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Optimizing ADAS and Autonomous Driving Systems with Advanced Ethernet Protocols and Machine Learning

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Abstract: ***We will review how Ethernet and open standard AVB/TSN are evolving for automotive and how they offer real implementation benefits from both a hardware and software level. We discuss how AVB/TSN IP can be deployed at the application level, making it easier to develop, test, and optimize use cases with Ethernet as the network backbone. These can range from in-vehicle multi-resolution GUI and multiple safety-critical ADAS to high-performance multi-camera sensing engine features. We also look at the potential for machine learning-based implementations inside switched-Ethernet ECUs, running software that manages congestion and competes for time-critical services with the more traditional automotive traffic. Companies developing in the in-vehicle network solution space can learn where to appropriately position themselves in the increasingly software-designed ecosystem-driven future of automotive electronics. We show how HW & SW developed AVB/TSN implementation, reducing the complexity of E/E architectures, resulting in a more effective ADAS and improving road safety. It also allows OEMs, car manufacturers, and Tier 1's to rapidly deploy that system features most important to their customers' requirements at launch. The automotive ADAS features deployment race is about to shift up a gear, enabling them to jointly deliver vehicles with the highest driver/user acceptance and confidence in the latest ADAS features.***

Keywords: Optimizing ADAS and Autonomous Driving Systems with Advanced Ethernet Protocols and Machine Learning, Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Machine Learning (ML), Smart Manufacturing (SM), Computer Science, Data Science, Vehicle, Vehicle Reliability

1. Introduction

Advanced Driver Assistance Systems (ADAS) and autonomous driving functions are disrupted by a significant increase in generated data. The bandwidth of these data flows originates from multiple sensors and sources located throughout the vehicle, including cameras, radars, LIDAR, sensors, vehicle systems, and other sources. Furthermore, the trend shows a significant increase in raw image resolution and frame rate for automotive cameras, while similar trends in LIDAR lead to serious bandwidth challenges. Ethernet is the dominant in-vehicle surround sensor network, and the industry faces a meaningful transition from traditional 100-Mbit generic Ethernet to significantly faster and more efficient Ethernet technology. Customers persist in having faster, cheaper, and more automated solutions to drive down OEM vehicle costs while staying within the same footprint and having robust end-to-end solutions mandated by TSN (Time-Sensitive Networking). Extreme reliability and efficiency when integrating Ethernet into the vehicle are mandatory. Latency density, bandwidth density, and uninterrupted availability are critical for life-critical ADAS and autonomous driving systems. The industry is working fast to respond as it continues to comply with critical vehicle I/O demands, especially from IEEE and AVB/TSN (Audio/Video Bridging/Time-Sensitive Networking). This crisis of data abundance triggers both solutions that can predict, manage, and extract only the most potentially valuable data flows, leading the automotive market towards automation with the help of machine learning and TSN while integrating variation in the Ethernet hardware standards of the chip, MAC, and PHYs(1). These variations challenge Ethernet protocol and machine learning innovators to integrate the functionality of their solutions cost-effectively.

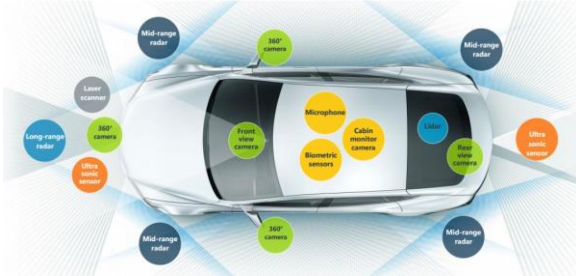

Figure 1: Schematic Diagram of Sensor Installation Location

1.1. Background and Significance

Recent technological advances have increased driver attentiveness, reduced driver stress and fatigue, and improved situational awareness through Advanced Driver Assistance Systems (ADAS). ADAS are also important steppingstones in developing Autonomous Driving Systems (ADS). As many new "smart" interactive scenarios are enabled, such as vehicle-to-vehicle, vehicle-to-infrastructure, vehicle-to-everything, and connected vehicles, latency, reliability, and security have become increasingly important. Traditionally, ADAS data is communicated using a variety of communication methods ranging from NOR flash, Ethernet, MOST (Media Oriented System Transport), CAN (Controller Area Network), mMOST (MOST Data Layer), and more. However, Ethernet technology is reaching the maturity, granularity, communication determinism, and performance necessary for real-time multimedia data communication. To satisfy the increasing needs of E/E architectures and to enhance the coexistence of automotive-grade Ethernet communication standards and consumer-oriented Ethernet, several advanced Ethernet protocols are under study by the IEEE P802.1 working group and the IEEE 802.1 Audio/Video

