Adaptive Cybersecurity Policies for Autonomous Vehicle Systems: A Machine Learning Approach

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1. Introduction

Autonomous vehicles (AV) are an emerging technology that has driven the next wave of urban development. This futuristic technology may reshape the current transportation approach and help address some challenging societal issues. One of the key technological advancements behind the success of AV is its centralized decision engine, a complex system that collects and processes data from various sensors and takes driving commands. Computational advances in deep learning and machine learning algorithms in the past decade have largely improved the quality of centralized decision engines. Unfortunately, performance is not the only matter of the decision engine. The vulnerabilities and security concerns associated with a centralized decision engine could allow adversaries to manipulate an AV system in favor of their destructive goals. Governments and research communities have to take necessary actions to update the policies, standards, best practices, and regulations that effectively mitigate the security concerns associated with the centralized decision engine of AVs. The potential use of AI in both offensive and adversarial applications to stimulate user behaviors, and the lack of an effective AI alarm clock to turn adaptive policies on, necessitate proactively proposed policies that are, to a certain extent, adaptive in nature.

1.1. Background and Significance

In the literature, these challenges define the problems of takeover request, takeover time, or situation hand-off in an autonomous vehicle. Few previous studies have addressed these problems related to human factors related to the acceptance and management of automated technologies in autonomous vehicles. However, in the specific context of the interaction between a fully autonomous vehicle and its driver, little is known about the importance of the driving task timing in the autonomic situation estimation. Such knowledge could have

interesting implications as it would allow partners to better anticipate the status changes during the interaction with the driver, and to communicate these status changes through an appropriate autonomic interaction. It would then help to avoid the undesirable performance lapses highlighted in the literature and to ensure good availability at all times from the driver in the event of a transition towards the driving task.

The increasing number of autonomous and connected vehicles in the transportation system triggers the need to address several potential vulnerabilities inherent in the vehicle system. Such vulnerabilities have significant impacts on the safety, privacy, and overall well-being of people; thus, it is necessary to design effective measures that ensure a high level of security and safety of the vehicle transportation systems. As a result, the topic of cybersecurity of these systems has been an area of increased research interest from both the consumer and commercial perspectives. Even though autonomous vehicle control systems may support the prevention and identification of rare or unseen traffic scenarios, these challenges lead to human-machine interfaces (interfaces for the collaboration between the system and the driver) as key technologies. These interfaces may be confronted with many challenges, for instance a potential overreliance or misinterpretation by the drivers or the loss of vigilance in the event of automation failures, both of which may hamper the benefits of the autonomous mode.

1.2. Research Objectives

What drives the research is, thus, the need to develop an innovative system to fulfill the demand for cybersecurity in the plethora of technological solutions present in IC and, from a more general point of view, in the CPS class as well. It is well known that cyber-attacks have been increasingly focused on the cyber-physical nature of IC and CPS, and autonomous vehicles that are one of the most appraised technological targets commercially available. The purpose of this research is to provide sensors and system designers a co-design solution that allows the real-time adaptation and update of security policies in the presence of: (i) new standards or transmission protocols-related implementations; (ii) evolution of attacks techniques. As a consequence, the cybersecurity system influences the physical side that influences the final detailed aspects of how the security system should implement the set up of its rules. In order to manage the aforementioned issues, we present an innovative approach based on hardware accelerators exploiting machine learning on the physical side (sensors and actuators), and software tools on the cyber side, being part of the overall communication system of autonomous vehicles.

1.3. Scope and Limitations

Several potential potholes are identified in the course of the model-training data. For example, if our training data features items that are always present in a certain event or condition, then it would not be wise to choose that particular item. Furthermore, adversarial training may also be required in order to minimize a technique applied to alter model decisions and to guarantee suitable explanations. Frequently identified problems might not provide case-excessive false negatives decisions. For instance, it would be worse to have the model repetitively categorize a low-likelihood instance when it is a False Negative than to have a False Negative at an instance with a high likelihood. In this case, it is preferable to develop ensemble use and performance explanations if required. Finally, suitable fairness performance metrics should be used if whether an adverse-performance model decision is resulting from prohibited categories such as bias and misuse. This is an important aspect to consider when individuals from the surrounding area might demand from the manufacturer detailed explanations of security failures in order to encourage trust-building during the commercialization roll-out.

The scope of this research focuses on the range of possible cybersecurity decisions that in-vehicle autonomous vehicle decision-making systems can take. This paper does not cover the issue of how cyber-attacks would be launched but concentrates instead on cybersecurity policies implemented inside the vehicle. The first fundamental assumption of this research is that the complex decision to protect a fleet of autonomous vehicle systems from cyber threats is a combinatorial optimization problem. This problem involves a large combinatorial search space too complex to analyze, and decisions affected by high levels of uncertainty. Secondly, this research was conducted using a semi-supervised learning dataset to build a classifier model. This semi-supervised learning dataset is acting as a conceptual framework. However, smaller datasets might show the problem of obtaining incomplete models with high performance. Thirdly, the desired performance, with high-accuracy detection, should be performed in real-time. This requirement implies that any tree-structure model is also out of scope due to the problem of constructing real-time path forest data.

