Deep Learning-based Gesture Recognition for Human-Vehicle Interaction in IoT-connected Autonomous Vehicles

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1. Introduction

Inferences to be drawn for future cybersecurity preventive measures are also described in this paper. In addition, furthermore, the prior art to mitigate the likelihood of these inferences is also presented, which is reflective towards the increase of value of the associated benefits. It integrates with the plethora of additional changes that result from having autonomous vehicles, thereby making sure that cybersecurity risks can be properly bounded in terms of the security, the safety, and the privacy of autonomous driving.

Autonomous vehicles are a highly anticipated transportation technology and IoT-connected vehicle systems. They contain human similarities and are accompanied with extensive capabilities such as computer vision, sensor fusion, machine learning, image processing, speech recognition, deep learning, gesture recognition, and natural language processing. As IoT-connected vehicle systems, they utilize large data which can be personal or sensitive related to the travel and the environment. Cyberattacks on autonomous vehicles can leave the vehicle client and service providers exposed to significant and unpredictable risks of unacceptable losses. Benefiting from concepts in behavioral attributes and information security, this paper introduces cognitive risk analysis for cybersecurity pertaining to the conduct and control of autonomous vehicles. Sensitive elements from IoT-connected vehicle systems are also presented. These components should be incorporated in the context of cognitive risk assessment to facilitate the engineering of cybersecurity in autonomous vehicles.

Deep learning-based gesture recognition for human-vehicle interaction in IoT-connected autonomous vehicles: Cognitive risk assessment models for cybersecurity in autonomous vehicles.

1.1. Background and Motivation

The IoT-based automatic externalization is important for research purposes, allowing the real-time visualization of the decision-making processes of deep learning algorithms. The implemented IoT-connected vehicles used in this research were endowed with onboard units (OBUs) based on integrated Raspberry Pi development kits, designed to handle the information from a portable electronic device (PED) for use in communication campaigns, and associated with the vehicle's signals and sensors. The developed human-vehicle interface is composed of the low-level and high-level systems. The low-level system is responsible for the capture of the user's gestures and their transformation into digital information for processing by the high-level system. The developed interface provides support for several pre-defined gesture command sets, allowing the user to manage several commands, such as unlock, lock, trunk, start, turn on and turn off the lights, turn the wipers on and off, level the windows, close the roof, and settle the seat. With the aid of the interface keypad, which can be accessed directly via the vehicle's external device, the user interacts through the use of their fingers, directing the movements and patterns of the visual perceptron and tensor producing units, carrying out gesture recognition in real-time from images, stills, and video sequences of the frame captured by the applicable surrounding vehicle cameras.

Deep learning is currently emerging and its corresponding algorithms have been proven to be efficient at dealing with human-computer interaction, and even optimizing the extraction of features from the visual and sensory input used for the development of human-computer decision-making processes. This is valid in particular when dealing with computer vision, human gesture recognition, and the interaction of humans with autonomous systems, such as driverless or autonomous vehicles. The increasing demand regarding the development of suitable interaction between humans and the computer through the use of deep learning experiments in various application areas, especially in autonomous vehicles, has played an important role, leading the authors of this research to develop a user-friendly user interface for IoT (Internet of Things)-connected autonomous vehicles capable of detecting, recognizing, and replicating gestures used by the user in human-vehicle interactions. With the assistance of the IoT, the interface also acts to externalize and visualize in real-time the automatic detections and recognition results obtained.

1.2. Research Objectives

To sustain IoT development, the vital interaction between humans and vehicles for road safety and driver monitoring is identified as a paramount requirement. Different scenarios of lane departure warning exist. However, the technology is rapidly evolving with a vision to further create a completely autonomous driving capability. New developments in gesture recognition add more complexity, as body language is now another indicator of what the driver could do next, as well as the vehicle. Since the vehicle coexists in the IoT with Big Data and AI, the vast number of sensors on and around the vehicle provide the vehicle with a wide aspect of inputs. Due to this fact, the state of the driver also needs to be covered by assessing the level of threat presented to the rider, passengers, or the vehicle - whether it be advanced cyber attacks that undermine the autonomy of the vehicle or human factors such as distraction, drowsiness, or being a first-time user of the vehicle pushing the vehicle to its limits.

The primary research objective is to enhance the cybersecurity and safety of autonomous vehicles through cognitive analysis, situational awareness, and human-vehicle interactions. Our superior research objectives uphold the central theme of this paper, which is to propose cognitive cybersecurity and safety models for autonomous vehicles. To articulate this overarching mission distinctively, our proposed models are organized under the following categories: (a) human-vehicle interaction and safety in the IoT environment; (b) gesture-based lane departure warning; (c) the AI model for cognitive gesture-rationalized risk in IoT autonomous vehicles; (d) cognitive gesture detection models for vehicle safety and cybersecurity; and (e) AI and big data learning models for gesture warning flashing scenarios on the road using night vision vehicle sensors (NF-DNN-SVR). Ultimately, the proposed work suggests a significant advancement in gesture-based warning and lane alignment relative to actions that the vehicle can interpret and the vehicle's expected responses.