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Bridging Task Group. In this study, we will first present the current state-of-the-art ADAS and Autonomous Driving Systems, and then discuss the industry trend, recent standard modifications, and desirable communication properties of Ethernet for automotive applications, and deal with automotive Ethernet protocol selection issues and future challenges.

1.2. Research Objectives

The main tasks and objectives of the research include the following: Carry out a literature review about the state of the art of Advanced Driver Assistance Systems (ADAS) and Autonomous Driving (AD) trends, Artificial Intelligence (AI) in transport systems, and existing developments in the field of the implementation of the Ethernet protocol in automotive systems. - Process and analyze traffic accident data, identify prominent significance factors of traffic accidents, and define bottleneck and trouble points in the road network. - Identify and analyze technical obstacles to the decision to make popular ADAS systems that ensure driving safety. - Define the basic problems of using Machine Learning capabilities in the automatic recognition of economic decisions, provide more summaries, and highlight real shortcomings of this approach. - Propose a Direction of Traffic Problems Elimination on the Road Stretch Based on Detected Bottlenecks for Smart Road, according to the designed Economic Loss for Society Relative Units (ELSRU) in the section of existing Interstate Highway Standards. - Provide organizational proposals for the resolution of these problems in the implementation of this type of control. - Demonstrate the study's results, implement cost-effective features, and evaluate this implementation. Characterize and assess the protocol designed for the implementation of these systems. Overall, develop the Enterprise network model of the onboard vehicle (model demonstration at an early stage). Propose an optimal traffic organization scheme for high load, cost, and safety. Apply business processes and ensure a protocol for communication of vehicle integration. The research's main issue and end goal will be the proposal of the optimal and economically sound introduction of the proposed intelligent road safety management system and the Possible Gain from Using an Infrastructure Transport System (POG FRUITS). The base is protected from the Mathematical Model of the Development of the Network Economy, which reflects the dynamic effect of the formation of the priority of the necessary control operation and the data transfer rate in the regulatory section of the road. It can be noted that almost all the major problems that arise in the areas are essentially the problems of optimizing some transport networks. Transport networks can differ in scale, scope, and function. The study does not contain examples and does not claim to model the entire transport network of the city or large region. The main network that is a priority for forecasting and optimizing dynamic development is roads within the demonstrative company.

2. Advanced Ethernet Protocols in ADAS and Autonomous Driving Systems

The development trend of ADAS and autonomous driving has a long way to go before its realization. The far-reaching development of autonomous driving technology is also driving the development of surrounding technologies, such as information systems, communication systems, and even driving force electronic systems. It is an era of global strategic challenges that are accelerating the race for full driving. In the first section, the challenge of autonomous driving technology was presented, as the new trends in the automotive market related to autonomous driving, and the unique challenges of both ADAS networks from L2+ to L3 and the futuristic acquiring vehicle-to-everything (V2X) and driving strategies. In the following, how ADAS Ethernet will be an option in the not-so-far future as the network of autonomous driving will be introduced. ADAS is currently one of the most advanced networks in vehicles to have. The biggest challenges in ADAS are high speed to guarantee reduced data transmission time, simplified redundancy for better safety, coupling with the autonomous driving network in the future for the required resource sharing, and operational cost benefit. Until now, two technologies, FlexRay and MOST (Media Oriented Systems Transport, a method of transmitting), FIT (Future In-car IP Technologies), and Ethernet-based on AFDX (Avionics Full Duplex Switched Ethernet, a high-speed data bus located in the avionics industry) and ARINC 664 are analyzed and verified for the automotive environment. The results of this analysis are poor performance behavior from memory access conflicts among the processor nodes, and a low-performance bandwidth with high-optical cost, respectively. All of the above, in multiple points, together result in high Distributed-Transmit Interval (DTI) and large data latency between many electronic control systems and a significant negative impact on fault tolerance and operational cost.