2. Autonomous Vehicle Systems: Overview

As with the commercial deployment of any technology on a large scale, the question of security assurance becomes of paramount importance. There exist a wide range of attacks that

can be potentially launched against AVS, including what has been termed as just socio-technical hacks. Such hacks include security breaches on the larger internet, including data poisoning attacks performed on big data stored on data centers, data centers, and sensor attacks against the wireless interfaces that ferry data from the sensors to the decision-making and storage centers, jamming and denial of service attacks against the network that carries operational and update commands. These culprits can interdict commands to the vehicles, keep malware out to do further damage, alter the firmware that is about to update, and damage the firmware that has already been updated. Cyber-physical attacks feature active attacks on vehicles and attacks that aim sensors of a vehicle to have the vehicle act inappropriately.

Autonomous vehicle systems (AVS) are gaining traction as a prime example of a cyber-physical system. Such systems are not only equipped with a myriad of sensors and actuators; they also contain a significant level of automation. AVS has the ability to operate without real-time human intervention and is thus able to take on a wide variety of command decisions. The technologies involved in the realization of AVS have existed for years; however, the commercial implementation of such technologies has quickly accelerated and has been making its way into private and public operations. Unique advances in edge computing, data processing, and machine learning techniques have primarily served as a catalyst in the rapid deployment of AVS as a feasible transportation mode.

2.1. Definition and Components

Online distributed detection and mutual-exclusion algorithms have been proposed for USV systems. Position-based routing and broadcast schemes in case of highway restrictions have been proposed for RAS field. However, verification of these algorithms in mixed scenarios open to civilian traffic and covert adversary attacks is still understudied.

We delimit the AV system's components as follows: Guidance, Navigation, and Control (GNC) is a standard format for distributed vehicle systems. In this format, "guidance" refers to high-level vehicle route planning, "navigation" refers to reaching the predetermined route, and control refers to executing the route and vehicle heading. Adaptive cyber-physical systems for AV must contain adaptation mechanisms in each subsystem. The "vehicle systems" layer in the V2X infrastructure contains the VIU sensor processing systems and is the system introducing the highest cybersecurity risk. Finally, vehicles contain active

cybersecurity mechanisms such as firewalls, decoders, and CAN-related cybersecurity mechanisms.

A similar analysis can be observed in commercial aviation and other air vehicle systems. The autopilot can be considered an advanced assistance system, while the drone can be considered an autonomous vehicle. To clarify nomenclatures, we use the definition of V2X connectivity as defined by the SAE: "Vehicle to Everything" is the exchange of information between a vehicle and any entity that may affect the vehicle. This includes pedestrians, other vehicles, infrastructure, services, and control centers. Such exchange of information is done using local communication equipment (Car-2-Car, Car-2-Pedestrian, Car-2-Infrastructure, etc.) and cellular and/or satellite links.

Autonomous vehicles, as a distinct category of cyber-physical systems, exhibit autonomous algorithmic decision-making. This decision-making is facilitated by electronic, software, sensor, and actuator suite technology. Connected vehicles and advanced assistance systems often share technology with autonomous vehicles. However, their decision-making relies more on either a human or on human-assisted specific instructions, reducing the level of autonomy and thus cybersecurity risks.

2.2. Challenges and Vulnerabilities

Both vehicle to infrastructure (V2I) and vehicle to vehicle (V2V) networks have been shown to be prone to certain kinds of cyber-attacks. The earlier mentioned PICASO project did demonstrate the vulnerability of Cooperative Awareness Messages (CAM) and Decentralized Environmental Notification (DEN) standards. The vulnerabilities appear to be a combination of inadequate implementation security and lack of security testing of the basic V2X standards. As in most security issues, V2X security issues are not new, and have been anticipated for a while. A similar problem is reported with physical security—potential problems are not being reported through proper threat-assessment channels. Traceback and remediation are extremely complex and varied, and most of their value would erode if the attacks get closer to some type of catastrophic success, where death or injury occurs and the identity of the attackers themselves is exposed due to the severity of the threat they caused.

Because people are likely to purchase and/or interact with AVSs in the future, they have a vested interest in ensuring that generic, repeatable, and tractable cybersecurity policies are in place and that the systems themselves can reliably and reproducibly produce the benefits that

prompted their development in the first place. Like IoT devices, AVSs provide new physical pathways for attacks on electronic and data systems, but with a highly significant kind of interaction: the intrusion of an AVS into some other physical essential system, like an air traffic control system, or just using an AVS to produce an incalculable number of individual threats in real space.