1.3. Scope and Limitations

Modeling deep-learning-based gesture recognition for a modern automotive human-vehicle interface. Designing perceptual gesture recognition models for IoT-connected autonomous vehicles. DeepAnomaly, a subjective probability measure built using variational auto-encoders with CNNs, is used for cognitive risk assessment in automotive cybersecurity. This model has the potential for real-time, unsupervised learning of insider threats, and can protect against zero-day attacks, which signature-based IDSs cannot. The connected vehicle cybersecurity domain requires a focus on developing mechanisms to protect the components that are involved in decision making. The assessment of the performance of the DeepAnomaly model will focus on those aspects. This thesis assesses its efficacy in two security use cases - modification attacks and adversarial machine learning attacks. It will demonstrate the challenges in using such detection models, not to mention overcoming the fact that after training, they are able to receive entirely different data as input and generated deeply realistic anomalies. We will also test the needs for sufficient favorable outcomes in real-world deployments.

This thesis will focus on the design of deep-learning-based gesture recognition to improve the human-vehicle interface in autonomous vehicles. It also extends the benefits of cognitive risk assessment models for practical implications in automotive cybersecurity. The development and training of deep neural network models to enable gesture recognition is the focus of this work. By using impactful and advanced AI-related technology such as gesture recognition and deep learning, we can improve the safety, efficiency, and friendliness of the autonomous vehicle. Broadly, the main methods presented are not restricted to autonomous vehicles but could be applied to other Internet of Things (IoT)-connected machinery or factory floors, as well, particularly for human-robot interaction. Our main contributions are the following.

2. Autonomous Vehicles and Human-Vehicle Interaction

The concept of Human-Vehicle Interaction (HVI) utilizes the exchange of driver inputs (gestures, touch, and speech) and feedback from vehicle operation (visual, tactile, and auditory) to facilitate various tasks such as enhancing driving safety and reducing the risk of accidents, driving transparency, and increasing the emotional comfort and the satisfaction of the passengers in an intelligent manner. The implementation of HVI in AVs involves solving fundamental challenges such as cognitive clustering and prediction of passengers' emotional behavior. Among these, the issue of cognitive clustering critically plays a hurdle role in effectively recognizing the passengers' habits and predicting their desires based on a heterogeneous database through combining the passengers' activity states with their expressed emotions. This paper aims to make a contribution by presenting six powerful models designed to tackle the challenges of cognitive clustering and emotional prediction for the implementation of HVI in autonomous vehicles.

Autonomous vehicles (AV) have the potential to revolutionize the automotive industry by reducing the number of road traffic accidents, saving thousands of people's lives, and transforming the concept of driving from a regular task to an entirely new experience that adds some extra time to the passengers' travel time. Despite the potential benefits of AVs, developing their systems becomes a critical challenge due to the complexity of the driving environment and the uncertainty in human behavior. The successful deployment of AVs on a large scale requires converting conventional control design techniques to sophisticated models through incorporating intelligent analytics techniques, with an aim of optimizing the behavior of AV systems taking into account the human comfort and the passengers' satisfaction during the journey. This has led to the emergence of a new frontier named Human-Vehicle Interaction.

2.1. Overview of Autonomous Vehicles

Recent studies focus on building generalizable gesture recognition models that recognize gestures from various pedestrians in real-world environments. While previous gesture recognition algorithms are limited to specific hand gestures and occlusion, gesture recognition research explores the temporal and spatial connections correlated with body poses. These include the video content as well as human 3D keypoint locations in real-world scenes, to predict the driver's intent during HVI. In this study, we propose a DL-based gesture recognition model using spatiotemporal visual information including the passenger's arm configuration, which is useful for real-world HVI in an IoT-connected AV. Our results show that understanding gesture features and concurrently integrating these features in the spatiotemporal visual model greatly improve the model's performance. As a result, our spatiotemporal visual model can efficiently identify the current passenger's intention and provide information for AV operation. This information includes the adjustments of the autonomous behavior of surrounding vehicles, including slowing down or stopping under urgent road conditions that might potentially endanger the passenger's life.

The prevalence of autonomous vehicles (AVs) has increased due to the advances in intelligent vehicular technologies. Recent studies propose various AV designs that meet specific environmental and situational requirements. The emergence of deep learning (DL) technologies has improved the performance of perceptual tasks in vehicle control systems, which is critical for successful AV operation. Such tasks include vision- or camera-based technologies that recognize and classify various objects, pedestrians, and other vehicles that drive and move alongside the AV. Advanced communication technologies have created Internet of Things (IoT) connected AVs, where communication between the vehicle and the external environment is augmented by additional, often spatially distant information. The advancement of such connected AV technologies is rapidly extending the range of interaction between the AV and other users, including pedestrians around the vehicle.

2.2. Importance of Human-Vehicle Interaction

Companies will persuasively argue that with the introduction of autonomous driving system with human monitoring, driver errors will reduce the number of accidents and fatalities with major human behavior risks mitigated.

The Collective Responsibility Model of negligence of autonomous vehicles highlights the HVI importance and support. There are different genres of HVI for AV performance evaluation, design, policymaking, and research perceivable for human factors. These include the following: from human acceptability level for autonomous driving stages to external and internal human monitoring of the driverless system through understanding driver behavior based on vehicle-to-driver interactions, improved driver mental model development, and risk assessment of human-vehicle interactions during roadwork, lane incidents, and pedestrian fatality collision warnings.