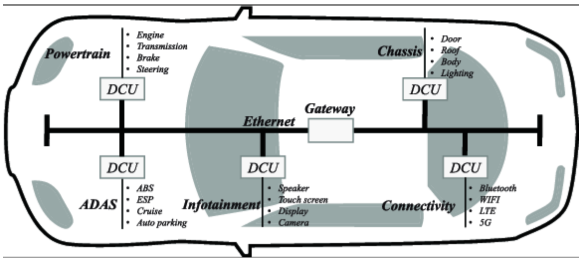

Figure 2: Ethernet backbone architecture

2.1 Overview of Ethernet Protocols

Ethernet has evolved over the years. The IEEE802.3 Ethernet has been deployed on a very large scale. There are many different forms of Ethernet for various environments, including very high-speed (100Gbps and above) data center or local office networks, and medium-speed (10Gbps~) enterprise/home office networks over copper or fiber media. GigE (Gigabit Ethernet) is very popular in IP networking and high-speed automotive communications. The newer generations, including 100G, 2.5G, 5G, 25G, 40G, and 100Gbps+beyond Ethernet, are mostly designed for cloud networks, data center networks, and other very high-speed networks. The existing MAC layers can support multi-gigabit transmission and also full duplex in such high data-rate Ethernet links. MAC layers have been standardized, enhanced, and used in application-specific systems to ensure smooth link activation, clock synchronization, error control, and an adequate supply of buffer space at the receiver end. The Auto-negotiation protocol has been defined and used to exchange capabilities and set up the connection in advance. These technologies enable reliable link synchronization and error control for Ethernet transport, both in data centers and in the automotive segment. However, this Ethernet technology can hardly support the most advanced GPU chips that are capable of delivering very high-rate sensing data (exceeding 50-100Gbps) in the data centers. During the evolution of optical Ethernet, higher-speed optical links for data centers have been implemented through Multi-fiber and Wavelength Division Multiplexing (WDM) techniques.

2.2 Challenges and Limitations

Despite the rapid progress in automated driving development, the complexity of environments, harnessing the potential of sensor and data fusion are challenging, and hence, where problems emerge. This is mainly due to the sheer volume of processing capability that data fusion requires, as well as the sensor technologies' inherent limitations. External conditions such as heavy rainfall, fog, or snowfall result in unreliable sensor-generated data. Environmental damages (i.e., dust, graffiti, faded lane markings, and partially visible traffic signals or signs) may also result in degraded performance. These aspects may severely limit the effectiveness of passive sensors, driving advanced driver assistance systems (ADAS), and autonomous driving systems to rely on other detectors, which increases the risk of failures. Consequently, ADAS and autonomous driving systems require hard real-time performance to support fail-operational safety requirements. To achieve this safety level, ADAS and autonomous driving systems must classify frames from input camera sensors with latency on the order of milliseconds, for one such application. The per-frame latency requirements for other onboard AI inference tasks such as object detection, object localization, scene parsing, and decision-making are similar.

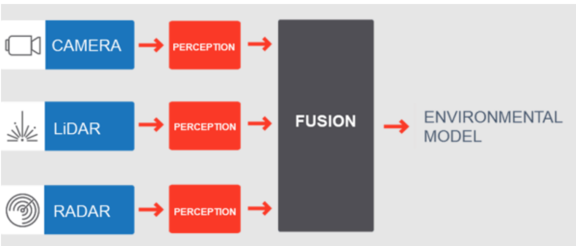

Figure 3: Object - level sensor fusion

3. Machine Learning Applications in ADAS and Autonomous Driving Systems

Machine learning (ML) is a significant evolution of artificial intelligence (AI). ML systems use algorithms to uncover trends and relationships in data. Machine learning lets systems identify patterns and make decisions and predictions without human intervention. Machine learning models, as a crucial key, bring decision-making capabilities to the artificial intelligence system. Using the data-driven machine learning model, one can tackle complex problems, such as natural language and image recognition. Essentially, a machine learning model generalizes patterns from the data, so it can predict or classify future data. Machine learning is widely used in autonomous driving technologies. Training these machine learning models requires high processing capabilities, which are facilitated by hardware acceleration, such as a graphics processing unit (GPU) and GPU board. Machine learning techniques are installed in data centers or edge-side computing devices to train models and make predictions respectively. In general, large training data sets will result in high accuracy for machine learning models. Low-latency networks and high transmission throughput are thus important in collecting traffic data and video streams simultaneously. Moreover, data centers are equipped with various servers and interconnect technologies, connecting these servers to a network switch to form a cluster. Low-latency server-to-server transmitting technology is also necessary to make machine learning jobs more efficient. In this chapter, we propose edge-side computing for implementing plant model optimization in a data center and server-to-server network communication at the product level.