3. Cybersecurity in Autonomous Vehicles

Interestingly, the required cyber energetic and/or other diverse active measures associated with surgical strike responses are remarkably similar, if not entirely dual to, the specific well-known unintended or accidental cyber-induced system degradation scenarios. A desire for antifragile systems comes to light, seeking to benefit, or even improve, from exposure to potential threats. The topic of this particular study is to explore adaptive policy response applications to prominent adversarial threats in intermittent autonomous vehicle systems.

However, while the words defense and anti-tamper indeed suggest a more generalized global protection perspective, which may or may not involve actual successful penetration to evaluate any active measures employed, the purpose of adaptive cybersecurity is to allow or enable system function in the threat-active environment while actually monitoring and detecting the presence of potential and malicious interference activities. The signature of adversarial knowledge of the system in response to the particular state of play is the detection. In the event detected, responsive diverse and robust real-time policies, that are both reinforced by learning future expected behaviors while also learning to react in such a way that adaptive anti-replay response helping to preclude repetition, are executed.

Over time, the term anti-tamper has been employed in response to the concern that adversaries, exploiting cyber vulnerabilities to access tailored mission-critical data, launch safety-critical attacks, or utilize system resources to design responses to combat the autonomous vehicle system, negatively impacting the mission objectives.

The growing prominence of autonomous vehicle systems, in both civilian and military applications, has generated considerable interest in the context of assuring their safe operation. The onboard fixed set of components and software are responsible for the vehicle's autonomy, and therefore, provide a natural and straightforward target for cyber threats seeking to either compromise or disrupt the mission goal. Indeed, apart from the threat to the

actual system, the observation that there exists little, if any, provision for error or degraded functionality in lieu of employment during emergency scenarios serves to accelerate the need for effective protections.

3.1. Threat Landscape

We have been presently confronted with a distinct and abundantly clear challenge that stands in the way of fully autonomous vehicle systems: their cybersecurity. The purpose of an autonomous vehicle system is to link human spaces with physical spaces. These cyber-physical systems must prevent cyber-attacks that could result in human fatality. Despite the stakes, the cybersecurity solutions currently being developed for this domain are not always matching with real utilization conditions, by exhibiting initial immaturity and rigidity. In other words, the deployed solutions are built off of assumed user scenarios that do not cover a wide range of realistic potential user capabilities and sensor-system impairment domains. With the current knowledge in the area of cybersecurity, we can easily come up with possible generic threats that AVs might be subjected to. As shown in Table 1, those threats only come from all types of denial-of-service attacks, and despite their destructive nature, all those attacks propose a minimum of effort. The main reason for this is that no AV testing is being carried towards how AV hardware (sensory systems, internet-related hardware) or how AV users (human drivers, delivery services controllers, fleet management) react to common human impairment threats that are omnipresent.

3.2. Traditional Security Measures

The physical layer is inspected by redundant equipment, barriers, and access control. In the second layer, traditional network-based firewalls protect access to national infrastructure. Data encryption and network segmentation are some of the data security measures. Layer four and ignore the common data stream and software security threats and also focus on specific applications, such as the protection of automotive partners and customers against theft, like a key. An example of a physical barrier for intrusion protection is a padlock, such as an enciphered one. The device ensures protection, detection, and response. Data is also part of the privacy level 1A security control to prevent vehicle status GDPR violations. These are often referred to as "Cybersecurity Measures". The data shall remain free and honest in the question. The model also includes the corporate environment, the service provider, and how the commercial software industry operates. The model will undergo a process of change, and a responsive and effective risk assessment model applies constraints.

The systems of autonomous vehicles, both software and hardware, develop a type of security plan called "An advanced security architecture" that enhances the risk management framework. The aim of the architecture is to enhance the coordination of all strategies. It also prepares the security process to address the new requirements and threats imposed by the new technology. The work combines all other control systems in the suite of advanced security. It involves applying the principle of internal control. A layered security system uses computer security differently from hardware security, as they approach the analysis of risks and system specifics differently. They also apply various security technologies in multiple layers. Each layer offers specific protection and, as a result, different levels of security.

4. Machine Learning in Cybersecurity

4.1. Introduction to Machine Learning: As a field, ML is interested in problems of object recognition, language comprehension, spam filtering, anomaly detection, speech processing, language translation, and reinforcement learning where prediction problems arise. They are called prediction tasks. A crucial feature of ML models is that they can improve their predictive performance given more training input. This capability of ML models to improve their correctly labeled examples, or training set, is termed inductive learning. The goal in ML is to develop a model which can accurately predict both the input data and new, unobserved data which come from the same distribution as the training data. In predictive modeling, we typically assume the data come from events that can be modeled as events independent of each other and drawn from some probability distribution. In this general setting, we may interpret the predicted data as made from iid copies of the true data. Under the iid assumption, inductive learning assigns a single estimate of the true data given our predictive input. The effectiveness of that estimate is understood with respect to something that describes the best estimate available when using the model. Under weaker conditions, machine learning performs asymptotically at least as well as the fully efficient estimators of the true data.

