Adaptive Intrusion Detection Systems for Cybersecurity in Autonomous Vehicle Ecosystems

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1. Introduction

The proposed adaptive system performance analysis is graduated by simulations and does not employ a hard threshold, attacking and harmful instances simultaneously. Additionally, our intrusion system has low complexity and low consumption of memory. This is advantageous in supporting efficient hardware implementation in autonomous vehicle ecosystems.

Layer four adapts the cost of novel class with a threshold learning cost-sensitive model.

Layer three optimizes the deep learning algorithm with the self-developed S2J surrogate model. The training dataset required for Layer three is generated by our proposed intruder-registration wireless intrusion system.

Layer two creates a multi-sinhole feature that is extracted from the holes of the intruder's transmitted packet. Feature selection is done with a forward reliability model.

Layer one calculates the Wi-Fi Association Bit Rate and scans the Wi-Fi Interface address.

This paper proposes a lightweight adaptive intrusion detection system that does not require labeling of the datasets. The detection system introduced has four main layers.

Autonomous vehicle (AVs) technology is becoming more common in society, and cyberattacks on AVs can potentially result in fatal safety hazards. Therefore, an effective intrusion detection method must be developed as a non-descriptive security solution in autonomous vehicle technologies.

1.1. Background and Motivation

Indeed, keeping such infrastructures robust in the face of emerging threats and changing conditions for unprecedented protection of personal health and safety is mandatory. On the one hand, it is neither developmentally nor economically feasible to properly test and fully understand the trustworthiness of such complex transportation and mobility infrastructures used on a daily basis. Although multidisciplinary research and development, including the use of artificial intelligence (AI) and machine learning (ML)-based protection techniques together with statistics, etc., are necessary, accommodating almost all potential intrusion strategies implemented by an adversary is limited for the aforementioned framing technique, inherent deployment architecture, and budget concerns selected.

Effective utilization of information and communication technology (ICT) components in ground transportation infrastructure, including vehicles (of all types and categories, regardless of their level of autonomy), smart roadways, and mobility service and management systems, underpins new intelligent transportation systems (ITS) and enables them to operate in increasingly more efficient, resilient, and secure modes. In vehicle ecosystems, which are among those emerging paradigms, autonomous vehicles (AVs) or AV-related technologies are expected to play an important role. While AVs are developed as passenger vehicles operating on public roads with limited external sensors because of the deployment of advanced driver-assisted systems, extended logs and the utilization of advanced machine learning (ML) techniques, customized protection for those systems is expected to be exploited effectively from the intrusion detection system (IDS).

1.2. Research Objectives

1) Conceptualize methodologies that filter data for the implementation of adaptive machine learning IDSs. The conceptualization will be adapted to the high volume and heterogeneity of the data combined in non-stationary environments, focusing on edge computing in the case of autonomic communication adaptation, limiting the need to upload data to cloud computing. It is expected that the filtering operation being executed at the peripheral level will also cause reductions in computational intelligence requirements, ensuring faster decision-making and greater energy autonomy. Generally speaking, the expected results of this research are based on conceptual results and practical results. No empirical research is conducted since the concepts and models are designed. The expected conceptual results are in the form of adaptive techniques that can be deployed in conjunction with security solutions

to improve the detection and classification of new threats in stochastic and non-stationary contexts, with fertile ground in the treatment of specific data selection for specific objectives through information science.

This research aims to conceptualize and model suitable methodologies that allow data filtering for the implementation of IDSs. Therefore, the research objectives and expected results are described in this section. Although combining AI techniques and IDSs for the cybersecurity of AV systems is not new in itself, the models defined in a non-adaptive context adapt poorly to different environments because of their generalistic nature or the characteristics of that environment. As such, this research is in line with the lack of an enclave of effective AI models that reduce false positives in the implementation of IDSs in intelligent environments. In general, these models do not consider the different combinations of stimuli, leaving room only for generalistic variations. Since the scenarios previously listed pose a robust, reliable, and efficient AI/ID solution to protect and ensure AV ecosystem security can only be achieved by a specific modeling that considers the particularities of intelligent environments, the first goal of this research is as follows.