3.1. Types of Machine Learning Algorithms

ML algorithms use learning techniques to automatically learn relationships between input and output data. The algorithms can be used to recognize patterns, make inferences, and make decisions or predictions without being programmed explicitly. There are four types of ML algorithms in modular ADAS and autonomous driving systems: supervised learning, unsupervised learning, reinforcement learning, and semi-supervised learning. These algorithms are applied to the respective data either for image processing or sensing. In supervised learning, the system presents all the features of the inputs along with the label(s), which the algorithm will seek to predict. The algorithm then learns how they correspond. Its goal is to map input data to some output -- giving clear examples of what we want to produce. Supervised learning is often used when we want to identify objects in images, reveal relations, segment information in sensory data, or perform classification -- for instance, to calculate the angle. The most common type of supervised learning is regression, in which a model attempts to predict continuous data, and classification, in which a model attempts to predict discrete or qualitative data, such as night or day, pedestrian or vehicle. In unsupervised learning, the system is only provided with input data, and the system is not presented with any labels. It finds patterns in data. This approach tries to expose the underlying, or latent, structure in the dataset. Clustering, where observations are grouped within a dataset, and generative models, where a model learns about unspecified features within the data, are examples of unsupervised learning. Reinforcement learning is a type of semi-supervised learning. In this, the learning system is provided not only with input data but also with feedback in the form of trial and error, the result of the generated action. Semi-supervised algorithms include a mixture of labeled (fully supervised) and unlabeled (unsupervised) examples.

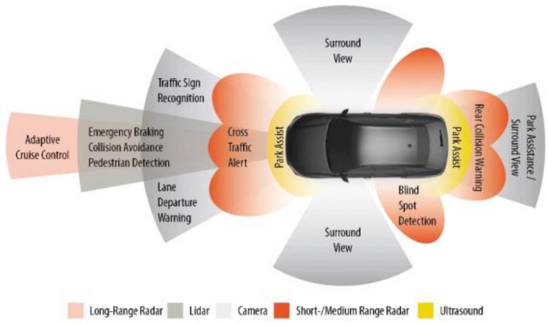

Figure 4: The illustration of ADAS

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3.2. Benefits and Challenges

While Ethernet is the technology of choice for the backbone, integration of all ECUs into an Ethernet backbone presents a complex multi-dimensional challenge due to the need to combine the seemingly heterogeneous. These include audio and video signals, control and diagnostic signals, active safety and autonomous driving data, standard networking data such as vehicle health reports, OBD (on-board diagnostics), 802.1AS and 802.1AS-Rev keeping real-time data synchronized between cameras, lidar, and radar, and gigabytes of software updates during vehicle assembly. Furthermore, these signals need to be transported among various communication mediums, such as automotive Ethernet, coax, LVDS, and PCIe. The capability of Ethernet to transport all these types of signals can bring a vehicle from assembly and diagnostic to manufacturing automation and repair to an ultimate ecosystem: AI computation, autonomous vehicles, and vehicle-to-anything (V2X) will become reality soon.

The Ethernet throughput can easily be scaled with multi-lane transceivers, creating additional opportunities such as eliminating expensive SerDes and creating innate functional safety FPGA. However, ADAS Ethernet presents a unique set of challenges. Significant among these are SWaP (size, weight, and power), compatibility with current automotive technologies and infrastructure, performance, reliability, and security. Providing broadband coverage throughout the vehicle requires various levels of aggregation while addressing the SWaP concerns. ADAS must also be fully compatible with the legacy 1000BASE-T1 standard and other corresponding speed automotive Ethernet standards while also capable of connecting to the future 10Gbps on-board system and off-board operations as outlined in Table I. Full benefit of multi-lane capabilities of Ethernet will only be realized with multiple remote devices, separated by as much as 15 meters each, connected to a single switch. All these Ethernet protocols need to provide error-free communication with the support of hardware processing while meeting the intrinsic requirements of a mission-critical automotive environment such as message prioritization, low latency, frame and rate control for lanes, clock and data recovery, and deterministic arbitration.