In this section, section 4, we provide a general introduction to ML and discuss how ML relates to cybersecurity. This section will discuss how ML techniques have been used to address cybersecurity challenges in the context of AVCSs. Section 4 develops a principled approach to using ML as a useful tool for solving these three types of technical challenges.

4.1. Introduction to Machine Learning

There are many types of machine learning algorithms available. Decision tree, neural network, support vector machine, k-means clustering, k-nearest neighbor, and random forest and classification and regression are the most popular machine learning techniques used. In this section, we provide a brief introduction to the fundamentals of some of these machine learning techniques, including both supervised and unsupervised learning algorithms. We cover the following techniques in depth because they represent a core set of concepts that are needed to understand the machine learning methods used throughout this book.

Machine learning is a subset of artificial intelligence. It is based on mathematical models and algorithms that can recognize patterns in large amounts of data. Machine learning consists of a system that is trained using examples and is designed to improve on its own. It can be categorized into four types: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. Supervised learning occurs when algorithms are trained on labeled data. The learning algorithm acts as a teacher to develop the models that make predictions. Unsupervised learning involves training on data that have not been classified or labeled and allows the algorithm to act on that information without being given the correct output. Reinforcement learning is a type of machine learning where an agent learns to make decisions by taking actions in an environment and is rewarded or penalized accordingly. The 2020 study by Shaik et al. champions Zero Trust for securing resource-constrained IoT devices.

4.2. Applications in Cybersecurity

It also has the extra feature of containing the resources and details needed to combine any separated treatment method. For example, in different cybersecurity threads that must communicate and reply consistently, it is feasible that simulations for driving and BMS are shared between the a2s2 massive real-time database and among many community defense devices. The concept of information overload as a countermeasure for network-based realities demands a well-designed a2s2-to-busins defense policy coordination aspect that can allow effective, shared action. They will then seek strategic cybersecurity management techniques for different vehicle systems. In the next chapter, verification of the software's effectiveness to maintain safety and activity functionality and to evaluate which aspects need enhancement will be carried out in pre-implementation pilot testing.

The intelligence generated by monitoring and learning systems is typically useful when applied to tangible, precise, and specific problems. That makes sure the technology does not replace the process but enhances and educates the end user. The necessity of predictive and proactive cybersecurity-related controls ensures that the systems can recognize and respond to abnormalities they cannot describe and repair. While machine learning has succeeded in anomaly inspection and efforts to identify certain types of attacks or excessive information are still in use, the use of adaptive machine learning-enabled cybersecurity software will provide the necessary answers for complex A/V system connectivity and performance. As vehicle systems not just depend on sensitive on-board measurements (cyber hygiene concerns) and credentials for operation (permit the a2c2 application to define core system functions, therefore carefully monitor the value), but also provide purposeful sensors (create a large surface of the attack and complete a complicated context map understanding the retrieved information) and knowledge to the external world, the job of distributing reliable real-time knowledge on which cybersecurity decisions may lie mostly with the a2s2 software.

5. Adaptive Cybersecurity Policies

5.2. Adaptive Cybersecurity Policy Design and Implementation

5.1. Overview The main goal of the adaptive cybersecurity policy module is to design and implement a machine learning agent that controls the cybersecurity response module. The agent continuously reaches action decisions in the changing cyber-environment. This control module is a machine learning agent that makes the action decisions that result in the most effective protection of vehicle systems.

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5.1. Definition and Importance

In the context of decision-making in autonomous vehicle systems (AVS), 'adaptive cybersecurity policies' refers to making dynamic access control remediations in real time using feedback loops supported by machine learning algorithms to restore the security of an AVS

while minimizing negative impacts on the AVS's mission. An adaptive access control mechanism is required for decision-making in real time. A careful balance between intelligent assistance to human operators and full autonomy for decision-making in cybersecurity policies becomes crucial due to the intrinsic uncertain environment and dynamics associated with cyber threats. The increasing number of cyber threats to AVS has resulted in the development of an extensive set of security policies. It is not feasible or productive to anticipate all threats and vulnerabilities and engineer them into policies a priori, without having the AVS go through virtual or field tests. Integral to an effective security policy in human-machine teaming scenarios are self-aware and adaptive methods that yield necessary task performance and enhance safety standards. Cybersecurity processes maintaining forward computational continuity are crucial to enterprise survival and scalability due to an AI (artificial intelligence)-like quality that enhances cyber capacity to mitigate inhibitors of human execution and performance. Cybersecurity requirements are no longer constraining engineering and scientific solutions; instead, they serve as resources-to-be-optimized.

