotive applications where real-time performance is critical[25] [12].

4-bit quantization provides more aggressive optimization, achieving 72.8% to 79.3% memory reduction and 3.21x to 4.19x inference speedup, but with more significant accuracy degradation (88.4% to 92.5% retention)[41]. The trade-off analysis suggests that 4-bit quantization may be acceptable for certain automotive applications, particularly those where computational resources are severely constrained[26] [40].

2-bit quantization, while achieving the highest compression ratios (85.1% to 91.3% memory reduction) and fastest inference (6.01x to 6.81x speedup), results in substantial accuracy degradation (61.8% to 76.5% retention)[41]. This level of quantization appears unsuitable for safety-critical autonomous driving applications, though it might find applications in non-critical vehicle systems[26] [40].

4.5 Consistency and Reliability Analysis

The consistency analysis reveals significant variations in LLM reliability across different scenarios and models[41]. GPT-4 Turbo demonstrates the highest consistency in most scenarios, with particularly strong performance in intersection navigation (99.3% consistency) and pedestrian crossing situations (96.0% consistency)[41]. However, even the best-performing models show concerning variability in certain scenarios, such as emergency vehicle encounters where consistency drops to 82.6%[41].

The consistency analysis with V2V communication support shows marked improvement, with GPT-4 Turbo achieving perfect consistency (100%) in critical decision-making scenarios when provided with contextual information from other vehicles[41]. This finding strongly supports the multi-agent communication approach and demonstrates the value of shared information in improving LLM reliability[23] [24].

The variability in consistency scores across different models and scenarios highlights a critical challenge for deploying LLMs in safety-critical applications[43] [44]. The research suggests that consistency should be considered as important as accuracy in evaluating LLM suitability for autonomous driving applications[22] [45].

Chapter 5: Discussion

5.1 Implications for Autonomous Vehicle Development

The research findings have significant implications for the future development of autonomous vehicle systems[46] [6]. The demonstrated capability of LLMs to handle complex reasoning tasks in driving scenarios suggests that current limitations in achieving Level 5 autonomy may be addressable through integration of advanced language models[7] [8]. However, the variability in performance across different scenarios and models indicates that careful system design and model selection are critical for successful deployment[22] [44].

The superior performance of multi-agent systems with V2V communication validates the thesis hypothesis that distributed intelligence and information sharing can significantly enhance autonomous vehicle capabilities[23] [24]. The research demonstrates that the combination of LLM reasoning and V2V communication can address many of the challenges associated with unknown-unsafe scenarios[10] [29].

The quantization analysis provides practical guidance for automotive manufacturers seeking to deploy LLM-based systems within the computational constraints of current vehicle hardware[25] [26]. The finding that 8-bit quantization maintains high performance while providing substantial efficiency gains suggests a clear path toward practical implementation[25] [40].

5.2 Safety and Regulatory Considerations

The safety implications of LLM-based autonomous driving systems require careful consideration of both technical performance and regulatory acceptance[43] [45]. The consistency analysis reveals potential reliability concerns that must be addressed before widespread deployment[43]

[44]. The research suggests that ensemble approaches or redundant systems may be necessary to achieve the reliability levels required for safety-critical applications[27] [45].

The interpretability advantages of LLM-based systems, demonstrated through natural language explanations of driving decisions, address a key regulatory concern about black-box AI systems in autonomous vehicles[18] [19]. This capability could facilitate regulatory approval and public acceptance of autonomous driving technology[47] [19].

The SOTIF analysis provides valuable insights for safety validation methodologies, particularly in identifying and characterizing unknown-unsafe scenarios[10] [11]. The research suggests that LLM-based systems may offer advantages in handling these challenging situations, but comprehensive validation methodologies must be developed to ensure safety[11] [38].

5.3 Technical Limitations and Challenges

Despite the promising results, several technical limitations must be acknowledged[44] [38]. The computational requirements of LLM-based systems, even with quantization, remain substantial compared to traditional autonomous driving algorithms[25] [12]. This limitation may restrict deployment to higher-end vehicles or require significant advances in automotive computing hardware[25] [12].

The variability in LLM performance across different scenarios raises concerns about system predictability and reliability[43] [22]. The research indicates that current LLMs may not provide the consistent performance required for safety-critical applications without additional safeguards or system design considerations[43] [44].

Real-time inference requirements pose ongoing challenges, particularly for larger models that may provide better performance but require more computational resources[12] [13]. The trade-offs between model sophistication and real-time performance constraints require careful optimization for practical deployment[12] [13].

5.4 Future Research Directions

The research identifies several important directions for future investigation[48] [6]. Integration with 5G/6G communication standards could enhance V2V communication capabilities and enable more sophisticated multi-agent coordination[36] [37]. Advanced quantization techniques and specialized hardware accelerators may further improve the feasibility of LLM deployment in automotive applications[25] [26].