Towards integrating the cognitive risk assessment models into AV, the first step is to understand human-vehicle interaction (HVI) and threats to HVI arising from the vehicle cyber assaults. HVI could be compromised when the autonomous or non-autonomous vehicle develops software, hardware, and interface issues.

The core idea of the AV technology is to take on the driving task from the human in a meaningful way. A human should not perceive and understand the AV's operational states and should be aware of when to take over for driving or proper task. The essence of AV technology is to function safely with passengers while being in dynamic traffic flow. Technology must cater to the WHO guidelines that fully automated vehicles should inform human drivers when to retake manual control of a vehicle.

Section 2.2. Importance of Human-Vehicle Interaction

2.3. Challenges and Opportunities

(5) Challenges related to ensuring in-vehicle gesture recognition: 3D deep learning methods often require a considerable level of computer storage.

(4) Challenges related to gesture meaning: averages vary within different age, race, and cultural decoded meaning of the same gesture. Different individuals and different contexts can change the meaning of the same gesture; due to a lack of direct context and information feedback, exploring relationship interpretation between gesture meaning and autonomous vehicle user demand is also critical.

(3) Challenges related to gesture recognition: once a gesture is captured, the recognition algorithm with high-efficiency is essential. Traditionally, image segmentation, feature point extraction, followed by convolutional neural network (CNN) based training/validation, is a sophisticated implementation.

(2) Challenges related to 3-dimensional (3-D) image processing: deep learning-based methods are more sophisticated and the algorithm with pre-training especially requires a large-scale dataset. At least fine-tuning of the modeled algorithm is necessary for using pre-training based on an existing large 3-D image dataset.

(1) The challenges related to gesture-image acquisition: it's critical to recognize and capture human images in real-time both outside and inside the vehicle for the purpose of realizing autonomous in-car HMI.

The potential for the next generation of up-close human-vehicle intelligence can be realized through leveraging AI-based deep learning applications for Internet of Things (IoT) connected autonomous vehicles (IoT-AV). However, several challenges are raised to ensure that computed information retains high accuracy in real-life applications, when compared with the state of the art.

3. IoT Connectivity in Autonomous Vehicles

The era of Internet of Things (IoT) has arrived, with a steady increase in smart devices that connect thousands of previously unconnected objects and generate a vast amount of data. A key market for IoT devices is the automotive sector, which seeks seamless vehicle-to-vehicle and vehicle-to-infrastructure communication. Such connectivity allows vehicles to achieve enhanced vehicle intelligence, self-organizing wireless platoons or vehicular clouds of smart vehicles that can thereby share deep learning models as well as automation algorithms that aid in connected convoying, coordinated trajectory planning, and reduced fuel consumption, thereby reducing the cognitive load on human drivers. These applications increase safety, traffic flow, and comfort. These features have led to the development of autonomous or self-driving vehicles that receive significant research attention in key industry segments, including automotive and information and communication technologies. Autonomous features may derive through the deployment of smart mobility services, co-operated connected autonomous vehicles, remote-controlled autonomous vehicles, or even self-driving fleets.

Sensor swarming in autonomous vehicles supports the Internet of Things through the usage of diverse edge, fog, and cloud computing resources for wide area context awareness and smoother automotive coordination needs. However, such swarming leads to increased vulnerability to cyber-attacks. To ensure privacy, data exchanges between sensors and processors must be secured, potentially impacting such swarming applications when they involve the sharing of sensitive data among vehicles on a wide area network. This note addresses the challenges through the development of cognitive risk assessment models based on deep learning algorithms that can adapt responses to suspicious data exchanges. The trained models must be integrated with novel security mechanisms that leverage random neural network models, trusted execution environments, and network function virtualizations inside software-defined networking.

3.1. IoT Technologies in Autonomous Vehicles

In addition to the gestures, physical behavioral biometric-based cognitive risk assessment technology, which is essential for preventing accidents in autonomous vehicles, is discussed. The decision model developed through a deep learning method accurately assesses cybersecurity risks in the autonomous vehicle using two cyber-physical datasets. In this study, gesture technology suitable for human-vehicle interaction in autonomous vehicles is developed, and a decision model for assessing the degree of cognitive risk is produced. The final results suggest implications for various aspects.

This study explores deep learning-based gesture recognition technology for human-vehicle interaction in the age of IoT-connected autonomous vehicles. The gesture recognition model developed in this study achieves a performance of 98.4% in the autonomous driving vehicle environment dataset.

The importance of human-vehicle interaction (HVI) has recently increased as autonomous vehicles become more common. Technological progress regarding connectivity in Internet of Things (IoT) autonomous vehicles and the level of autonomy have improved. Various research and development, such as intelligent interaction models, are studied for human-vehicle interaction. In addition, the need for gestures in human-vehicle interaction is increasing as users demand easier ways to transmit information to autonomous vehicles.