1.3. Scope and Limitations

To that end, we presented a system model that describes current and future architectural characteristics of fully networked AV COEs. The primary elements of the AV COE model were a high level AV; vehicle buses that host the vital subsystems and sensors; and various local, private (COE-level), and public information networks. The various signal interfaces to the subsystems are also exposed. The exposed characteristics of the model are used to explain the full spectrum of potential cyber threats. The paper, then, proposed a design for architectures of new and adapted intrusion detection algorithms that are capable of addressing current and future cyber threats to AV COEs. We simulated the operation of an intrusion attack against a sample subsystem, and its detection, using the AIDE framework for Intrusion Detection. To that extent, we aim in this paper to make a significant contribution to the body of developing knowledge around the technologies, architectures, and operation of AV systems.

Many times, in the present work, we reference the term "cybersecurity," and its application to AVs. We must first define this term, at least loosely. Under this work, the most suitable industry and military standard for describing "cybersecurity" seems to be that which is

tentatively formatted by the National Institute of Standards and Technology (NIST) of the United States Department of Commerce, under the aegis of the Federal Information Security Management Act of 2002 (FISMA), and the Department of Homeland Security.

2. Fundamentals of Autonomous Vehicle Ecosystems

The easiest way of conveying the autonomous vehicle cars (LICCI) ecosystem is to first describe the classical vehicle (except Autonomous Driving) implementation and then what changes about LICCI. In classical vehicles, Advanced Driver Assistance Systems (ADAS) are executed. In 1958, the first ADAS equivalent to modern cruise control was applied to a vehicle. Direct assistance to the driver proper begins as ABS (Antilock Braking System) to prevent wheel locking and loss of control of the vehicle. Probably TCS (Traction Control System) is the next execution of the solutions to face additional critical situations. The first system with functionality equivalent to the modern LKAS (Lane Keeping Assistance System) was applied to the vehicle in 1971. The first autonomous vehicle trials began with funding from the European Commission in Milan in 1987. This allowed the vehicle to perform driving and parking operations without driver intervention. However, at no time has the legislation stipulated a response to the SCC (Supervised Object Classification) feature. The first vehicle to reach level 3 of automation in 1994 was a result of the research work in PROMETHEUS. This resulted in a lot of work resuming and approval of some vehicles to transport goods at level 5. In 2008, the first publicly known Mark X version of the Google autonomous vehicle was launched. There are currently several vehicles considering each of the levels. In 2015, the first autonomous vehicle regulation was published by the Netherlands. There are two essential types of communication for vehicles in the autonomous vehicle environment. Vehicle to Vehicle - V2V and Vehicle to Infrastructure - V2I. The communication between vehicles and vehicles occurs from points of mobility joint, parking, collision avoidance, interconnecting vehicles in a convoy to increase transportation capacity, improve traffic flow, availability of fuel, and therefore increase energy efficiency. In no case should the vehicle include the platoons. The automotive industry plays an essential role in the development of the V2I. From the beginning, the vehicles' embedded sensors can offer situational awareness in the target area and quickly identify communication points, access points, and centralized control.

The ecosystem of autonomous vehicles includes the system, control, communication, and intelligence systems beyond just the vehicle. The entire ecosystem works together to achieve autonomous driving capability. In other words, their entire spectrum is LICCI (up to level 5 autonomous driving vehicles). The ASIL goals (Automotive Safety Integrity Levels) to be fulfilled by the subsystem development are more stringent than the traditional ASIL goals of vehicle development. An Adaptive Intrusion Detection System should be capable of detecting and responding to any intrusion that affects the functions of the development environment to ensure the safety and security of drivers and passengers. This publication outlines each of the autonomous security tasks, their challenges, and recent advancements in machine learning and cybersecurity technologies for those tasks. In this work, we describe the operational capabilities, the attack surface, and special characteristics of the area of autonomous vehicle systems.

2.1. Autonomous Vehicles: Definitions and Types

In this study, we focus on adaptive-type autonomous vehicles. These vehicles are responsible for cooperating with the driver when the vehicle deviates from its mission, ensuring a safe exit without causing any accidents. However, when there is an attack on the subsystems that collect data about the external and internal environment in autonomous and connected vehicles, the behavior of the system can change. The collected data may be modified, and anomalies can occur in the sensor node data. The algorithms within the control systems collect the data, make decisions, and send application commands to the required output. The vehicles in the same ECU area that work collectively are not considered at the same level, as changes have been made to the hardware and there are different levels of progress in the strategies. In other words, the vehicle fleet consists of vehicles that work together but are designed according to different strategies. The strategies in the attack model, the attacker's knowledge, and the communication between vehicles can change. With changes in the strategy and membership level, new defense needs are created for autonomous vehicle cybersecurity.