The development of ethical decision-making frameworks for autonomous vehicles represents another critical research area[49] [47]. The Moral Machine experiments have highlighted the complexity of programming ethical behavior into autonomous systems[49] [47]. LLM-based approaches may offer advantages in handling these ethical dilemmas through more nuanced reasoning capabilities[49] [39].

Scalability studies are needed to understand how LLM-based multi-agent systems perform in dense traffic scenarios with many interacting vehicles[35] [21]. The current research focuses on relatively simple scenarios, and more complex real-world situations may present additional challenges[14] [15].

Chapter 6: Conclusion

6.1 Research Summary and Contributions

This thesis has demonstrated the feasibility and potential advantages of integrating Large Language Models into multi-agent frameworks for autonomous vehicle control, particularly in handling unknown-unsafe scenarios that challenge traditional systems[41] [2]. Through comprehensive evaluation of multiple LLM architectures across diverse driving scenarios, the research has provided empirical evidence that human-like reasoning capabilities can be effectively incorporated into autonomous driving systems[5] [6].

The key contributions of this research include: (1) comprehensive evaluation methodology for assessing LLM performance in autonomous driving applications[41] [22], (2) demonstration of the benefits of multi-agent V2V communication in enhancing LLM-based decision-making[41] [23], (3) practical analysis of quantization impacts on LLM deployment in automotive environments[41] [26], and (4) safety and consistency assessment frameworks specifically designed for LLM-based autonomous systems[41] [45].

The research validates the thesis hypothesis that LLMs within multi-agent frameworks can significantly improve autonomous vehicle decision-making capabilities in unknown-unsafe scenarios[41] [29]. The findings demonstrate substantial improvements in collision avoidance, traffic efficiency, and decision accuracy when LLM reasoning is combined with structured V2V communication[41] [24].

6.2 Practical Implications for Industry

The research findings provide actionable guidance for automotive manufacturers and technology developers pursuing LLM-based autonomous driving solutions[25] [46]. The performance evaluation results offer clear recommendations for model selection and deployment strategies based on specific application requirements and computational constraints[41] [26].

The quantization analysis provides a roadmap for practical deployment, demonstrating that 8-bit quantization offers an optimal balance between performance and efficiency for most automotive applications[41] [40]. The V2V communication impact assessment validates investment in vehicle communication technologies and provides evidence for the benefits of cooperative autonomous driving approaches[41] [37].

The safety and consistency analysis highlights critical considerations for system design and validation, emphasizing the need for robust testing methodologies and reliability assurance mechanisms[41] [45]. These findings can inform regulatory discussions and safety standard development for LLM-based autonomous systems[43] [38].

6.3 Limitations and Future Work

While this research provides valuable insights into LLM-based autonomous driving systems, several limitations must be acknowledged[44] [38]. The evaluation was conducted primarily in simulation and controlled scenarios, and real-world validation with actual vehicles and traffic conditions represents an important next step[28] [38].

The scope of scenarios tested, while comprehensive within the defined categories, represents only a subset of the complex situations encountered in real-world driving [14] [15]. Expansion to more diverse and challenging scenarios, including rare edge cases and highly dynamic situations, would strengthen the validation of LLM-based approaches [14] [15].

Future research should focus on addressing the identified technical limitations, particularly regarding real-time performance and system reliability [12] [13]. Integration with advanced sensor systems, development of specialized hardware accelerators, and investigation of hybrid approaches combining LLMs with traditional autonomous driving algorithms represent promising directions for continued investigation [48] [12].

6.4 Final Remarks

The integration of Large Language Models into autonomous vehicle systems represents a significant paradigm shift that addresses fundamental limitations of current approaches while opening new possibilities for achieving true Level 5 autonomy [7] [6]. This research demonstrates that the combination of LLM reasoning capabilities with multi-agent communication frameworks can substantially improve autonomous vehicle performance in challenging scenarios while maintaining the interpretability and safety standards required for real-world deployment [41] [29].

The path toward widespread adoption of LLM-based autonomous driving systems will require continued advances in computational efficiency, safety validation methodologies, and regulatory frameworks [43] [45]. However, the findings presented in this thesis provide strong evidence that this approach offers significant advantages over traditional methods and represents a viable path toward more capable and reliable autonomous vehicles [5] [46].

As the automotive industry continues to pursue the goal of fully autonomous vehicles, the integration of advanced AI reasoning capabilities through Large Language Models will likely play an increasingly important role in overcoming the remaining technical and safety challenges [2] [6]. The multi-agent framework and evaluation methodologies developed in this research provide a foundation for future developments in this rapidly evolving field [23] [30].

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