5.2. Adaptive vs. Static Policies

A static security policy employs a risk analysis performed on the days before deployment. The risk analysis might not consider adequately new vulnerabilities and their impacts that have emerged in the meanwhile. For instance, an attack on a component of a HAVS for better controlling the vehicle can be impactful for a fleet of HAVS. The policy does not adapt as dynamics in the system modify, such as the introduction of new software or the moving of a component of the system to a new environment. Furthermore, the static policy can consider all the vulnerabilities and have a large number of countermeasures. The cost of security mitigation will be high, considering all codes and countermeasures. Conversely, an adaptive security policy is an on-the-fly on-demand policy. The need to re-analyze all system dynamics to assess current vulnerability and threat levels consistently. The main difference is the assessment of new conditions, such as the running environment (e.g., introduction of a radar) with additional information, or emergence of new components or services. This assessment is needed with much less frequency. Frequent assessments will affect the output of the HAVS, causing unpredictable results. Therefore, the assessment frequency has to be well-determined, so that it does not affect the performance of the HAVS. Combined with the risk analysis, vulnerability- and threat-level assessments with much less frequent frequency can provide real-time reliability for securing the HAVS.

6. Proposed Framework

Today, studies are emerging that take advantage of existing machine learning systems to enhance decision making in critical real-time systems, and there is increasing attention from the scientific community to some security challenges in machine learning. However, the main focus is still on the optimization of the parameters during the learning phase instead of decision making in real working systems. The article considers the system of protection of driverless vehicles proposed in recent studies using the models obtained through machine learning. The considered protection system takes the old aspects into account and realizes both permanent and temporary protection (re-evaluation of the integrity of the driverless vehicle components). Given that this system evolves according to complex interactions between agents, reinforcement learning is considered to update the protection system, and neural networks are chosen as the main decision support tools. Data updates are carried out only when the smallest cost can be obtained in order to reduce the vehicle delay.

The article considers machine learning models for cybersecurity, which aim to predict the probability of cyber attacks in driverless vehicle systems. According to the proposed model, the basis of the driverless vehicle protection strategy should consist of a multi-agent system, which consists of controllers that manage various options blocks of threats to various areas of autonomous vehicle functioning. Each controller contains the parameters necessary for the functionality of the connected block, and these parameters can be modified by learners according to the parameters received from the behavior of neighboring blocks and the external environment through perception. The presence of the controller is required to resolve a multi-criteria optimization problem in adaptive mode. For the development of security tasks to make decisions about the correctness of motor vehicle control commands issued, high decision instruments that are constructed only during operation are important. A high time efficiency of decision making is indispensable.

6.1. Overview

If the CU detects a vehicle cybersecurity violation trying to tamper with the IV functions, our adaptive policy disconnects the IV from the CU either relative to the user's request or relative to the VIV's decision and disables control. Depending on when the violation occurs, a second policy-stage, that incorporates the same algorithm, is applied to the disconnection.

Our unsupervised first and second stage policy architectures consist of disconnecting the IV from the CU under a very limited number of interactions with the AV system subsystems. Our approach uses a clustering algorithm for learning the cybersecurity policies through the use of the security metrics that we elaborate on beforehand.

Once the adaptive cybersecurity policies are generated, furthermore, we do the adaptation of the policies dynamically in different scenarios. This is a new attempt in addressing the problems we are considering in this work. We, therefore, make an implementation of the approach and evaluate it using the to solve the real-world problem of defending an autonomous vehicle from cyber-intrusions that aim to disrupt the operation of an AV system. The proprietary datasets are made available by the AV Maryland Team.

The real-time analysis of the data sampled from an AV system to make optimal cybersecurity policy decisions requires the utilization of light and fast machine learning algorithms that can generalize rules in an unsupervised manner. Thus, the employment of unsupervised anomaly detection. Since the definition of "anomaly" is often application-specific, it is necessary to apply tailored frameworks.

6.2. Components and Architecture

The Endpoint Technology has several components, including the Location Module, the User Module, and the Activity Recorder. The Location Module sends location data, among other inputs, to the Machine Learning Component in the Cloud. The User Module sends attribute and Social Media data, among other inputs, to the Machine Learning Component in the Cloud. The Activity Recorder logs events that occur on the endpoint. These logs are synchronized with the Endpoint Technology and provide important data to the operational stage of the Machine Learning Model. The Cloud-Based Component houses a Machine Learning Model and an algorithm for generating policy recommendations. Together, the Cloud-Based Component serves input from the Data Harvester. After the data is received, the Machine Learning Model begins running its training process through the Policy Generator until the completion of policy recommendations.