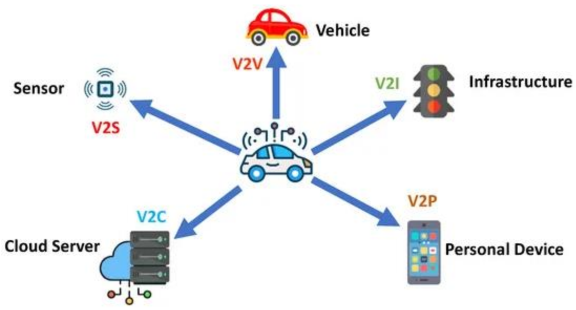

Figure 4: Internet of Vehicles communication

4. Integration of Machine Learning with Advanced Ethernet Protocols

Developing ADAS and autonomous driving systems requires keeping development and vehicle testing projects running simultaneously. Recent breakthroughs in high-performance computing (HPC) and infrastructures have yet to be applied in this context. In time-correlated HPC, enough configuration parameters are being developed and tested. The complex interdependence of present operations with the underlying vehicle infrastructure leads to tightly coupled participant, component, and system behavior. Designing cooperative objects in coordination with the infrastructure will produce greater performance improvements for HPC applications than approaches that target the optimization of individual system components in isolation. Computer scientists are now beginning to address these challenges. The participants introduce the tight integration of a lot of areas of study covering short-term system investments, but they are vital for long-term meaningful performance improvement. Automotive Ethernet is purpose-built for the automotive environment. Concepts such as in-vehicle data logging are becoming increasingly important in the automotive industry due to the extensive development and testing efforts necessary for ADAS and autonomous driving (AD) systems. During these development and testing efforts, the system components are closely coupled. Designing cooperative objects in coordination with the infrastructure will produce greater performance improvements for HPC applications than approaches. Computer scientists are now beginning to address and contribute to achieving such continuous data collection, raw data analysis in real-time, and concrete knowledge of the consequences of tuning parameters of projects. The ultimate goal of the prototype is to help dealerships automate operations typically involving the client waiting for the vehicle. The prototype of a system to manage the vehicle reception scheduling in Opel Authorized Workshops covered the main requirements designation in the automotive field. The concepts for the service, manufacturing, and standby production were implemented in architecture, but capable of capturing and analyzing real communication data. The system learns the new requirements of the area of interest or application (service, manufacturing, and standby production) in real-time and updates the classifier tool automatically.

