Deep Learning for Autonomous Vehicle Sensor Data Analysis and Interpretation

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1. Introduction to Autonomous Vehicles and Sensor Data

As the number and the availability of sensors is increasing, deep learning-based data analytics also has already started to be introduced to process and interpret AV sensor data. Features extracted from sensor data are usually high-dimensional, complex, dynamic, noisy, chaotic, redundant, slow-ticking and multi-modal. In order to analyze and process such high-dimensional data, the traditional algorithms failed to cope with the analysis due to their intrinsic limitations. Special feature extraction needs pretty specific pre-knowledge and a lot of experiences by human. But deep learning models can calculate manifold effortly and can drive directly for sensor data and human can interpret only when it is failure case. Investigating modality-separated deep learning models are needed in depth for all sensor datas and to find unsupervised feature extraction methods without label information another expected research area. Training and fine-tuning of deep learning models for big-sized sensor data requires a lot of time and energy, and computer vision GPU and TPUs are important hardware to ease learning processes. Finally, a model optimization, hardware sensors and software architectural research is required for real-time systems [1].

The fast development of Artificial Intelligence (AI) and Deep Learning (DL) has revolutionized many areas, including Robotics and Autonomous Vehicles (AVs) [2]. Deep learning algorithms have already started to outperform traditional methods in perception, detection, tracking, scene understanding, action recognition, decision making, planning, control, navigation, and many other problems. Since 2011, the accuracy of object detection has been increasing dramatically after the introduction of Convolutional Neural Networks (CNNs). This has been used widely, and MIT started the road traffic recognition dataset Road32km from a car sensor, and also used Search Results dataset for object tracking in 2D and 3D using stereo and bird-eye view from several cameras and sensors. Deep learning has been successfully used in road traffic prediction as well. Deep Reinforcement Learning has been another way to assign values to actions and states, assign policies, and to optimize the environment decision-making problem by maximizing the Agent's reward with respect to designed and learned policies. Consequently, in the last years, deep learning and deep reinforcement learning performance for autonomous navigation has significantly improved, with many smart applications and commercial systems emerging. To achieve improved performance, there are hundreds of labs, SMEs, and companies working on precise maps, defined rules for AV networks, sensors development, and problems. Still, several challenges need to be solved based on sensor faults, sensor noise, instability, redundant knowledge, very large volume of sensor data, and sensor-consuming time for real-time tasks [3].

1.1. Overview of Autonomous Vehicles

Deep learning is increasingly being used to analyse the various sensor data coming from autonomous vehicles. Beyond traditional deep learning, unsupervised learning strategies known as self-supervised learning have also been introduced. As the amount of data collected, the number of sensors and the complexity of the data generated by these sensors are growing, detection and recognition of a surrounding environment and the prediction of what will happen in that environment have become a crucial point. Within this chapter, the various deep learning methods that are used to enrich the understanding of automotive sensors data are presented. These methods are capable to detect and recognize the surrounding environment, predict future events and improve hard sensor fusion. In each case, the chapter explains the most relevant works that are able to accomplish a specific task and also how the self-supervised learning seems to be a good strategy for training since it significantly reduces the problem of manual annotations [4]. Methods and architectures focus on computer vision and deep learning applied to camera images and also LiDAR data. Some other deep learning architectures have also been considered to improve the understanding of Inertial Measurement Unit (IMU) data and automotive Radar data, that are the most suitable sensors to collect informations left uncovered by cameras and LiDAR.

1.2. Types of Sensors Used in Autonomous Vehicles

LIDAR data provides a dense 3D point cloud of the environment. It hence gives exceptional depth perception compared to the other types of vision data. Point clouds and associated calibration methods are also less prone to showing scene-relative motions generated by the movement of ego vehicles, and hence provides immediate sub-meter scale accuracy without integration of the sensor model or an additional processing layer. LIDARs also provide direct geometrical properties such as cuboid dimensions, distances to various points and not just the reprojections of worldpoints into the camera's image plane. It is also one of the most expensive sensors. It faces a problem of sparse point clouds in adverse weather conditions (dust, smoke, fog etc.), and also have problems with specular surfaces like mirrors. But given the fact that a lot of useful information is not contained in skewed sensor modalities, additional multimodal sensors must be deployed. The primary overlap between LIDAR and camera is to employ RGB data being combined with the LIDAR data.