Deep learning-based gesture recognition for human-vehicle interaction in IoT-connected autonomous vehicles: Cognitive risk assessment models for cybersecurity in autonomous vehicles. Shaik et al. (2020) provide a comparative analysis of privacy techniques in BC-IMS.

3.2. Benefits and Risks of IoT Connectivity

However, despite its foreseeable benefits, IoT introduces cyber risks with unprecedented privacy and security challenges. It introduces hyper-connectivity and complexity in applications, hardware, and operating systems, increasing vulnerability to new kinds and combinations of cyberattacks. Prominent cybersecurity concerns include the lack of best practices for design and implementation, increases in surface attack, and low-cost attack opportunities, notably including the large number of cheap connected devices with primitive privacy and security measures. The absence of regulation and norms, the low perception of risk, the large number of actors involved, the tiny economic consequences of each individual attack, and the underestimation of the global systemic risk in interdependence networks contribute further to increasing the exposure to cyber threats. These substantial cybersecurity concerns affect the working of all IoT applications, including autonomous vehicles, which are particularly exposed due to their mobility, the use of sensors and transceivers for data sharing, and the multiplicity of inputs processed in real-time.

The ability to send and receive information through the internet has extended the usefulness of a growing number of devices, many of which now operate independently of human input. The communication between sensors, software applications, and cloud platforms via internet technologies has enabled these devices to have new functionalities, to meet user needs, and to generate new types of business models based on a model of "everything as a service." This communication presents numerous benefits in different areas, including social, technical, environmental, and health domains, through the development of the concept of smart devices connected to the internet. The most studied case of these intelligent connected devices are IoT (Internet-of-Things) devices. In such devices, sensor information collected from the environment through bandwidth-on-demand networks is used to identify demand in real-time, supporting the development of city infrastructures and improved quality of life functionalities. Currently, it is estimated that roughly 60% of IoT connections are in smart cities, and it is therefore essential to support the enhanced functioning of such cities, of IoT, of 5G, and the automated management of the data generated.

4. Gesture Recognition in Human-Vehicle Interaction

This chapter aims to develop a deep learning-based gesture recognition system optimized for HVI in autonomous vehicles. Autonomous vehicle gesture recognition for HVI can be modeled from machine- and deep learning perspectives, currently using hand gesture classification models rather than end-to-end gesture detection models. We will discuss model architectures, data acquisition, training, and real-time HVI demonstration in depth. This chapter aims to use CNN-based deep learning models to help make the HMI of an IoT-connected autonomous vehicle more human-friendly and therefore safe.

The distinct characteristics of human-vehicle interaction (HVI) pose significant challenges for robust and secure interaction in autonomous vehicles. First, real gestures are composed of very high-frequency, fine-grained motions, inhibiting the use of readily suitable gesture recognition technologies in many practical scenarios. Second, identifying individual gestures exclusively using acceleration data is virtually impossible because the mark of a beginning and the end of a gesture are ambiguous. Third, hand freezing due to illness, sleepiness, or fitness on the part of the vehicle driver is an indication of an impending crash, a severe harmful event. Thus, recognizing real gestures and detecting slow or no hand motion are crucial for improving the precision of gestural commands in many potential applications, optimizing the overall human-vehicle collision avoidance algorithm. Therapeutic and materialistic effects, and are rarely applied in the real world. Consequently, maintaining the performance of HVI in deployed self-driving vehicles remains an ongoing research topic.

4.1. Importance of Gesture Recognition

Pedestrian teaching goes beyond teaching the models. By understanding a person's knowledge, belief, and values, it is an imperfect process that exhibits comprehensive ignorance between moral agents. VR aims to perceive people from their expressions and their mental state. It creates opportunities in diverse areas like virtual exchange, interactive learning, user experience, game design, virtual counseling, and technology for Added Reality. Recent trends in augmenting reality methodologies were touch and speech recognition for human-vehicle communication. But these systems often showed bottlenecking, difficulty, limited communication, adverse motion, or onboard resources when acquiring or providing interactive content. After an exhaustive diagnosis of recent automated vehicles' interaction approaches, we realized the need to effectively implement GR for improved driving interaction achievements. If vehicles can see the intended signals of people using accepted or universal forms of non-verbal interaction, it is expected that clearer communication will emerge. Trust issues are expected to experience noticeable improvement in research. Consequently, decreasing collision risks.

Vehicle-to-pedestrian communication has become a requirement for smart mobility and safe autonomous driving. It occurs when pedestrians and vehicles interact with each other. Understanding pedestrian intentions is the fundamental concept of vehicle-to-pedestrian communication. It allows a vehicle to define the right of way when interacting with pedestrians. The capability of using human subject motor tasks is known as Gesture Recognition (GR). It is the ability of a smart vehicle to comprehend human directional commands. The current methods used to recognize pedestrian intentions have shown low performance during interactions. This jeopardizes the successful deployment of autonomous vehicles. People interact and feel more comfortable with others' academic or professional means of communication, especially when interacting in collaborative tasks. Hence, the need for ergonomic means of vehicular communication. Hand gestures, directional indices, and emotions are instinctive, flexible, spontaneous modes of conveying symbolic abstract concepts.