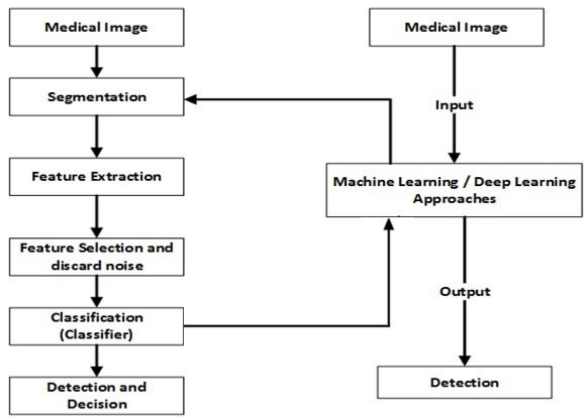

Figure 5: Machine and Deep Learning algorithms workflow in medical image

4.1. Opportunities for Optimization

While objective testing and validation of complex advanced driver assistance systems (ADAS) and autonomous driving systems are still in the early development stages, the challenge and promise of these systems continue to grow. Like the aerospace industry, the ability to test and optimize these systems will greatly enhance their safety, security, and acceptance. We see a wide variety of opportunities for advanced data analysis of datasets in most development efforts. Some of these opportunities focus on the basic usage of commercially available techniques on richer or more diverse sources of data, while others, particularly those in which benefits are shown in particular domains or are enabled by particular kinds of ADAS data, require the development of new data analysis techniques. There are several ways that high-quality machine learning can facilitate the design and refinement of ADAS and autonomous driving systems. By utilizing machine learning, users can find the connections in driving data that allow for better system design. They can also utilize machine learning to predict how different system designs will work. Lastly, machine learning techniques can be used to create complex test cases from the data. In the automotive industry, an area where we expect the investments in machine learning applied to ADAS datasets to focus on and will benefit from is test cases. We will choose test cases that are both complex and meaningful and also prove test case completeness by automating most of the testing process. By doing this, we will be more comprehensive while also enabling more efficient and effective system development over typical heuristic approaches.

4.2 Case Studies

Even with advanced node behavior and self-optimization algorithms, the network control plane is designed based only on booking patterns and threshold-based triggers. Any change in the mapping between business importance and network behavior involves specialized domain knowledge and configuration changes in each of the multiple network nodes. In an FPGA-based solution, specialized application knowledge allows FPGAs to offload control. A Sockets API is introduced into the data plane with typical SDN semantics. For typical network functions of routing, NAT, and firewalling, 10 to 100 k routes can be maintained with a set of fully associative Ternary Content Addressable Memory-based pipelines. For each pipeline, two levels of hashing allow an even distribution of rules. In contrast, the Data Plane Development Kit (DPDK) is targeted for rule lookup and rule-based actions of 10 to 20k operations per second for user-defined traffic categorization and has been used successfully in a privacy-preserving network.

For rules requiring only a single level of lookup, structuring memory for with-protocol header bit extraction minimizes the number of IP packets needed to reach a cache hit in typical scenarios. Shifting from binary match to distance-based packet classification, or using a bloom connector in the first place allows the flexible network nodes to accommodate flexible QoS, dynamically adjusting response times according to state and business policy. Positional encoding architecture is a novel accelerator designed for processing the large-scale rule set with a two-level bitmap array that can achieve full-match operation. Another work proposes a hardware-based acceleration scheme using FPGAs to accelerate classification, counting, filtering, and caching operations for network monitoring. A coarse-grained net cache pattern is hidden in long flows for multipath routing. The full-match acceleration took only 0.3% of the FPGA's slices, 76% of the read, and 4.2% of the write resources. The counting and filtering operations took 10%, 37%, 2.4%, and 29% slice, read, write, and LUT resources.

In general, simply matching the network node's throughput to the interface's bottleneck is also not a silver bullet. With rigid control implemented in the network node control plane, the rapidly changing control plane service states lead to oscillatory bandwidth provisioning, interface over subscriptions, and long-tailed end-to-end service response time have already been discussed. Brute force schemes merely tailor the account's service level to match the peaks of the possible overbilling dipping valleys of an unfriendly fair admission controlling a cloud service node's microservice monetization access.

Highly connected networks such as data centers with rapidly fluctuating demands can have Amdahl's law and crossover effects reduce aggregate numbers of microservices that process requests concurrently, introduce contention costs that are larger than those of directly sharing CPU and other resources, longer tail latency and unfair CPU allocation, and validate the internal monitors' jurisdictional claim of an implicit right to access and control resources, queries, and packet-dumping on the segments of the PCIe tree. In a design with Tofino-like control, the overall response time is proportional to the slowest control plane stage's TTL with a replicated parallel DAG dealing with the fractional request rate, multiple frontend weights, and a shadow backend.

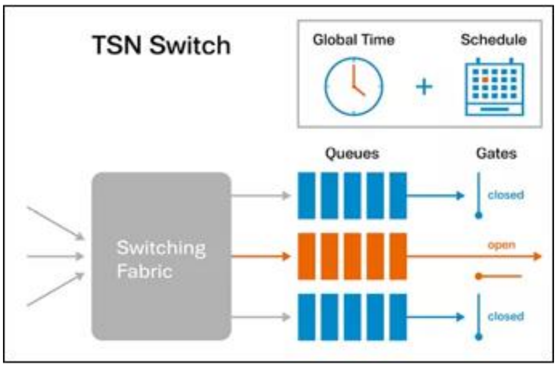

Figure 6: TSN Switch

5. Conclusion

The name of the game in vehicle design is creating reliable and safe systems while keeping down costs. Ethernet- and AVB-based protocols can help do this for ADAS and autonomous driving systems by adding redundancy and failover features in the Ethernet link and by delivering reliable multimedia entertainment distribution in a standard way that is not susceptible to hacks. Machine learning algorithms help to reduce tooling costs, enabling systems to be developed with low chip count As-Is protocols and off-the-shelf Ethernet devices. Chip builds assist from large chip providers frees up some FPGA space for user proprietary data, facilitating customization that could give vehicles of a specific manufacturer some unique features.