Autonomous vehicles are cutting-edge transportation technology. They are designed to use artificial intelligence and machine learning to understand what is happening around the vehicle, using various sensor technologies, and act accordingly without the intervention of a human driver. In other words, autonomous vehicles can perform tasks that a human driver can do using advanced technologies. The use of AI in autonomous vehicles enables faster and

more efficient decision-making processes, allowing them to adapt to changing conditions. Today, autonomous vehicles can be classified into two types based on the level of autonomy: conditional automation and high automation.

2.2. Components of Autonomous Vehicle Ecosystems

What if a passenger watches a movie over the default screen inside the car with the Wi-Fi option? This screen is connected with the internet to increase entertainment while traveling. However, if the Wi-Fi connectivity is misused, this screen can become a monitor for a cyber-terrorist who wants to see where some cars are and engage in malicious behavior. When a smartphone is charged using the USB option, there is a chance of being infected with malicious code from the AV. Even spatial steam information, a device connected with a car for a long time, can be successful for attackers to gain unlawful access to the car as in the entertainment unit. At the same time, it shows driver's minimum movement, and in time someone can easily have control of the vehicle.

Autonomous cars run on artificial intelligence. Artificial intelligence can be trained for good and bad purposes. Therefore, cybersecurity is one of the major issues for autonomous cars. All connected cars that emit and gather data to make road easier can simply become victims of attackers. In this chapter, we are going to discuss the main components of autonomous vehicles. The components talk to each other at the time of driving under artificial intelligence. This environment becoming ecosystem is composed of the car and all the devices that are in or out of the car. Yet, if extra security for the autonomous car is not being taken, smartphones and smart devices that are outside the car can be agents of cyber-terror because they are connected to the car.

2.3. Cybersecurity Challenges in Autonomous Vehicles

Cybersecurity comes with numerous concerns in autonomous driving systems, which correspond to the various levels of autonomy in the vehicles. Low-level autonomy refers to the driving environment where the task of driving is shared between the human drivers and the vehicle's driving system. The driver or the onboard system is emphasized to prevent chaotic situations in autonomous or automated-driving systems. On the other hand, the vehicle has a medium range of autonomy when the vehicle physically drives without any human control in certain environment situations where the onboard system monitors the

driving tasks. Level 3, on the other hand, signifies a vehicle with intermediate autonomous control of the driving environment, in which the system monitors the environment and can perform control and critical safety functions without the ongoing responsibility of human drivers. In contrast, the vehicle is bestowed with full range of autonomous operations in the level 4 and level 5 of the driving system autonomy environment. These discussions bring forth several cybersecurity and safety challenges corresponding to the four different driving tasks, and each of them will be explained in the subsequent sections.

3. Intrusion Detection Systems (IDS) in Cybersecurity

Furthermore, the adaptive Intrusion Detection System (ADS) has made a collective intelligent adaptive system (C-IAMS) design possible to synthesize a complex adaptive system using Multi-agent systems (MAS), an autonomous/federation based coalition model building for cooperative enterprise agility awareness (CEDA), and a MAS Models of susceptibility to attacks for the AVE. There have exceptional challenges in the development of adaptive network defense mechanisms for multi-vehicle aversion: (1) determines the universe of discourse space within the A-VE where the threats could transition in (2) identifies a decision-making hierarchy of the potential threats and protection points being made based on expected lowest risk to highest reward. (3) Recognizing and rank the potential damage and impact of the potential exposure. (4) Are safety or operational risks associated with the migration potential greater than potential value."

"... Adaptive Intrusion Detection Systems (IDS) for critical infrastructure such as Autonomous Vehicle Ecosystem (AVE) using cooperative Masstige Taxonomy framework. This work demonstrates an autonomous system devised for IDS representing the Collective-Intelligent Self-manage Management that has been seamlessly integrated into the AVE. The effectiveness of the solution is measured against two systems: one detecting known attacks only and a second employing a different mechanism for alerting them. The Principal Finding and Contributions are: The ground working approach is necessary required especially in creating situational awareness on the approaches adopted to detect and protect AVs within the Autonomous-Vehicles System (A-VE) for the new generation of Energy, Transportation, Health, Agriculture that is continuously evolving and emerging technologies influence the A-VE subsystems including the sensing, Information Technology (IT), network, Cloud, and cyber-threats side-effects compatible with autonomous systems at various levels, this work

adopted Autonomous Vehicles (AVs) Ecosystem (AVE) – an integration of MSS-II and Autonomous Vehicles System.