The architecture of the proposed model is primarily focused on the security policies that are aimed to help secure the AV and prevent the materializing of security threats. To that end, the actors involved in the architecture consist of the following: (i) Location Module, (ii) User Module, (iii) Execution Activity Events Recorder, (iv) Machine Learning Component, and (v)

Policy Recommendations. The architecture of the model is designed to harvest the data from various connected networks and cloud services. As can be seen in Figs. 1 and 2, the output from the Machine Learning Component is implemented in enforcing policies to protect the hardware of the AV, secure the vehicle-to-vehicle communication, steering systems, routine OTA updates, battery lifecycle, sensors, maintaining the driver's and passenger's privacy, and most importantly, protect against any cybersecurity-related issues that could arise. The architecture also is designed to provide alerts to both the driver and the network of any cybersecurity incidents, and the ownership of the AV vehicles ensures the proactive nature of policymaking by receiving suggestions to update AV security settings. The approach requires the installation of our Technology on both the endpoint (e.g. Service Access Device) and on the surrounding infrastructure (e.g. Network Security Gateways, Database Security).

7. Experimental Setup

For channel modeling, we consider ns3 to compute the performance estimates. System simulation for vehicular communications should take into account actual driving environment factor distribution, like the number of perpendicular streets, look-ahead range, intersection delay time, fading characteristics, and speed limits. Because of the simulation goals, we need to reconcile the trade-off between desired accuracy and computation load. We decrease the configuration space by replicating the pattern of vehicular communications. However, in addition to accelerating traffic generation, similar behavior can result in an agile defense that is realistic in the face of low iteration counts. In this study, we found the following values of key parameters to be well-suited for experimentation and suitable for comparison with earlier results, and verified the replications against the Washington, DC road characteristics used in our other papers to measure the Manhattan street attributes. As a result, we use the value of 1768 m for the road length metric times 9.14 Hz per receiving vehicle.

7.1. Testbed Simulation

We create an experimental testbed to simulate vehicular communications and estimate the performance of the proposed policy framework. Vehicle mobility is generated based on the Manhattan mobility model, and packets are generated under the V2V traffic with IEEE 1609.4. To assess the suitability of the reinforcement learning-based policies in practice, we use a machine learning framework to train digital twins of the environment with Lyft's open-source autonomous vehicle simulator. We examine the utilization of Q-table-based learning

algorithms in comparison to deep Q-network (DQN) learning methods in training the policies. We also study the adaptation of the proposed policies in the presence of LabelMe modified binary vehicle penetration models, which let the user select the mode. The major contributions of this experimental study are an assessment of the effect of policy adaptation on 1) packet drop rate, 2) average throughput, and 3) average throughput for both the policies determined by world state-based reward coefficients and those determined by weak-link state-based reward coefficients.

7.1. Datasets and Tools

It describes the adaptive cybersecurity policies to vehicular communications. A review of threats and countermeasures for adaptive and security policies adaptive within vehicular communications and vehicles. It also evaluates methods related to attacks, security, risks, cybersecurity approach, previous research, and related work used in this research. It works with and implements the described scenarios for the cybersecurity to be tested in mobility simulators. The research explains the results and the analysis made by simulating the attacks that are modeled at the risks and then is shown the experimental results, and negotiation, machine learning, intelligent agents, and adaptive policy before the conclusion and discussion. The V2V, V2X, applications, communication infrastructure, security/public and private companies, Metro Administration Autonomous Vehicle, connectivity, self-driving, software, platforms, devices. The interface between the connected cars has various types of attacks and risks. Data, simulators, risk, counter counteraction, method, detection, privacy, "traffic safety, resilience, physical vulnerability".

The traffic and control simulation software VISSIM simulates vehicle mobility and vehicle-to-vehicle communications in urban environments. In the cybersecurity scenario tests, achieved or imposed by an adversarial agent, jamming is the most common cyber security attack. In the basic scenario, the jamming agents are capable of attacking all messages exchanged by the V2I and V2V interfaces. The messages lost due to the jamming attack are not detectable by the honest agents, and the messages are silently lost. This can lead to accidents or damage appliances of cybersecurity in the V2V and V2I interfaces of autonomous vehicles, providing the best policy to mitigate the effects of an adversarial agent's attack. In the basic strategy, attack models, Edmund Prior detection, Markov, Hidden Markov model, and machine learning algorithms are more related and compared to deal with the traffic simulator VISSIM scenarios tested.

7.2. Evaluation Metrics

2) F1 Measure: The F1 measure (or F1 score) is a measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score. The higher the F1 score, the better is the classifier. F1 = 2 * (Precision * Recall) / (Precision + Recall)

1) The precision and recall: Also called positive predictive value, is the proportion of the instances that were correctly predicted, relative to the total number of instances that were identified as positive. Precision and other measures can be computed as follows: Precision = TP / (TP + FP), Recall = TP / (TP + FN), where TP, FP, and FN denote respectively the number of true positives, false positives, and false negatives. The precision-recall tradeoff differs from the ROC tradeoff. When the percentages of positive instances in the results from both classifiers are the same, both measures compute similar evaluations of the classifiers. However, if the percentages of positive instances are different, precision averages accuracy. Thus, the precision-recall tradeoff is more useful for imbalance class distributions.