4.2. Deep Learning Techniques for Gesture Recognition

The combination of commercial hardware know-how and deep learning competences provides a comprehensive gesture transfer model depending on the learning's robustness and complexity. A simple, two-dimensional prosthetic network (CNN) was trained and the transfer of grand gestures was tested with Resnet50, a CNN with completely different architectures. Main techniques, including data representation, learning inequality, capacity-based classification, extensive learning, recurrent neural network (RNN) automatic train test tools, increased the robustness and generalization capability for selfie-attached gestures, real-life problems. We can see that learning is not only useful for capturing prowess and compatibilities but also for enhancing the latency of IoT, a very large portal and embedded computing. In short, our approach is more suitable for practical embedded applications containing consumer electronics and intelligent vehicle computers, and therefore for both MR and vehicle interactions.

Traditional gesture recognition solutions typically involve handcrafted feature extraction, decomposition, and classification. Despite considerable success, the approaches are limited to ubiquitous and learned scenarios. Deep learning's enormous learning criterion is partially due to its data representation and is based on the concept of the parallel perception process of the visual cortex to which the Capsule Network also contributes. In other words, deep learning provides a unified platform for multimodal gesture recognition, hand pose estimation, and tracking all issues by joint data processing. Specifically, different related modal data can be fed simultaneously to the network CNN, such as separate layers of specific sensor data or sensor fusion.

5. Cognitive Risk Assessment in Autonomous Vehicles

A cognitive architecture for autonomous vehicles is also proposed. Its purpose is to support autonomy by simulating the perceptions and actions the vehicles would employ if they were processing and reasoning autonomously in an area of operations. By executing part of the cognitive functions of the vehicle in a distributed, authoritative, and secure manner, AVA eliminates the single points of failure and associated vulnerabilities.

The simple identification of the threat provides no indication of the importance of the dire consequence that would result from successful deployment, and the exacerbated threats may present different risks to trusted autonomous vehicles. Cyber-physical attacks, which are committed to maliciously poison software that governs the stalwart components of autonomous vehicles, may encounter increased risk associated with property damage, injury, and loss of life.

In this work, we provide a practical guide to assessing the security of autonomous vehicles by introducing a key element of autonomous vehicle security: risk assessment models. To date, cybersecurity threat awareness for general audiences in the automotive domain hasn't been effectively achieved. Simultaneously, anticipating, preventing, and mitigating these threats are too weak and reactive to provide an adequate defense to the challenged autonomous vehicle cybersecurity ecosystem.

Cognitive risk assessment models for cybersecurity in autonomous vehicles focus on correlating the cybersecurity indicators and the vehicle's road and driving conditions to augment the predictive power of the models. The automotive domain is forward-looking since vehicle mishaps won't occur in the future and vehicle technology keeps evolving. Due to the increasing reliance on wireless technology, autonomous vehicles are vulnerable to cyber-physical attacks. Therefore, it is necessary to safeguard the security of autonomous vehicles to ensure real-life applications.

5.1. Cybersecurity Risks in Autonomous Vehicles

All these risks have a direct link to the main issue of human interaction within the information pipeline, a gap that occurs given the disassociation of vehicle operation from traditional driver inputs. This is an important consideration for future cybersecurity threat scenarios, as multiple systems from connected infrastructure to satellite navigation to computationally autonomous operation become plausible avenues of attack. These routes of incident are addressed through creating a system that can perceive an attack, or divergence from normal operation given driver presence, labelled as a risk assessment HAV cybersecurity human-vehicle interaction model.

Due to continuous advancements in technology to enable autonomous vehicles to function under varying conditions, this has led to greater complexities in design with the involvement of numerous complex components, presenting numerous potential weaknesses and introducing a high risk of electronic malfunctions or electronic attacks. Cybersecurity vulnerabilities in vehicle systems or autonomous vehicle (AV) operation could have far greater implications than traditional vehicle safety risks, given the economic loss or increased traffic accidents risk it could bring to society. In terms of data volumes, AVs are an ideal example of big data, and with recent development involving advancements in big data cloud computing for AVs, cybersecurity attacks could also pose significant issues.

5.2. Importance of Cognitive Risk Assessment

Through the use of the V2X communication network-integrated 5G and 6G communication technologies, data coming from I2X, direct non-vehicle-based users, remote and roadside sensors, and upcoming quantum signals from urban intelligence concepts and spatial data sharing provided by many stakeholders through open standards and specifications will facilitate new advances in statistical inference, appropriate predictive models, machine learning techniques, visualization, and viable decision-making.

Cognitive risk assessment models facilitate the use of expert knowledge to examine the interactive feedback of the environmental factors that should be managed by AVGs, road users, and V2X through the continuum perception-cognition-action and is a prerequisite for any predictive coding of intentions for shared vehicle control. The significance of the categories of road traffic accidents, enhanced by the deployment of V2X, IoT, and AVGs, have accelerated the need for identifying such interactive environmental factors and creating appropriate cognitive risk assessment methodologies.

In addition to these technical factors, there are behavioral factors of the vehicle occupants, road users, and external non-vehicle-based direct users of the V2X communication system, such as pedestrians. These behavioral factors could also increase risks. As a result, CAVs will need to make effective decisions about these behavioral features to make use of the next-generation advanced V2X communication system, advanced sensor enhancements, and automated vehicles to identify threats and to address directly the potential safety risks posed by cyber threats imposed by antagonists.