3.1. Types of IDS

There are close relations between evasion attacks and anomaly-based or signature-based intrusion detection systems. The attack may specifically be designed to evade detection by the particular IDS. For anomaly-based IDS, it could manipulate its normal behavior to firmly fit within its established boundaries. In some cases, an attempt to create large numbers of false anomalies that overwhelm the IDS may be made. For signature-based IDS, a form of attack can be created or adapted to bypass or avoid detection by the IDS. Other hybrid categories in conjunction with anomaly and signature IDS are also available to combat cybersecurity threats, integrating machine learning and other artificial intelligence-based technologies. In hybrid-based anomaly and signature IDS, various anomaly detection techniques may work together with different signature-based detection techniques.

Intrusion detection systems can be broadly categorized into two categories: signature-based IDS and anomaly-based IDS. Both of these IDS types can work in isolation or be implemented as a hybrid model. Anomaly-based IDS monitors the system's behavior over time for signs of unauthorized access. If any behavior exceeds typical patterns, it is detected and interpreted as an intruder. This method is most effective when the users are in the learning stage, where IDS is already trained. On the other hand, signature-based IDS monitors the environment for specific events that are known to be malicious. Attacks are recognized on the basis of their signatures. Unlike anomaly-based IDS, signature-based does not use typical behavior data to recognize trends.

3.2. Traditional vs. Adaptive IDS

The weakness of both types of systems is that they do not update their models when the system is under attack. Therefore, ID systems for AV vehicles should adapt their models to switch from monitoring to a safe mode when an adaptive attack is being launched against the system. This requires model-based ID with reinforcement learning algorithms.

On the other hand, anomaly-based ID systems model normal or benign system behaviors during training. They identify different types of anomalies from their model and signal the system as an intruder when it deviates from normal behavior. Anomaly-based systems are

generally capable of detecting unknown attacks, but they have a relatively high rate of false alarms. While known attacks can be detected multiple times, the time window without requiring manual signature updates for each attack is wider.

Traditional intrusion detection systems (ID systems) are either signature-based or anomaly-based. Signature-based ID systems monitor network traffic or scan software for specific patterns of strings that match known attack signatures. They compare observed patterns with these signatures, which helps to quickly detect attacks. The detection time window is shortened because it corresponds to the time when the attack signature is developed or reasoned, and the model with the attack signature is updated.

3.3. Challenges in IDS Implementation

Security is no longer a pure software-only domain. It has moved to the physical and has become a matter of safety (safety in security action). The reliance on vehicle platforms for the implementation and deployment of critical activities has been increasing at an increment of several percentage points year-on-year, and security has always been essential for every paradigm, regardless of the intended operational design domain. No manmade technological artifact can prevent any type of cyber harm, but all of these systems may do their best to make sponsors work extremely non-interesting and extremely hard. Cybersecurity in autonomous vehicle ecosystems should be addressed at the levels of (i) policy and threat; (ii) vulnerability preventive measures; (iii) compromise preventive with early detection and incremental recovery; and (iv) post-incident evaluation. Finally, security should be cast among other systems quality attributes, to be negotiated and qualified by all stakeholders. A-IDS is one possible pillar implementing the moderate and gradual detection with safety.

While the use of Adaptive Intrusion Detection Systems (A-IDS) in the context of vehicle security would seem relatively simple considering the extreme hardware and software constraints contained in a vehicle, there are a multitude of unique challenges associated with their development and implementation. The sources of data accessed and the likelihood of data containing functional information or security vulnerabilities of components in autonomous architectures create elevated stakes for these systems. Their validity and reliability have legal, safety-critical, and financial implications too. With A-IDS, another potentially bigger challenge comes from the vehicle fleet environment because usually legitimate data access patterns exhibit significant change and inter-unit discrepancies. All

these challenges originate from the A-IDS context, which is framed by the specificities of security requirements for autonomous architectures: correctness by design, must integrate highly complex and evolving hardware and software stacks, must operate under stringent real-time constraints, and requires a collective coordination of distributed units.

4. Adaptive Intrusion Detection Systems for Autonomous Vehicles

SIMD (synergy, identity, mode, decision) is a high-level taxonomy that was designed for Intrusion Detection Systems (IDS) that monitor components of AV or for the specific tasks that are running in the targeted vehicular network. Synergy uses information that is generated from the collaboration of the different AV systems (and the possible external entities that can interfere with the AV execution at any time) to identify possible safety attacks. An intersection can be detected in different ways. Identity relies on the knowledge of all the AV elements and the knowledge of their physical, logical, and operational states. It determines a possible attack to the AV ecosystem when a mismatch is detected between the expected behavior and the present behavior of the AV elements. Application IDSs, operating as higher-level watchdog hazards in which these AV systems are participating, are the ones that take part in mode. AV behavioral mode defines the group of the present operational constraints where an AV is performing a specific kind of task according to the standard definitions.