[5] There are three primary categories of sensors typically available for data acquisition in autonomous vehicles–vision, that provides images composed of objects captured with cameras, that provide images composed of captured objects presented as points in space, and that provide angular and radial position information about captured objects. While machine learning algorithms have made considerable advances, inductive biases in reasoning about agents based on their visual stimuli still exist. As such, accompanied by the use of deep multimodal learning techniques, autonomous vehicles are commonly equipped with other types of sensors (e.g. LIDARs, RADARs) to complement perceptual data provided by cameras. Strategies for combining sensor modalities based on maximal utilization of multimodal models (e.g. metrics based on mutual information) rather than ad-hoc heuristics, alongside training models on multimodal training data that is spatially, temporally, and biologically aligned algorithms are vital for achieving accurate estimation of multimodal data [6]

1.3. Importance of Sensor Data Analysis

In this paper, an extensive overview of deep learning strategies for AVs was presented. A summary of state-of-the-art sensor data analysis and sensor fusion strategies was presented, highlighting appropriate activation functions, loss functions, architectures, pre-trained transfer learning-based models, loss functions, regularization techniques, verbalizations, spectral decomposition, intensively benchmarked strategies, and training data, providing a comprehensive annotation of 135 layer-wise datasets. GoogLeNet has been ranked the top pre-trained deep Gait analysis and visual representation, and natural language processing research has been ranked as the most widely used pre-trained Transfer learning are widely used to prioritize pre-trained models and data. This database can be beneficial for researchers in AV applications and can be used to encrypt AV-based sensor fingerprint analysis applications and autonomous operations.

They offer robust, accurate, and precise properties and can solve a variety of different computer and statistical vision tasks, including object detection, image segmentation, object tracking, gesture recognition, human body reading, edge extraction, super-resolution and denoising, etc. For visual information representation, Convolutional Neural Networks, and for object detection information classification, Recurrent Neural Networks are widely used conventional network architectures. In this paper, we analyzed deep learning, fingerprints, designed for AVs by sensors, type, benchmarking, website, highlight specific, and brief activation functions, loss functions, and regularization existing in mainstream sensor-fingerprint-specific strategies.

[7] Autonomous vehicles (AVs) (Figure below) are a powerful tool to reduce greenhouse gas emissions and improve transportation system efficiency. Autonomous vehicles (AVs) with no human drivers at the wheel, and they are poised to disrupt the trillion-dollar transportation industry. Realizing the promise of AVs, however, requires they are designed and operated safely, efficiently, and in a manner that promotes the use of shared, electrified, and connected vehicle platforms while facilitating public transportation and shared mobility as a crucial component of the Multi-Modal Integrated Automated Low-Speed Vehicles (MIALV) ecosystem.[8] Although a variety of sensor technologies can be used in AVs, data from cameras, Light Detection and Ranging (LiDAR), and Radio Detection and Ranging (Radar) are most commonly used due to their active and passive advantages. To safely navigate in unprecedented and challenging environments, AVs continuously scale and track their surrounding by utilizing the sun's uncertainty from the sensory data. This information is much useful in challenging scenarios such as when waiting for the driver, when lane markings are covered, or when there are no solid driver and infrastructure, etc.

2. Fundamentals of Deep Learning

Sensors are designed to perceive and understand the local environment around the vehicle. For example, a LIDAR sensor is excellent at perceiving the shape of surrounding 3D objects, a radar sensor is great at observing the relative speed of these surrounding objects and a stereo vision system is great for extracting the 3D position and appearance of the surrounding environment [9]. Although each individual sensor is designed with its own unique ability and limitations, the output of each sensor contains information about the surrounding environment. In addition, it is believed that the collective understanding of the whole sensor set is a likely path forward to achieving a higher level of understanding of the local environment [10].

End-to-end learning, in which a neural network calculates the driving commands from the vehicle's input sensory data, is one of the most significant contributions that Deep Learning has made to designing intelligent vehicles . Existing research shows that deep neural networks, recurrent neural networks (RNN) in particular, are suitable for mapping sensory data to vehicle commands in order to carry out tasks like trajectory prediction and trajectory generation. In addition, we have observed self-supervised learning approaches that leverage large amounts of sensory data to train such neural networks by design, in order to create a strong supplementary learning signal [11]. Finally, a modular architecture for end-to-end vehicle control allows us to use different intermediate representations and to train lightweight, specialized networks in order to make this technique useful in real time.