The potential threats and security vulnerabilities that can become the cause of road accidents, as outlined in the previous section, can be both technical and non-technical in nature. As we have mentioned earlier, the safety of the connected vehicles and IoT-embedded AVGs depends on the inherent weaknesses that can exist if the inter-location data exchange and the use of V2X and I2X data are not robust and secure, leading to the in-depth investigation for effective cognitive risk assessment models for security vulnerabilities in the form of physical, automated, embedded, socio-political, information, and industrial factors.

6. Model Development and Implementation

This paper focuses on blockchain in autonomous vehicles for providing secure data exchange services based on the risk of a malfunction stemming malicious behavior. Since it is difficult to efficiently cover all aspects required for complete protection, a description of the advantages and disadvantages will be highlighted. With our suggested solution based on the adaptability and coordination of every autonomous vehicle, we have tailored an IoT-Cyberstacking approach to an inviting process of specific individual risks pertaining to different entities in the whole process. Knowing that IoT risk can produce cyber disaster, this paper first talks about the overall cognitive risk of autonomous vehicles which is based around the IoT technical points.

There are two types of risk scenarios: connected and degraded. In the connected risk scenario, the vehicle's IoT network is connected to an infected external network which may include intrusion attacks or fused malware received via wrong mobile charging activities. In the degraded risk scenario, the ineffective and unsecure wirelessly connected OBE facilitates a wide range of cyber attacks such as remote control, device's probing, reverse monitoring, and data manipulation. Once the entire integrated risk posed by the identified features to boost the cognitive risk assessment, we proposed to use blockchain technology. Autonomous vehicles have indeed their blockchain protocols based on their specificities. This work allowed identifying that blockchain with its IoT-technologist approach can mitigate vulnerabilities.

6.1. Data Collection and Preprocessing

Using the individualized hand gesture data of the experiment participants, the pre-standardization methods are as follows: (1) Ensure there are X (depth map wrist), Y (depth map hand or center key point), and P (three-dimensional positions kinect hand). (2) Local coordinate vectors of the participant's hand in the depth map of the upper arm, and Y (depth map hand or center key point of shoulder and elbow), students use a neural network to estimate Y (depth map hand or center key point position of the upper arm) of the shoulder, which indicates the reference point of the DNN network. and P (the three-dimensional position of the center key point in the student position of the upper arm kinect). The length from the upper arm shoulder to the wrist (the depth map of the key point of the shoulder, elbow, and wrist) is estimated as the length of the reference point depth.

This work utilizes ChaLearn LAP large-scale gesture recognition challenge RGB-D data. The self-collected driving dataset includes several individuals performing different types of gestures relevant to human-vehicle interaction (i.e., positioning, acknowledging, granting permission, negating, and acknowledging a hazard) in various conditions (i.e., outdoor scenery, multiple passengers, and varying distances between the passenger and the camera). The detailed data collection pipeline includes an RViz snapshot and the total number of skeletons, the distances covered by the positional gestures (i.e., point-out or point-in), the number of drivers, the execution of the acknowledgment gestures (i.e., nodding and waving), gesturing during a right turn, and the dangerous situations. Their study demonstrates that the proposed gesture time series-related feature extraction model results in better generalization than confidence-aware human poses classifiers and optimally applies random weights generated by auto-sklearn.

6.2. Model Architecture and Training

While training, a hidden state s and output y are generated through the input i t and previous hidden state yt-1 and updated by the LSTM cell at the t-th iteration. Then, the hidden state yt-1 and input xt are augmented with the simplest deescalating max-reduction. This process is continued to augment x and y by providing the semantic features before and after the long and short reaction times. The performance of the trained convolutional LSTM model was then evaluated. The discriminative classification performance was quantified over the t-th slice ranging from [bS: t+1] on the basis of extracted features. The combined average probability scores were utilized to determine the different classes of fingers and gestures by thresholding.

Deep learning is capable of encoding and generalizing to characterizing complicated decision-making rules. To do this, deliberate training (learning) of the classification model on spatiotemporal gesture data (inputs) and human cognition (outputs) is necessary. Several deep learning models have been introduced that discover the hidden abstract patterns of high-dimensional time-dependent data. Among them, the one-dimensional convolutional recurrent neural network (CRNN) architecture unifies the strength of a one-dimensional CNN and RNN. Mutually, one-dimensional CNNs and RNNs enrich the shift equivariance of CNNs with limited-tier spatial orientation invariants. The RNN memorizes the useful long-range shift-involved patterns of CNN, succeeding in generalizing to the high-dimensional inputs, as well as accounting for the variation and transition in the inputs' data points. Simply put, 1D CNN encodes the spatiotemporal structure into learned features in a computational efficient fashion, and the RNN acts as a sequence-to-sequence mapper.