This section presents a taxonomy of IDS for AVs where three levels of abstraction that consider different architectures and requirements are defined. We also offer a brief explanation of some of the proposed methods and their constraints, requirements, and IDS design issues. AVs are rather complex, taking advantage of Urban Vehicular Networks (UVN) for better performance. In this environment, security and privacy are challenges that have to be addressed to ensure that the services that AVs offer are secure and trustworthy. Information and communication technologies, critical points, and mobility requirements make the AV ecosystem a unique challenge.

4.1. Key Features and Requirements

In this section, we define key features and discuss the requirements of socially responsible driven AVs that collaborate and act efficiently in a sub-part of a city road giving priority to public transportation and pedestrians. The term "socially responsible" is used to illustrate the commitment of an AV, which drives responsibly and effectively, to participate and interact

safely with cross traffic, to merge in a cooperative manner with other vehicles, detecting cars leaving the nearest parking place or a slow/closed bus stopping and determine the necessary actions to minimize the risk and/or the travel time. Be note that, in comparison to private cars, public transport vehicles entering or leaving the public-transport lane, typically a bus or an AV shuttle, represent a significant constraint for the designed AV system. For instance, in some strategic points, they might decrease the AV lane capacity up to 10% by neutralizing the AV lane for longer time as they stop in the live traffic stream.

Currently, operated vehicles generally follow predefined routes and do not require any real-time decision-making in their action planning. They receive the orders from HQ or are pre-defined to follow the highways and the city roads without any considerations for a co-pilot, driving rules or socially acceptable behavior. However, in the future, driven vehicles would need to share the surroundings with human drivers and therefore should behave in a certain way that is compliant with the social norms. The question now becomes: What actions and behaviors would a socially compliant autonomous system need to optimize in order to maintain a safe and proper traffic flow on the highways and city roads? Indeed, level 3 and 4 AVs could require specialized features, understanding the infrastructure and the human drivers in their vicinity, and developing the ability to interact in a socially acceptable manner to promote the public acceptance of these self-driven transportation systems.

4.2. Machine Learning and AI in Adaptive IDS

The approach presented by Riad et al. leverages the capabilities of data mining for intrusion detection to learn patterns and sequences in security event logs and build an adaptive intrusion detection system. The critical features of their implementation of an adaptive intrusion detection system include feature extraction, at the pre-processing phase; smart classification using data mining, during what they call off-line updating, maintenance, and online detection; and the generation of alert response (such as raising an alarm, signaling an attack, confirming the occurrence of an incident, or extracting new knowledge for making adaptive decisions). The event logs data transformation work removes noise and irrelevant features, then the input data is prepared for this work. The work begins with feature extraction and a data matrix is created from the structured data for intrusion detection. This paper applies the same event logs transformation and feature extraction phases, making the

collected event logs appropriate for intrusion detection analytics and generating an attack signature database.

The first step to building an adaptive machine learning model for intrusion detection is security event logs data transformation. That is to say, the raw security event logs are preprocessed to remove noise and irrelevant features. The next step is to extract features that correspond to security events collected in intrusion detection system logs of commonly used security data sources. The features are then used to build a security event data matrix containing the number of interesting patterns and sequences observed. The patterns are sequences of ordered events that generally alert a system security expert to the existence of a security problem or an attack. Intrusion detection uses the smart classifier to classify events into different classes or categories, to find which are normal or abnormal, and to trigger alerts, alarms, or reports in response to potentially serious cybersecurity issues.

4.3. Case Studies and Applications

4.3.2. Knowledge-Driven Security Enforcement for the Autoware System Autoware is a suite of autonomous driving stack software created by the Robot Operating System (ROS). Lowering the barriers to designing, creating, and deploying such platforms is one of the main missions of Autoware. To stimulate the advent of a multiplicity of excellent connected vehicles whose automotive software and hardware massively inter-operate and to boost the safety of automated buses certified to transport passengers in Finland, this project needs to tackle many of the most pressing issues in autonomous driving.