2.1. Neural Networks

A neural network consists of many interconnections between artificial neurons, and these neurons can perform both linear and non-linear computations. The input layer of the neural network receives input from the environment, processes the data, and produces outputs in real time according to the universally learning algorithm, which is called the "weight update rule". The procedure of weight update is called "learning" [12]. Different learning tasks can correspond to different layer settings in a neural network. The full representation of the input data is often referred to as a "hidden layer", and has the function of extracting different features from the raw input data, while the output layer provides the final decoding. In the last step of the learning process, the neural network is repeatedly provided with a training sample until the relationship of the input and the output is automatically established when the training is successfully finished.

A type of artificial intelligence, "deep learning" emulates the biological neuron network mechanism of the human brain in an attempt to imbue a device with intelligence similar to the human brain's learning ability [13]. In data analytic applications, deep learning has been shown to be a very powerful tool to capture and replace human expertise and intuition, as well as being especially effective when sensory data from autonomous vehicles is to be interpreted rapidly and in real-time when a prediction or decision is required. In some sense, the term of "deep learning" is exchanged with "deep neural network" [14]. A neural network is an information processing paradigm that is inspired by the structure and functional features of biological neural networks, which attempts to get new knowledge or rules by means of "learning" from empirical data.

2.2. Deep Learning Architectures

Thus, nowadays, in autonomous driving, the segmentation of traffic scenes means to rely on more and more deep learning-based systems, which now show impressive performances. Actually, regarding segmentation performance, semi-supervised learning methods like those using LIDAR reflections, which could be a constraint to handle, helps even all of the most famous methodologies UVIS, UVNet, DV-Net to improve an upper bound of all the algorithms on a realistic and complex datasets especially in nighttime or adverse weather.

[15] [16] CNNs are the most appealing variant for vision-related tasks within the autonomous driving field. They are perceived as the strongest architecture to extract features from 2D image data. Deep architectural variants such as CNNs, Fully Convolutional Networks (FCNs) or U-nets have improved segmentation task performances since the end of 2015, when the famous FCN model was published. Lately, complex semantic segmentation networks like DeepLabv2 and pspnet were presented, forming a perceiving hierarchy over input that has been proven to significantly improve segmentation performance during the ImageNet Large Scale Visual Recognition Challenge 2012. Note that FCN performs well on the Cityscapes dataset with 20% unlabeled data out of training samples. Another technique using depth information and related to FCN and U-net architectures are the ones of the light-weighted DeepLab Mobile-LN, or the 3D SCNN and LedNet adaptable for real-time inferences, being very useful for the autonomous driving safety matter. Then, we have designed our own multi-sensor perfect understanding of traffic scenes approach that allows to predict high quality depth data.

2.3. Training and Optimization Techniques

The application based on this work with solutions from the bio-inspired autonomous energy-fueled vehicle is promising and can provide important further motivation for the continuation of the research. Primarily, these models anticipate the suitable adaptability of the add-on non-intrusive sensors: 3D cameras, laser sensors, and other Plug and Play designed in for the future mass production. The high performance is also expected under realistic conditions due to the replacement of the individual protective elements by the whole vehicle movements. Future work could be done with the usage of the deep learning models as the CBEV controller, for new generation periodic movement of CA-MECUEV. It is also shown that deep learning techniques can surpass the threshold compared with traditional exhaustive controllers, and minimize produce predictive and prescriptive forecasts.

[17] A branch of reinforcement deep learning called Q- Learning has been conducted to predict safe maneuver, especially for steering/accelerating/ braking, based on current state and future target states. Once again, the identified most promising technique is the Explainable metaphorically termed PX-Grad-CAM that has been applied to predict vehicle dynamics. It is a two-step application of the most recent, explainable denoiseCNN-LSTM model (trained for vehicle dynamics) with the PatchOverlap Grad-CAM matrix. PX-Grad-CAM is first used to help DeepQ- Learning (Action $Training Level), and then together to reveal that sensitive regions of input sensor frames which directly contribute to the "safe" predictions of dynamics. This study summarized information on the concerned application possibility of deep learning in the auto university energy conservation mobility system. More general concepts are also included. Often the trends of the most impactful preliminary study of deep learning techniques for the autonomous vehicle have been discussed. The work that appeared to be the most interesting, combined the most successful models, but also attempted to base the neural networks models on analyzed and interpreted data [field,.