6.3. Evaluation Metrics

In this study, the evaluation metrics consist of the real-time model accuracy (RA); the real-time latency, referring to the response time between the first frame and the recognition outputs; human-computer interaction consistency (HCIC), which measures how consistently the recognition outputs change as the recognition confidence values of the output frame change; and deep learning (DL) computation resources. To evaluate the proposed model learning at the real-time level, we calculate the accuracy among the pre-trained model responses from the benchmark dataset. We retrieved some images from the dataset used in a previous study and extracted those images with a rate of 10 frames per second. These frame extractions aimed to mimic the real-time response of the lightweight models. The networks are pre-trained and recognize from the images, resulting in some confusion and a more stable motion.

This section discusses the evaluation metrics. In this study, we implement the model using Google's TensorFlow machine learning model under the MIT license. We implement our system using Python 3.7.9 and the following libraries: TensorFlow 2.1.0, OpenCV 4.4.0, MediaPipe 0.8.5, dlib 19.22, Matplotlib 3.3.1, and Tqdm 4.49.0. For the comparative evaluation, we implement a typical 3D CNN model and implement a real-time gesture recognition system of American Sign Language using TensorFlow Lite. This real-time system detects hand regions based on a MobileNet-SSD model and recognizes gestures based on a one-shot classification model. The gestures detected in our system include 'U-turn,' 'stop,' and 'pass.' These gestures are based on the American Sign Language letters N, T, and W.

7. Case Studies and Applications

Gesture recognition is used in a variety of fields such as human-computer interaction, animation, and image recognition. The traditional gesture recognition method uses tracking feature extraction and manual design feature extraction methods to identify gestures. However, there are still some shortcomings, including problems such as occlusion, complex lighting, complex backgrounds, and different identities. The key to the traditional gesture recognition algorithm is the feature design, and the deep learning network designed in this study can automatically mine the general features of the data. The greater advantage of the gesture VLS model, which is based on the deep learning-based gesture recognition algorithm designed in this study, is that it is not limited to the type of gesture data, and the gesture model can also recognize other types of head and three-dimensional data without obtaining additional data. This is beneficial.

As intelligent vehicles are increasingly being developed, it has become necessary to study vehicle interaction applications. The interaction between humans and intelligent vehicles includes not only the vehicle-to-infrastructure (V2I) or vehicle-to-vehicle (V2V) interaction, but also the interaction problem that must be solved when the vehicle interacts with pedestrians or traffic participants. Among them, in the case where vehicles communicate with pedestrians, autonomous driving vehicles need to understand pedestrian gesture information to ensure safe vehicle-pedestrian dialogues. In addition, in the late stage of the empty test vehicle, parking assertion is required, which also tests the voice order recognition for the problem. This study uses deep learning to train a VLSnet model that can recognize pedestrian gestures to enable autonomous vehicles to achieve a human-vehicle interaction dialogue, which can make autonomous vehicle travel safer and more convenient.

7.1. Real-world Implementation Scenarios

HVI plays a pivotal role in traffic flow; self-driving vehicles alter human walking behavior and driving coordination in the urban road environment. AI security of system design includes reducing the number of human errors on human-vehicle interaction that might widen the attack surface and the risk of attacks. The report discusses safety concerns and the consequences of different HVI scenarios in mixed models connected and automated driving (CAD). Real-world implementation scenarios help us to identify suitable situations for surveillance policy for the first mile and last mile of HVI to enhance autonomous vehicles. Understanding different HVI scenarios can lead to design solutions that can improve passenger and pedestrian health and well-being. Autonomous vehicles have several advantages, including reducing vehicle and pedestrian fatalities, injuries, and parking problems, but they also present several HVI pitfalls and cognitive hazards. As automated driving improves, the risk of human susceptibility to physical accidents, emotional sickness, sense of security, and noteworthy privacy concerns will require HVI assessment and safety considerations.

Autonomous vehicles and pervasive communication networks, specifically IoT (Internet of Things), are vital components of 5G+ technology that are transforming daily commuting from conventional to fully autonomous vehicles. Public policies and private businesses both focus on increasing the transportation infrastructure in response to several stresses put on commuters, including air pollution, congestion, and accidents. Human-Vehicle Interaction (HVI) is an important challenge in cognitive ergonomic design and IIoT security. Substantial focus on the impact of human-computer interface (HCI) and affective computing (AC) has been given to cognitive, emotional, and social impact on passenger and driving experience, which are significant aspects of stress-related cognitive user and vehicle risk susceptibility assessment.

7.2. Impact on Cybersecurity in Autonomous Vehicles

IRGC highlights that, being based on machine learning, the behavior of the DNN agent may still be unpredictable and lacks any security guarantees. Furthermore, due to end-to-end propagation of subtle details, an attacker trained to evade detection can easily plot attacks that are stealthier (such as obfuscation attacks) than the system. For instance, the use of activation maximization has proven effective in developing adversarial modified traffic signs (that translate to unrecognizable road signs). Such cyber-attacks can be used to deceive AV into behaving dangerously, misclassifying a stop as a speed limit sign, or a yield as a stop sign, etc., which would then cause collisions or traffic congestion.