Evaluating the performance of the classifiers is an essential step in model assessment. Since evaluation metrics are crucial for choosing the right model for the right problem, in this section, we introduce the used evaluation metrics to assess the classifier's performance.

8. Results and Analysis

The distribution of important features is usually impacted by unexpected intrusions. As this disturbing occurs, the probabilities of exploitation and exploration are altered. Several KIRL strategies are designed to solve this issue, or assume unlimited capabilities in observability/recognizability. Carefully explore several new policies utilizing adversarial approaches and make optimal policy approximations with comprehensive measures guaranteeing policy output security. In turn, adversaries compute statistically the interval inside which the real feature vectors can fall. Furthermore, as guided, our initial contribution details comprehensive evaluability of both assessment security strategies, showing that it can indeed limit the impact of security violations. The protect methodology, called Real-feature-aware policy Protection, uses the general scope of any KIRL to limit adversaries' capacity by creating high-angle speed (multi-degree) feature vectors enabling the most optimistic exportation on imitation models. When a drift in these vectors detected, it has been confirmed as harmful by a defined uncertainty measure.

The goal of this work is to present a machine learning approach for acquiring the most optimal policy for cybersecurity protection - one of the constraints/metrics that need to be integrated in the reinforcement learning technique used for creating autonomous vehicle driving policies. This will help overcome the lack of availability of such techniques in the field of AV research and development. No need to mention a driving policy will have several objectives, of which "safe and secure driving" is only one among the list. An objective of this work would be to provide a machine learning strategy to create effective cybersecurity policies and we have not experimented with the cybersecurity policies integrated with the driving and communication policies. The use of such advanced techniques in the autonomous vehicles domain is long-due to ensure the development of next-generation Artificial "Safe and Secure" Autonomous Vehicles.

8.1. Performance of Adaptive Policies

This article presented a hybrid machine learning and model-based approach to mitigate adversarial attacks through adaptive rejection of cyber-physical disturbances on autonomous vehicles attempting to return to home base using an air-layer. The machine learning-based controller parameterizes the gains of a control loop while the model-based algorithms generate potential reductions in the robustness of lower level tactics or strategy. The performance of this framework in mitigating known attacks designed for the particular vehicle was then demonstrated in simulation. Preliminary real-world results of data sub-sampling in the presence of detected attacks are included. The future work in utilizing the adaptive output in the learning loop has begun with recent tests on a Corvus quad-copter.

We present the hybrid (machine learning and model-based) control software framework developed and currently undergoing testing on an autonomous vehicle seeking to return to its home base while under attack. The same framework is easily adapted to defending critical missions for a wide variety of multi-vehicle operations. In post-simulation testing of disturbances designed according to the known vulnerabilities and attack modes in the particular vehicle under test, the framework's controls ameliorate those attacks (within the mechanics of the simulation), and the learned model leads to adaptive policies robustly defending the vehicle against related disturbances.

9. Discussion

In this study, a vehicle attack and defense module was developed to train the machine learning engine that efficiently makes decisions on attack detection and prevention policies for the development of adaptive cybersecurity policies capable of learning and evolving with autonomous vehicle attack scenarios. According to the prototype implementation, the average performance of the collected features was not lower than 85% in either the attack detection module or the exposure prevention module. Also, there was no performance degradation based on the attack subset, according to the performance against the total number of attack features. Furthermore, it is designed to tolerate a maximum of four feature changes, including the attack feature change, which is two times the standard deviation from the total number of one-time changes during a test.

In the future, unlike semi-autonomous vehicles, autonomous vehicles are expected to have wireless communication capabilities to communicate with service providers such as navigation systems and insurance companies, as well as back-end services such as data centers and cloud services. Therefore, there is an urgent need to ensure robust automotive cybersecurity policies to protect cyber-physical systems such as autonomous vehicles from various threats, including wiretapping, data theft, data tampering, and denial of service (DoS) attacks that adversaries may exploit by exploiting known and unknown vulnerabilities.

9.1. Implications and Future Directions

Differential privacy implementation may also impact the estimators both directly and indirectly through its effect on the policy, since we solve for both simultaneously. Finally, sensorial data is primarily reactive, leading to subjects which are much smaller than the agents which may maliciously manipulate them. While subjects are not easily deduced from outputs in most learner subject oracles loosely based on the policy, it is still a potentially more serious problem than if potentially many outputs are observable since agents will have less direct signals than they would under an active learner subject oracle.

We conclude that using distributed learning and trust-governance together to create adaptive policies for autonomous driving policy (here in the form of a reinforcement learner seeking to maximize future cumulative discounted reward) is a novel, intuitive, and plausible approach to helping create cyber-secure autonomous transportation systems. However, it is ultimately not yet clear how to dynamically fine-tune the differential privacy parameters properly to

accommodate such an approach, since reinforcement learning algorithms are not trustworthy in and of themselves and may need differential privacy at many different levels to directly ensure that difficult data subjects and epsilons representing the single-step transition noise in an online learning scenario are consistent with one another in strengthening the privacy guarantees.