3. Preprocessing Techniques for Sensor Data

Exploratory data analysis and preprocessing are used to understand, visualize, and detect outliers in sensor data [18]. Techniques such as scaling, quantization, and binarization are applied to reduce noise and remove outliers. Dimensionality reduction, feature extraction, and building feature vectors are essential for machine learning algorithms. Common extracted features for mental states detection include arithmetic mean, standard deviation, min, max, and others. Classification and clustering models are trained on 95% of the data and tested with the remaining 5%. Observations were taken from motion tracking sensors, and physiological and environmental sensors.relu activation function, one fully connected layer for each dataset.

Deep Learning-based methods have been widely used for deep sensor data analytical and interpretative tasks [19]. Feature selection is a crucial step in a classification problem due to its impact on the statistical properties of the output. As mentioned, the classification of real-time sensor data with deep learning methods is a rather challenging task due to the high variance of the sensor signal, correlated multivariate signals, unknown failure patterns, and noisy falsified signals. Herein the application of a qualitative, framework involving feature selection techniques is discussed to select pertinent features from a large array and quantify the feature set to facilitate a data classification task. The effectiveness of this feature selection technique is subsequently analyzed as it is implemented: using a complex, real-time signal from the powertrain collaboration of a car and the sensor bottleneck where less clarity in the captured sensor data in the auto sector.

3.1. Data Cleaning and Imputation

[20] The 3D time-series sensor data collected for the vehicle was pre-processed to clean the data by identifying the exercise sessions, removing erroneous or noisy data points, and dealing with the inconsistencies in sensor measurements. The IMU sensor data collected was thoroughly analyzed to remove irrelevant exercise sessions and to handle inconsistencies in the sensor measurements. The notebook IMU readings captured over time with sessions of exercises scattered in between each other. To only use relevant exercises, they were selected and disjoint the sessions from the other non-relevant content in the IMU readings. The start and the end of each session were identified using the kinematic solver algorithm, in which any session would have a start or end point when the sensor hanged upright for more than eight seconds. Once the relevant IMU content was selected after the kinematic solver algorithm, sessions started that were connected with each other. In all the valid sessions, there was an interruption maximum of 1.5 seconds at max in between different exercises, and that was removed manually.[21] The vehicle's IMU (Inertial Measurement Unit) data is stored as a sequential dataset containing thousands of data points within a session. However, the inertial sensor measurements are of human body motion sensor data, which is susceptible to being noisy. The pre-processing phase involved removing erroneous or noisy data points and handling inconsistencies in the sensor measurements. The cleaning and reconditioning of the relevant data was important so as to minimize the dataset's redundancy, which is the removal of overlapping and repeated exercises recorded with a second or third sensor. Furthermore, the relevant number of exercises is identified and sorted from the whole IMU data. To

accomplish the data pre-processing for the model training process of the Multimodal Deep Fusion Network (MDFN), the input data tensors for the MDFN were created.

3.2. Normalization and Standardization

Normalisation-based scaling of the battery voltage feature resulted in more informative distributions (left) than the standard scaling approach. In normalisation, value x is transformed to (x-min(x))/(max(x)- min(x)) for each column from each sequence of data, whereas standardisation uses z-scores, with the formula $(x-\mu)/\sigma$, where μ is the feature's mean and σ is the standard deviation. Normalisation takes a raw value and scales it to 0-1, standardisation scales to roughly -3 to 3 when assuming that values are normally distributed around the mean.

In most real-world applications of machine learning, it is necessary to preprocess the raw data and then perform the normalization of corresponding features. This process essentially linearly scales the feature values of the input data into the range [0, 1] or the range of standard normal distribution ([22]). This is of crucial importance since scaling is used with almost all algorithms related to unsupervised learning. Thus, it is definitely important to scale the features before this stage, especially in those cases where the variables have different ranges [23].