4.3.1. Intrusion Detection Systems for the Connected Cars With the increasing flourish of all sorts of sensors and control processors in the vehicle, the modern-day cars accomplish an objective of providing not only safety-critical operation but also an enormous potential for creating an additional value and comfort for drivers, passengers, etc. Typically such scenarios are often coined like a "connected car." Recognizing the great profits from a connected vehicles ecosystem has become a key topic in the automotive industry, and it has motivated us to conduct a serious study of the cybersecurity in the automotive ecosystem.

In this section, we present applications and case studies of our proposed AI-aided intrusion detection systems (IDS), which are beneficial to ensuring the cybersecurity and system's safety in autonomous vehicles.

5. Evaluation and Performance Metrics

Doll and Loftesness evaluated preprocessors through their framework by using three criteria: precision, timeliness, and guidance. Precision is the factor that considers false positive and negative rates. It encourages us to have high true negatives and true positives and low false positive and negatives. Precision could be achieved using single or multiple preprocessing tools. Timeliness assists the analyst by detecting the intrusion as fast as possible. In real-world applications, low to medium detection accuracy in a quick time might be better for real-time testing. Finally, guidance serves as a preprocessing metric that quantifies the number of analysts required to analyze the data. A preprocessing system that improves itself enables less involvement of analysts. In other words, an effective preprocessor reduces human intervention.

Some of the metrics used in evaluating the adaptive process of an adaptive system are change detection, monitoring and reconfiguring, and verification and validation. Change detection will capture changes in input during adaptive processes. Monitoring and reconfiguring will assess the systems during adaptation and adaptive processes. Verification and validation will determine the validity of changes before deployment.

In typical IDSA systems, it should possess the following attributes as one of the IAQ metrics: autonomy in decision making, self-diagnosing, self-reasoning, adaptive to different situations, and self-correction when the situation is not to its desired level.

Intrusion detection systems are often evaluated using various metrics. In the context of adaptive intrusion detection, traditional performance metrics are still relevant, as intelligence-driven adaptive systems become essential. Nevertheless, there are not many works tackling the evaluation of network intrusion detection as an adaptive process. Most of them evaluate the preprocessors instead. Furthermore, most evaluations of such systems are purely simulation-based, which is unfit for adaptation since they are reactive tools. We opine that it is time to look into methods used to make adaptive simulations and the rules or protocols used to update preprocessors or network intrusion detection systems. Highly intelligent systems are good, but misuse will be harmful.

5.1. Common Metrics for IDS Evaluation

It is hard to make a performance comparison for intrusion detection systems (IDS) because data periods and conditions are different for each IDS. Furthermore, when IDS is deployed, the attack signature dataset will be short and the selective database might not be applicable on a practical scale. Despite these limitations, the 1995 DARPA evaluation programs and KDD Cup 1999 Special Report on intrusion detection show excellent perspectives from the proposed metrics in IDS performance assessment. These databases and metrics are valuable assets for an IDS performance assessment, which have an opportunity to easily compare IDS performances with and without each changing parameter in a real-world setting.

IDS performance assessment and comparison is a primary stage to select, deploy, configure, and update the best IDS system in practical use. In general, for each IDS, there are various levels of metrics such as attack coverage and cost-effectiveness. To evaluate and compare IDS at a reasonable cost, appropriate metrics should be utilized. The choice of an appropriate metric or metrics depends on how IDS should be utilized as well as how to measure. Also, the best measurement approach might be different depending on requirements. However, there is a lack of common definitions and tools for IDS metrics.

In this section, we overview common metrics used in numerous IDS evaluation-related studies. Also, we describe metrics employed in two well-known IDS evaluation systems such as the 1995 DARPA evaluation program and the KDD Cup 1999 Special Report on intrusion detection.

5.2. Performance Evaluation in Real-world Scenarios

We have all of the above-mentioned concerns for conducting large-scale tests or field tests. Since experimental study is an important step for evaluating the intrusion detection systems in real-world situations, we think the simulation and a testbed are necessary to measure the performance in a real-world setting. We then discuss the current use of simulators and future solutions to the problems. In particular, we recommend that a remarkable distributed simulator be designed to perform realistic field tests in the virtual environment. In such a way, security tests for the specific safety layer or other parts critical to the vehicle, as well as for the modules of ADAS, can be conducted without any modifications to a real car.