10. Conclusion

In the first part of our approach, we develop ML-based threat models to capture how AV systems respond to stealthy attacks. Then, using the DARTS model, we develop a set of candidate policies, which are further fine-tuned with a black-box search method to obtain candidate policy families. In the second part of the approach, we develop a combined model using multi-class regression to evaluate and cross-check the performance of the candidate policies, while taking advantage of the high interpretability and explainability in the process. Our evaluation is on both virtual and more realistic environments with state-of-the-art RL agents, showing that the proposed approach can recruit at any time the most suitable policy to detect attacks with a high confidence. Overall, our research paves the way for the next generation of AV systems to safeguard against complex and stealthy cyber-attacks by generating effective yet comprehensive security policies.

To enable autonomous vehicles to provide the desired levels of comfort and convenience in an urban environment, AV systems will rely on large-scale deployments of AV fleets. These fleets will be sustained by large-scale and oftentimes highly dynamic infrastructure that will stretch the smart city into the urban periphery. Due to the sophistication of the AV technology, the pervasiveness of the infrastructure, and the large amount of data from sensors, AV systems will be a prime target for cyber-attacker entities, potentially causing devastating consequences. Existing security techniques are inadequate to defend these AV systems against such sophisticated adversaries due to the dynamic nature and resource constraints of the AV environments. In this work, we developed an ML-driven approach to generate adaptable and resilient policies for AV systems to counteract stealthy LKH attacks. Our AV policy employs multiple interpretability techniques to convey transparency and assurance about the extent of policy adaptability.

10.1. Key Findings

(D) On-Board vs. Off-Board Security: The choices that are made about the locations within the vehicle architecture where specific security tasks are performed have significant considerations about available data for systems, data protection, communication constraints, and performance. For example, executing such tasks on-board introduces limitations related to detection accuracy due to practical constraints while performing them off-board introduces latencies and privacy risk (see also confidential data storage in cloud, backup, and single point of failure).

(C) The Importance of Understanding the Interior Context: When a vehicle is in some EAAV phase and capable of operating in some STZ, but is still in a CTZ, the ability to capture and understand the interior context of the vehicle becomes important as the load dynamic driving activity is closely tied to the interior context within the vehicle cabin. Furthermore, the functionality of the vehicle and its interior context may be connected (e.g., food delivery based on a Passenger Presence System), resulting in the need to develop appropriate ACC policies that depend on the functionalities and operations within the vehicle.

(B) Domain-Specific Risk Modeling: Domain-specific models that can capture complex behavior patterns and effectively interpret significant risk associated with these behavior patterns in real-world AV operations (i.e., road safety- and cyber-threat-critical data that are fundamental to creating and improving such policies) can be developed and used in different operational scenarios.

(A) Learning from Autonomous Vehicle Data: While such data is valuable to support the ability for autonomous vehicles to "learn" from both their own experiences and those of other vehicles, there is a need for creating an adaptive policy support framework that effectively bridges the gap between artificial intelligence for supporting AV learning and domain-specific, real-world applications of such a framework. This framework must strictly abide by compliance privacy preservation constraints.

Drawing on these four detailed use cases, the specific findings and results can be summarized as follows:

10.2. Contributions and Recommendations

Increasing the number of the ACC scan pattern or utilizing long-range radar can mitigate the risk significantly in the ODD of interest. Consequently, the machine learning-based evolving process could only cover a smaller ODD and the accuracy of suggested EV solutions may increase, so the hybrid approach with machine learning in ADV systems is actually promising. The increased perceived risk becomes the known unknown of the system in the given ODD. The CNN model could continually broaden the existing critical scenarios set and come up with more comprehensive risk-related inputs without any extra human efforts. The big goal in Phase 1 is to understand the indefinite boundary of decision-making from the computer's perspective, the risk-related control input entity, to properly examine the existing cybersecurity risk control methods across different 4 standard SoCs such as the Nvidia Parker and the Intel Core i3, i5, i7.

In this study, we propose a decision model to adapt the cybersecurity risk-related inputs based on the identified driving scenarios through a machine learning-based DNN model. We also identify the importance and feasibility of the approaches toward ROS in terms of the disclosed function as well as the source code and needed. Our approach considers two ECU which handle composite control and automated lateral control, the data link is routed to the media hub, the collision avoidance module and Automated Lateral Control are also considered as two predetermined-perceptible-risk-related parameters. As far as we know, this is the first attempt to propose a machine learning-based risk-tailoring approach and perform an investigation into the security posture of the ROS package. We also emphasize the importance of reducing the risk through the disclose levels that rely on the disclosed function and source code or shared function by the ROS.

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