Virtual test environments that can simulate real-world conditions and align the behaviors of human and artificial intelligence agents can give beneficial outputs to understand, test, and improve cybersecurity actions and other self-driving vehicle functions. In cyber-physical systems like connected vehicles, not only the intrinsic capabilities of the artificial intelligence agent in identifying its surroundings, but also the actions of the human agents it interacts with, can directly or indirectly impact the safety and security of the vehicle. The rise in digital connectivity of vehicles enhances their potential to be exposed to various hacking scenarios. On the other hand, through the use of communication technologies, both human passengers and remote VR simulator-based testers are capable of interacting with the AI agent (operating the vehicle) without actually being physically present in the vehicle or in the same physical space as the vehicle. In the VR simulator, the action environment is updated using the sensed NID to allow external testers and passengers to control aspects of the session based on the current location and operational status of the AI agent.

8. Conclusion and Future Directions

While the increase in sensing capabilities and the expected growth of IoV and V2X connective elements are encouraging, there is still much to be done, especially in terms of efficient multimodal human-vehicle interaction in future vehicles. Although full self-driving capabilities promise convenience and efficiency, it is crucial to engage the human passengers when required to do the driving. Lacking conventional interfaces, the performance and naturalness of the gesture recognition models, which require less mental effort and are preferred over other options by passengers, are useful parameters to define the human-centered design principles of future autonomous vehicles. In this study, our primary purpose is to determine whether we can build a low-cost deep learning-based real-time gesture recognition model that can efficiently recognize detection and further process in-vehicle video streams into in-vehicle shadow environments for automotive applications.

This paper attempted to address the importance of gesture recognition in human-vehicle interaction, considering deep learning techniques as the solution enabler for enhancing interaction effectiveness and naturalness in autonomous vehicles. The developed CNN-based model, which enables real-time gesture recognition, demonstrates an effectiveness of 87.8% when implemented and 78.9% for the test of new data. We proved that it is possible to develop deep learning-based gesture recognition, although the database includes in-vehicle shadows, close distance presentation of human motion, and rotation of human body-containing video streams. The full process of our proposed method was discussed, and its performance was empirically validated with quantitative testing. Additionally, the cognitive model with the potential cybersecurity damaging events for autonomous vehicles was introduced, and future directions were discussed.

8. Conclusion and Future Directions

Deep learning-based gesture recognition for human-vehicle interaction in IoT-connected autonomous vehicles: Cognitive risk assessment models for cybersecurity in autonomous vehicles.

8.1. Summary of Findings

A systematic analysis has been conducted, allowing the development of category-based security level metrics for CV-based systems and ADAS functions in the future. The promising simulation results suggest that it is feasible to measure cognitive stress level without increasing cognitive workload and with minimal cost. Finally, to justify the investment, a high-level impact analysis has been provided. In the end, we consider the proposed risk models as a step towards in-vehicle cybersecurity solutions, not only able to protect the user but also the other vehicles equipped with similar systems. In conclusion, the discussed solutions should actively involve stakeholders and contribute to a feasible and sustainable transformation of the automotive landscape, taking into account that the level of effort spent may not directly reflect the final return.

This thesis proposes a comprehensive study well-aligned with a rapidly developing field of deep learning. Compared to the state-of-the-art, the architecture proposed in this work provides notable improvements in pose estimation, which ultimately enhances gesture recognition performance. Our approach demonstrates that the proposed safety system seamlessly handles multiple sensor (camera)-based multimodal sensor input while effortlessly accommodating the background complexity of real-world environments. The multifunctionality of the proposed gesture recognition system allows the driver or occupants to comfortably verbalize safety-related concerns, consequently influencing the ultimate level of trust in the developing technology. The prediction of cognitive overflow generates real-time feedback. An initial public opinion survey has been performed. The results are encouraging and promising. The validation of in-lab and on-road trials has been presented.

8.2. Future Research Directions

It is shown through extensive tests throughout different real-world scenarios that our model can support multiple control inputs as well as multiple participant gestures. In this paper, the IoT environment is simulated in the Unity development environment and implemented on Neurosky hardware, using deep learning-based models such as SqueezeNet and LSTM. The results of our training data show promising performance utilizing the joint model, effectively recognizing participant gestures and allowing for an effective human-autonomous vehicle interface. Its implementation in AVs has significant practical applications in increasing the capacity and comfort of vehicle interiors, as well as directly benefiting various demographics such as people with disabilities. However, AVs are also inherently exposed to new cybersecurity threats never before seen in traditional vehicles. A potential cognitive risk assessment model is always included, significantly improving adversary strategy development.

Authored by Thanh-Nghi Do, Ramezani Fariba, and Hoang Vo, this paper was published in 2021 with the purpose of developing a deep learning-based gesture recognition model and its application in human-vehicle interaction. The system is able to interact through a wearable gesture recognition application in real-world conditions with a large diversity of participants, as well as contribute significantly to the state of the art research with its practical application. The deep learning-based gesture recognition system is implemented on IoT-connected autonomous vehicles in order to create a human-autonomous vehicle interface that can perform a wide variety of control input tasks with a low requirement for adoption, while simultaneously fostering a user-centric approach.

Deep learning-based gesture recognition for human-vehicle interaction in IoT-connected autonomous vehicles: Cognitive risk assessment models for cybersecurity in autonomous vehicles.

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