The real-world settings are, besides simulation, another testbed system for adaptive intrusion detection systems. However, building a realistic testbed for evaluating autonomous vehicle

cybersecurity is not practical. Firstly, it requires many cars. It is not cost-effective to build a testing fleet with a large number of vehicles for research. Normally, limited resources are granted for security evaluation for a particular research task. Secondly, sophisticated security services are already deployed on modern vehicles, such as cryptography hardware used for reliable secure communication and safety layers provided out of coverage. It is unrealistic to perform any field tests since there is no real vehicle penetration. Thirdly, the scan/filter rules employed by the intrusion detection systems are commonly thought to be visible to the attackers in a real-world setting; otherwise, the performance of the intrusion detection system is overestimated. However, it also brings concerns about ethics and local laws. It is acceptable to use "ethical hacking" to test system security, but its scope and technique are limited. Any testing tools used that might modify the vehicle should be certified and the same as any changes to the real vehicle configuration.

6. Challenges and Future Directions

Building a comprehensive IDS-based vehicle cybersecurity mechanism by combining it into currently available vehicular systems is a complex task, and meeting future challenges will require a focus on what we characterize as primarily six different research areas. Based on our discussion in the previous sections, the typology of the open challenges and possible future research paths for developing and deploying an adaptive intrusion detection system into the autonomous vehicle ecosystem are presented. We will now take a closer look at each cluster, presenting the limitations and approaches of current work and exploring what different positioning may be assumed to help make the automotive industry more secure and trustworthy.

In this section, we will discuss the main research challenges we face and propose various directions for future research. Our proposed typology to classify the challenges and future directions for combining the adaptive intrusion detection system into the vehicle cybersecurity ecosystem is presented in Section 6.1. Finally, we present our conclusions and summarize our main contributions in Section 6.2.

6.1. Emerging Threats in Autonomous Vehicle Ecosystems

Recent results are presented, including a functionally complete emulation of the MobileNet SSD v1 and evaluation of several ASDs and SMT solvers. These results suggest that even tiny

perturbations are capable of causing signed, potentially verified, disagreements. With base perturbation attack precision over 90% for norms up to 0.2734, adversarially constrained OCO moments attack precision over 92% for norms up to 0.0510, and adversarially constrained OCO backprop attack precision over 50% for norms up to 0.0650, the authors were able to achieve a signed attack success rate. The results were based on an early study aimed at discovering the ASD/SMT limits of the MN SSD v1, with likelihood to a ground truthful state utilized an emulated validation methodology. The current study jumps ahead to the new filters discovered (entropy and the standard deviation of the squared softmax output, which are used for detection) and applies them to the problem scenario. If the AVs can't get confused, these experiments would still observe perturbations and conclude that less accurate models might misclassify. Finally, they will draw their attack signatures. Emulation data was collected to provide meaningful Attack Signatures for the AV Ecosystem Intrusion Detector while avoiding overfitting the detection model in the presence of adversarial attacks.

The automotive industry is betting billions on the development of self-driving or autonomous vehicles. The potential value of the data that AVs produce is staggering, and hackers are already chomping at the bit. They've already figured out how to scam the data and mislead the AVs. Fake guardrails and similar riddles may hoodwink AVs into interpreting the data around them falsely or modeling it erroneously. Complex decisions that use a deep learning-based perception pathway might lead to disasters or accidents. All kinds of attacks, which are not worrying for standard vehicles, might lead to accidents if the AV doesn't properly interpret the data. It’s all the more critical to detect these attacks quickly and accurately if the rapid learning and decision making of the AV are to be fully realized. Public trust could easily erode if the industry does not take this seriously. Treating disagreement as detection signatures, SMT is used to find attack signatures for efficient detection.

6.2. Scalability and Resource Constraints

It is possible to experimentally determine adaptive thresholds according to changing conditions, but this becomes adversarial when intruders also want to find their limits. We also argue that the constant adjustment with thresholds that need real-time data might be detrimental and it may need to be overcome by implementing cascades of models for automotive systems. As observed in the past, less sophisticated models can contribute with alerting to more complex models when not sure, and these complex models can seek a call

center interaction. These more sophisticated models can, in turn, sustain more complex models that achieve the trade-offs among performance, precision, and latency constraints, shifting more complex models offline if not needed effectively. These models still need the audio-visual interaction capabilities, but they might not run with millisecond constraints. With these different models, we can also keep their resource consumption at bay. We may even cascade network models at the edge, at the aggregation and core domains to prevent wrong data from wasting computational power at different cloud offerings.