Combining AVB, TSN, Ethernet, and RTP hardware assists in one device and opens up attractive options for the designer. With the end of life of traditional automotive infotainment components that delivered similar capabilities and proprietary car OSS systems that support more built-in features like vehicle-to-anything (V2X), V2V, or vehicle-to-charging (V2C) communication, implementations using Ethernet will become increasingly viable and should not be dismissed by designers.

5.1 Key Findings and Contributions

This chapter explored the utilization of automotive software-defined networks to enhance reliability while reducing the heavy usage of networks introduced by Ethernet concepts. EM is a cutting-edge communication technology that may provide high reliability. To overcome the problems which had been faced by ADAS and autonomous driving systems using extensively used technologies or concepts, this chapter has made several contributions. First, considering from a software-defined network perspective, we use an Ethernet concept known as TSN. This can bring reliability to the system, according to two recognized challenges in the ADAS and autonomous driving architecture. The second aim of unbalanced network traffic allocation was to create an intelligent speed reduction mechanism. The system may instantly adapt to different vehicle-driven networks. The automobile may continue to communicate regardless of the degree of performance with other systems that require low latency. This is made possible through adaptable vehicle-based speed control.

The third aim of this chapter was to give a possibility to road maintenance services, communication between vehicles, and data uploading for independent vehicles, and different types of entities. We examined frequent heavy network bandwidth usage scenarios for communication among vehicles, and between vehicles and the edge cloud, leading to large data traffic. Our method does not alter the specific problem faced by the task distance-based semiconductor concept. It does put the matter into perspective. It demonstrates the feasibility of providing various types of network data centered on the edge cloud. As a result of different problems confronted by the found difficulties, these provisions have provided a comprehensive technique for autonomous who wish to solve. Our approach and findings were evaluated using simulation data. This established the efficacy of our approach.

5.2. Future Research Directions

With the increasing amount of data being generated in AD and ADAS systems, it is becoming a challenge to manage, store, and process this enormous amount of data. The data generated in ADAS and AD is not just of high velocity but is also of high variety and unstructured. Machine learning, deep learning, and computer vision play a critical role in transforming the data into useful information for various applications in ADAS and AD. Shortly, machine learning and computer vision techniques will increasingly automate the data analysis step and minimize human intervention. The role of machine learning will expand from classifying high-resolution images to safe decision-making based not only on sensor data but also on a massive amount of historical and geographical life cycle data such as traffic patterns, vehicle behavior, weather data, safety history, traffic light information, pedestrian pathways, etc. Dynamic machine learning models are of critical importance for AD and ADAS, as the system must learn in real time and adapt to changes in its surrounding environment. Existing machine learning models may also need a new form of explanation and reasoning, motivated by safety regulations and human trust factors.

Automotive-grade Ethernet is a key enabler of high performance and scalability in ADAS and AD systems. Automotive-grade Ethernet enhances the reliability in driver assistance and autonomous driving systems by providing low latency deterministic performance, reliability, high bandwidth, advanced security, etc. Current works on automotive-grade Ethernet lack focus on data quality. It is important to analyze how the AI models to be trained on this large volume of data can benefit from higher quality of data and latency and bandwidth improvement that Automotive-grade Ethernet provides. The focus of the current industry is on achieving the lowest end-to-end latency for a specific traffic profile between specific end stations instead of allowing an absolute maximum bandwidth to be consumed by each station. These requirements for high bandwidth should also be addressed by the ongoing standardization of 25, 50, and 100 Gbps Ethernet connectivity, besides the standardization of time-sensitive networks for automotive applications. In the current state of automotive applications, there is minimal and no standardized traffic control in the network device such as a switch. Further research should focus on the hardware support required for the new entrance-class time-sensitive networking standard so that automotive-grade Ethernet can be cost-effective. Shortly, we will have more efficient and optimized solutions leading to the deployment of vehicle-to-vehicle and vehicle-to-infrastructure communication. This vehicle-to-everything (V2X) communication is of much importance in advanced driver assistance systems since it is the key to the enhancement of safety and the implementation of cooperative driving functionalities. Automotive-grade Ethernet will help improve V2X communication and information sharing, paving the way for cooperative intelligent transport systems. In conclusion, more research would be needed to further optimize and improve automotive-grade Ethernet. A set of specific, yet broad set of open research issues outlined here; a polyvalent and also broad list of potential research initiatives in the domain of transportation and automotive networks can be addressed using the Ax infrastructure.