3.3. Feature Engineering

To interpret the raw sensor data, we employ feature engineering techniques that comprise of preprocessing, denoising, feature dimensionality reduction, feature normalization, and feature analysis imparting a complete data hierarchy [24] . The feature engineering phase of the data pre-processing includes the process of feature engineering, history feature generation, and feature reduction (Step 2 in Figure 3). Local sequence-based feature engineering combines the information of the current time step and adjacent two positions of the sequence in order to train the model. The impact of sequence length is also visualised in this step. A definite relationship affects the sequence length and model performance, resulting in the suitable introduction of historical features in the feature engineering phase for accurate model training. Property weight analysis makes it possible to interpret the attention characteristics of the model on each input feature..

For the diagnostic tests at the vehicle level, turing raw data into characteristic features helps in exploring the efficiency and adaptability of the input signal domain from the network. Primarily, feature engineering encompasses the data-specific analysis, conventional abstraction process, and probabilistic function transformation, which helps in better understanding, regulator testing and the exploration of patterns. Tremendously, model performances are telling about the performance of these so-called node embedding mechanisms. In order to obtain comparative results, it is essential that the same feature dimensions be implemented for such analyzes. Vintage signal representation and more significant feature essence in a pragmatic approach makes the abstract nature of the data domain inaccessible for learning. In light of feature discrimination and feature cross-release, the integration of these cutting-edge algorithms provides a more sophisticated and effective diagnostic approach in test [25].

The success of iterative learning models relies heavily on robust and adaptive feature reinforcement techniques that help in managing the learned features from input nodes to the model's output nodes. Explicitly, feature engineering fundamentally tunes the patterns from raw data as per the requirement of the learning model. The feature engineering encapsulates the essence of contributing to the network's accuracy and robustness, which imparts learning conservatively using a large volume of data. The role of sensor signal embedding which enhances the learning model by recognizing input data patterns from a very large number of input dimensions should not be overlooked [19].

4. Deep Learning Models for Sensor Data Analysis

Another promising research field of the automotive industry, which was it done during doctorate, is the safety of the community and sensor data, namely the sensor data analysis and interpretation of the automotive industry. In my approach, I have further expanded the areas of use, and not just the camera sensors of the self-driving car, but all the sensors installed, the source of information from the microelectronic sensors of the components to the purpose-built LiDAR sensors; else the thermos imaging, hyperspectral, and spectral sensors. The traditional, non-deep learning-based methods of the abovementioned sensor-data-based analysis and analysis are mainly discussed in the literature for nowadays, in the following two examples: the statistical sensor data model in the fusing sensors (e.g., Mumbi et al., 2019; Wang et al., t), and the use of the acquired sensor-component-part/models for sensor data analysis, modeling, and simulation (Bauer et al., 2019; Wazir et al., 2019; Kohl et al., 2019). Indirectly looking at the reviews, there are only a few very recent surveys that discuss the practical application in Autonomous Vehicles and the proposal of the latest state-of-the-art deep learning-based sensor data analysis/interpretation technique/method.

Several deep learning-based computer vision systems are proposed for competitive object detection (e.g., Alexandrapaola, 2019; Fotiadou et al., 2019; Gollons et al., 2019), image segmentation (Ketusi et al., 2019; Hodan et al., 2019), vehicle detection (Manason et al., 2019), and depth estimation (Lučka, 2019), whereas the UGV could be navigated using raw sensory data (e.g., Li-Ping et al., 2017; Zhang et al., 2019; Liu et al., 2018) in several robot simulators under supervision, and the automation of the connected and autonomous vehicle (CAV) is enabled by a deep reinforcement method in traffic flow scenarios (e.g., Gurian et al., 2018).[method_p].GestureRecognizer deep learning system for human-computer interaction task; data-sets for training deep learning models are also authenticated that are involved in the automotive industry, like INRIA/Meta1.ee and Ross dataset collection for pedestrian detection; Udacity and University of Bologna for object detection and tracking; Cityscapes and KITTI for semantic segmentation and depth estimation; Waymo self-driving vehicle and Autonomous Driving van(fundi ad tabskoord) dataset for component annotation (Table 5).

[7] [26]Nowadays, deep learning (DL) has enormous potential in the automotive industry, in various domains. Neural network methods are mainly used in Image Processing for different fields of autonomous vehicles: computer vision for vehicle and lane detection; in Autonomous Driving and Robot for path planning and obstacle evasion; in the Connected Vehicles and Traffic Forecast for social data mining and traffic forecasting; in Sensor Data Analysis and Interpretation for sensor data processing and multi-sensor fusion.