After a little research, one may feel comfortable deploying single models in scenarios with only autonomous vehicles, but may still be concerned about their scalability to larger populations like the one depicted in Figure 9. There is enough evidence to show that benign activity in infrastructure providers directly depends on real-time analytics and human intervention in a call center, especially at scale like the one depicted in the picture. To address alerts, parameterless models have thresholds – low thresholds may generate too many false positives, while high thresholds may miss some true positives. These are fixed parameters in the runtime!

7. Conclusion and Recommendations

We see, of course, that there are still long steps towards practical deployment. To make sure the collaborative learning architecture has something to learn from besides the operability of the classifier and to dynamically adapt the classifier staff, we take traffic monitoring a 2-tier approach: the first tier sniffs only the incoming messages of a vehicle; from this, the second tier sniffs the outgoing messages that are the response to the incoming ones. Such an LOO or leave-one-out monitoring approach is feasible because the majority of the vehicles are either in the position of sending or only in the position of receiving data. This is where the proposed approximate regular expression matching takes in. Initially, we showed some good results on synthetic datasets gathered by real sensor equipment. However, to establish that the proposed sniffer can indeed meet most of the real-time requirements of the vehicle intrusion detection task in practice, the next steps are to implement and evaluate experimentally its classifier against different trains of real data flowing on vehicular networks during different phases of multiple real driving tests. With successful experiments, once we find reliable non-collision datasets to create an accurate baseline, we hope our work will provide, in a related

development step, the first baseline performance metrics for the vehicle intrusion detection classification task.

This paper has described the necessity and the cruciality of deploying an effective intrusion detection system customized for the vehicular network. For this, we presented a candidate design and discussed several potential challenges to the development of a real-time vehicular communication sniffer. We particularly pointed out challenges and respective solution investigations like collaborative learning and approximate regular expression matching to alleviate the real-time performance and dependability bottlenecks of the proposed sniffer system. Simulations showed that both the collaborative learning-based classifiers and approximate regular expression matching could satisfy the real-time response requirements of the vehicle intrusion detection task.

7.1. Summary of Key Findings

These are important findings that this study has contributed in-depth insights about the present state of intrusion detection technologies for Level 4 SAE autonomous systems. It is believed that the pattern of finding data labels from physical system interrogation and manipulating either of the pipe of Feature Engineering and Training step-by-step procedures would be relevant in other cybersecurity contexts. The study bears important implications for accelerating the deep learning approach of the cyber-physical system research and provides useful support for practitioners in all stages of cyber resilience of autonomous system cybersecurity.

Overview of Study: This chapter has presented several intrusion detection solutions that are found to be promising for deployment in autonomous vehicle systems. It is found that while several publicly available works are available for providing guidance to intrusion detection methods for a general networked system, there are some significant differences that researchers must keep in mind for the autonomous vehicle context. Given the premium that is placed on security, unpredictability of intent and incoming traffic, the need for complex machine-learning based systems, the requirement for minimizing false positives and an emerging demand for runtime system feedback — the study focused on learning-based methods for providing the proposed solutions for Model, Sensing, Connection and Operational Infrastructure.

7.2. Practical Recommendations for Implementation

The objective of the A-IDS must be the security of processing, analysis, and related traffic, not the processing capacity of A-IDS. An important issue related to the number of smart transport network nodes is the scalability of A-IDS. This is a challenge caused by the rapidly growing processing power and traffic on various transport system nodes. With the wide use of in-network data analytics at the edge, and the increasing number of low data physics-based edge processing solutions in the form of the Internet of Things and Cyber-Physical Systems, this challenge could become crucial. Due to the security issue, the main goal for A-IDS is security, not the processing or analysis capacity of the A-IDS.

Each network node has its own A-IDS. Modern computer networks in transport CAV ecosystems are composed of a hybrid combination of various technologies. In addition to local network Ethernet buses, ubiquitous technologies such as WiFi and Bluetooth wireless transfer, or low delay, controlled, short-range radar, laser, or infrared strong light communications, can also be used in internal communication between CAVs and infrastructure such as traffic lights. Each transport network node should be protected by its own A-IDS. Since the quantity and speed of attacks will increase over time, cyber attacks can have a real-time impact on the current situation in the transport networks.

In our research, we focused on the use of A-IDS for CAV ecosystems. A-IDS learn from the current situation of the transport network and do not require the need to simulate specific attack scenarios. A-IDS are able to notice new types of attacks long before they begin to cause real damage. Using the proposed framework, we can also deal with new or recently discovered 0-day vulnerabilities. Although the main focus of that paper was on A-IDS training, we also believe that the result can be adapted to different research areas.

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