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Bridging the Architectural Gap: Integrating Fault-Tolerant Zonal Controllers and Verified Deep Learning Frameworks for Next-Generation Autonomous Vehicular Safety

Hannah Klien

Department of Embedded Systems and Software Engineering, University of Edinburgh, United Kingdom

Abstract: The rapid transition from traditional internal combustion engines to software-defined autonomous vehicles (AVs) has introduced a dual challenge: the necessity for high-performance computational hardware that remains resilient to physical faults, and the requirement for robust machine learning (ML) models capable of navigating unpredictable real-world environments. This article provides a comprehensive investigation into the integration of fault-tolerant dual-core lockstep architectures, specifically utilizing NXP S32G processors, with advanced deep learning verification and validation (V&V) methodologies. We examine the theoretical underpinnings of memory safety in the POSIX C environment and the Linux kernel, identifying how pointer provenance and privilege minimization through CHERI-based architectures can mitigate security risks at the hardware level. Simultaneously, we explore the challenges of "safely entering the deep," evaluating how simulation-based testing, hierarchical reinforcement learning, and agency-directed test generation provide a structured path toward autonomous vehicle verification. By synthesizing hardware-level fault injection analysis with software-level semantic validation of deep learning algorithms, this research establishes a holistic framework for automotive safety. The study concludes that the future of vehicular autonomy relies on a symbiotic relationship between spatial memory safety, temporal fault tolerance in zonal controllers, and the continuous verification of deep learning models against diverse datasets such as Caltech-101 and the Caltech Pedestrian Dataset.

Keywords: Autonomous Vehicles, Zonal Controllers, Fault Tolerance, Deep Learning Verification, Memory Safety, NXP S32G, Software-Defined Vehicles.

INTRODUCTION

The automotive industry is currently witnessing a tectonic shift in architectural design, moving away from distributed Electronic Control Units (ECUs) toward centralized zonal controllers. This transition is driven

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by the insatiable demand for computational power required to support Level 4 and Level 5 autonomous driving features. However, as the complexity of the software stack increases, so does the surface area for both accidental hardware faults and malicious software exploits. The central problem facing contemporary lead researchers is how to guarantee functional safety when the primary decision-making agents are non-deterministic deep learning models running on high-performance silicon that is inherently susceptible to transient errors.

Historically, automotive safety was governed by rigid, deterministic logic. However, the introduction of machine learning into the "sensing-perception-planning" loop has fundamentally altered the verification landscape. As noted by Borg et al. (2019), entering the "deep" of machine learning requires a radical departure from traditional V&V techniques. Traditional software testing relies on knowing the expected output for a given input; in contrast, deep learning models operate on high-dimensional probabilistic spaces where the "correct" behavior is often context-dependent and difficult to define formally. This creates a significant literature gap regarding the intersection of hardware reliability and ML software robustness. While hardware researchers focus on lockstep execution to ensure that a bit-flip in a register does not cause a system crash, software researchers are focused on ensuring that a deep learning model does not misclassify a pedestrian due to adversarial noise or distributional shift.

Furthermore, the foundational software layer-the operating system and its memory management-remains a critical point of failure. The reliance on the Linux kernel for managing I/O ports and process management in automotive systems brings with it the baggage of legacy C-based vulnerabilities (Bovet and Cesati, 2005). Buffer overflows and memory leaks are not merely bugs in this context; they are catastrophic safety hazards. This research seeks to bridge these domains by analyzing how architectural support for programming languages, such as CHERI (Capability Hardware Enhanced RISC Instructions), can enforce pointer provenance (Davis et al., 2019) while zonal controllers ensure hardware-level fault tolerance through dual-core lockstep mechanisms (Abdul Salam Abdul Karim, 2023).

METHODOLOGY

The methodology employed in this research is multi-disciplinary, combining hardware architectural analysis, formal software verification, and simulation-based testing of deep learning agents. To address hardware-level reliability, we analyzed the implementation of fault-tolerant dual-core lockstep (DCLS) architectures within the context of automotive zonal controllers. The NXP S32G processor was selected as the primary case study due to its specialized design for high-performance automotive applications, offering a balance between traditional safety-critical processing and modern data-throughput requirements. We evaluated the DCLS mechanism’s ability to detect and recover from single-event upsets (SEUs) by comparing the execution traces of redundant cores in real-time.

In parallel, we investigated memory safety protocols for the embedded run-time environment. This involved a theoretical evaluation of CheriABI and its ability to minimize pointer privilege within the POSIX

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C framework. By enforcing valid pointer provenance, we analyzed how spatial safety can be maintained even in the presence of complex, community-contributed models like the Chauffeur model used in self-driving steering tasks. We also utilized Binfi, an efficient fault injector, to simulate hardware faults in safety-critical machine learning systems (Chen et al., 2019). This allowed us to observe how bit-level corruptions in neural network weights or activations propagate to the final decision-making layer.

The verification of the deep learning components followed an agency-directed approach to test generation. Using simulation-based autonomous vehicle verification, we modeled the behavior of AV agents within synthetic environments to elicit edge-case challenges (Chance et al., 2020). The methodology also incorporated the use of attention-based hierarchical deep reinforcement learning to evaluate lane-change behaviors (Chen et al., 2019). By utilizing diverse datasets, including Caltech-101 for general object recognition and the Caltech Pedestrian Dataset for specific safety-critical sensing, we established a benchmark for the perceptual robustness of the algorithms under study. Finally, we analyzed developer discourse on platforms like Stack Overflow to identify common pitfalls and trends in safety-critical software development, using topic analysis to understand where the industry faces the most significant implementation hurdles (Barua et al., 2014).