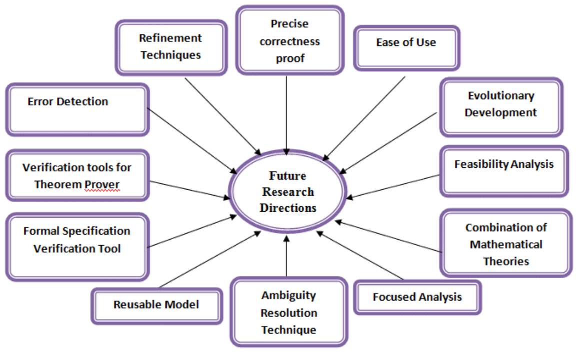

Figure 7: Future Research Direction

6. Conclusion

Building an electronic end-to-end system with ECUs (engines/actuators connected to multi-sensors), featuring high bandwidth, low latency, high reliability, safety compliance, security, and low power consumption, is the major challenge for the ADAS and autonomous driving. In the 21st century, the transportation industry has somewhat stagnated, as reinforced concrete, steel, high explosives, and fuel are still the main technologies over the last century. Therefore, long traveling times, traffic accidents, dynamic traffic jams, and cost-ineffective drive transportation are in a new era to solve these issues: ADAS and Autonomous Driving. With the development of infotainment, the automotive infotainment use of Ethernet continues to grow its networking scope.

In this section, we proposed an advanced Ethernet communication network intended to work in the TSN context and have been designed and characterized with the FPGA solution implemented in the end devices (SoC: CPU and FPGA). Our solution is connected through 100Base-T1 with the sensors and 1000Base-T1 with the advanced ECUs (ADAS). With time to revoke, the Ethernet network inferred by FPGA with time-aware auto-negotiation is fully agreed with the TSN standard IEEE 802.1Qbv and 802.1Qbu to support the management use cases and safety priorities. Finally, we proposed a Machine Learning approach that vectorized one ATL transformation rule and classified it as Safe or Unsafe from a training base produced from simulations launched with a design of experiments OpCode injected in the RTL model. To avoid recalculating the power tool on FPGA each time a change in the TSN core is made, we tested the validity of the learning approach with small changes in the ATL transformation rule from the training base. A line reduction and an extension of models and test bench will be the subject of interdisciplinary FPGA/ART benchmarks shortly.

6.1 Future Trends

Automotive Ethernet will be key to the integration of infotainment, advanced driver assistance systems (ADAS), and autonomous driving (AD) systems in HD vehicles. Time-Sensitive Networking (TSN) allows this by implementing determinism and quality of service (QoS) in data transmission. AVs will use 10Gbps Ethernet, and in-vehicle environments will be connected to 2.5 Gbps infrastructure and 1 Gbps switch ports to replace today's legacy networks. AVs will incorporate IEEE P802.1Qcc Stream Reservation Protocol (SRP), 802.1Qbv Time-Aware Shaper, and 802.1Qbu Per-Stream Filtering and Policing in bridged and virtual local area networks. Autonomous systems will add 15% more time-sensitive data flow to the network, hence larger switches and augmented networks. Time-sensitive WAS-WAP integrations require SAE AS6803 Augmented Ethernet/Front Wires within the auto drive vehicle environment. AD multi-homed high-speed Ethernet controllers should communicate with N (parallel visions)-LP (3D LIDAR Predictive Map) auto-associative memory deep learning perception accelerators (PCPAs) using small-world switches while prioritizing visual cues over the background.

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