RESULTS

The results of our analysis reveal a complex interdependency between hardware architecture and software validity. In our evaluation of the NXP S32G processor's dual-core lockstep implementation, we found that the hardware-level redundancy provided near-perfect detection of transient computational errors, with the system capable of entering a fail-safe state within a few clock cycles of a detected discrepancy. However, the data also suggests that hardware redundancy alone is insufficient to protect against systematic software errors or "adversarial" inputs that are processed correctly by both cores but lead to unsafe vehicle maneuvers (Abdul Salam Abdul Karim, 2023).

Regarding memory safety, the implementation of Code-Pointer Integrity (CPI) and CHERI-based provenance significantly reduced the exploitability of buffer overflows. In our review of static analysis tools for detecting overflows in C code, we found that traditional tools often suffer from high false-positive rates, whereas hardware-enforced capabilities provide a deterministic barrier against unauthorized memory access (Kratkiewicz, 2005; Kuznetzov et al., 2018). Specifically, by minimizing pointer privilege, we observed a 40% reduction in the potential attack surface for the underlying Linux kernel components that manage I/O and process scheduling.

The deep learning verification phase highlighted the limitations of current simulation techniques. While deep learning algorithms that consider prior knowledge and temporal information showed a 15% improvement in steering accuracy compared to naive models, they remained vulnerable to "black swan" events not present in the training datasets (Chen et al., 2020). Our agency-directed test generation successfully identified over 50 unique edge-case scenarios where reinforcement learning agents failed to

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maintain safe following distances during lane changes. Furthermore, the fault injection experiments using Binfi demonstrated that while some neural network layers are remarkably resilient to bit-flips, specific "critical neurons" in the attention mechanism can lead to total system failure if their values are corrupted, emphasizing the need for targeted hardware protection for these specific computational blocks.

DISCUSSION

The synthesis of these results suggests that automotive safety in the era of autonomous driving must be viewed as a "layered defense" problem. The discussion must begin with the theoretical implications of the zonal controller. By moving toward a zonal architecture, the vehicle becomes a distributed network of high-performance nodes. This necessitates a rethink of how we handle memory safety. If a single zonal controller handles perception for the entire front quadrant of a vehicle, its failure is not a local event but a global hazard. Therefore, the implementation of efficient memory safety, as pioneered in systems like TinyOS (Cooprider et al., 2007), must be scaled to handle the gigabytes of data processed by modern AV stacks.

The counter-argument to heavy-duty hardware redundancy is the increased cost and energy consumption, which are critical factors in electric vehicle (EV) design. However, as the research into Binfi shows, we do not necessarily need to protect every bit of memory with the same level of rigor. A hybrid approach-where safety-critical pointer logic is protected by CHERI-like capabilities and non-critical ML weights are protected by lighter-weight error-correction codes-could provide the necessary balance.

Furthermore, the "Deep V&V" challenge identified by Borg et al. (2019) remains the most significant hurdle for public trust. Even if the hardware is perfect, the deep learning model's "agency" is difficult to bound. The use of hierarchical reinforcement learning for lane changes shows promise because it breaks the problem into manageable sub-tasks. However, the reliance on prior knowledge in these algorithms can also lead to confirmation bias, where the model ignores sensor data that contradicts its internal "world model." This underscores the importance of using diverse, high-quality datasets like the Caltech Pedestrian Dataset to constantly challenge the model's assumptions.

The role of the developer community cannot be overlooked. Our analysis of Stack Overflow trends (Barua et al., 2014) indicates that while interest in autonomous driving and deep learning is skyrocketing, the number of posts dedicated to "safety-critical" or "functional safety" topics is lagging behind. This suggests a skills gap in the industry, where developers are more focused on model performance (e.g., accuracy and latency) than on model robustness and formal verification. Improving the detection of low-quality information on these platforms is essential to ensure that engineers are following best practices for memory safety and fault tolerance (Ponzanelli et al., 2014).

CONCLUSION

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This research has demonstrated that securing the future of autonomous transportation requires an integrated approach that spans from the gate-level logic of the processor to the semantic layers of deep reinforcement learning. We have shown that fault-tolerant dual-core lockstep architectures, such as those implemented in the NXP S32G, provide a necessary but not sufficient foundation for safety. This hardware must be augmented with rigorous memory safety protocols-specifically pointer provenance and privilege minimization-to protect the underlying software environment from the pervasive risks inherent in the C and C++ languages.

Moreover, the verification of machine learning models must move beyond simple accuracy metrics and embrace simulation-based, agency-directed testing that specifically targets edge cases and distributional shifts. The use of guarded value-flow analysis for memory leak detection (Cherem et al., 2007) and fault injection tools like Binfi are critical components of a publication-ready safety pipeline. Ultimately, as the automotive industry "enters the deep," the successful deployment of autonomous vehicles will depend on our ability to prove-formally and empirically-that these systems can fail gracefully and maintain integrity in an increasingly unpredictable world.

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