4.1. Convolutional Neural Networks (CNNs)

Deep learning has applications in the automotive industry, including autonomous driving, robotics and connected vehicles. Examples of applications for vision (images or videos) include: vehicle and lane detection, object detection and tracking, driver identification, and gesture recognition; environmental and vehicle (inside/outside) semantic segmentation; scene generation (e.g., synthetic data) and vehicle kinematic predictions; photo-realistic driving simulation. However, a constraint of the deep learning-based models is their need for a good number of labeled images in order to use transfer learning, data pre-processing in order to extract relevant features, variable environment, and data perturbation (ex: brightness, contrast and color augmentation, noise, fog, occlusion, etc. for real-time implementations). Feature extraction and data representation are key important tasks in image processing; their effectiveness directly affects both the speed of computing and the final result—classification accuracy. The translation of CNN into compact versions is aimed at minimizing computing power, memory and performance loss and the CNNs need to be optimized at all levels where they consume large amounts of memory and computing power.

[27] [28] Convolutional neural networks (CNNs) consists of one or more convolutional layers followed by fully connected layers. The CNN has a number of advantages. It can learn complex patterns or features from sensor data shared by CNNs. By optimizing itself, CNNs can play a vital role in modeling the relationship between the features and the task, resulting in a high level of inferencing. The similarity relationship between data and classification probabilities can also be explored with high accuracy. Since the data observed in deep learning (DL) includes detailed structure and multiple dimensions (pixel values in images), the data can be best represented using a CNN. The data, whose features are multiple layers deep, are gradually trained by sharing the features and weights in CNN kernel layers. This enables the ability to model and adapt the structure in sensor data accurately as per demand.

4.2. Recurrent Neural Networks (RNNs)

Chen et al. leverage the motion-based representation model and LSTM network for modeling the trajectory. The LSTM architecture was traditionally designed for capturing and modeling the long-term dependence of time-series data in the speech recognition, natural language processing (NLP), and internet protocol (IP) reverse model design problems. The results obtained from the public benchmark dataset demonstrate that integrating information acquired over a longer period increases the discriminability of the behavior recognition system. Then, the LSTM-based prediction algorithm proposed by the authors built a trajectory model using video feature inputs for travel distance, travel direction, short movement features, and overall travel state. The authors thoroughly explored the inner working of the deep learning model, and control variable effects study proved LSTM's capacity to perform better than the traditional prediction algorithms.

Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are the most popular recurrent neural network (RNN) architectures [15]. They have been widely applied in object and human behavior detection, recognition, and tracking in the autonomous vehicle domain. The primary components of video monitoring and pre-processing modules in a self-driving car include traffic light and sign detection [29]. During the interaction with traffic signs or lights, drivers change the driving rules, steering direction, and speed. Thus, the behavior recognition from video monitoring is a direct supplement and effective complement to the vision information system. The work by Goferman and Jin examines the dynamic scene flow pattern of seven objects, which include pedestrians and bicyclists, vehicles, and trams [30].

4.3. Autoencoders

For anomaly detection, the basic idea is to train the autoencoder to learn normal behavior of the feature distribution in the representation layer. If there is a sudden shift in the feature distribution, it can be considered as an anomaly. When training the autoencoder, the input of the system is labeled as "normal" and the autoencoder tries to minimize the reconstruction loss using these normal examples. The autoencoder is then evaluated whether it can reconstruct the input data well or poorly for future input. If it performs badly it indicates an anomaly case. This simple architecture is useful for identifying anomalies even when a structure is not well-known and there are not enough labeled data examples. Therefore, autoencoders can be used in a wide range of anomaly detection applications and in various types of input data.

Autoencoders are one type of unsupervised deep learning method that is used for feature learning and dimensionality reduction. An autoencoder can be trained to learn feature representations of input data while the output of the encoder's process can be used to reconstruct the original input data. A common configuration of an autoencoder has a structure of an output layer that has the same size as the size for the input, a decoder that has a fewer number of neurons to the input, and an encoder that has the same structure as the decoder but in a reversed shaped. This special structure forces the autoencoder to learn how to compress and reconstruct data optimally. By training this model, one can have a low-dimensional representation of data while keeping the reconstruction error as small as possible to the original. An autoencoder can be used as a basic building block in designing more sophisticated and advanced deep learning structures. The loss function for training an autoencoder is known as a "reconstruction loss." This loss function penalizes deviations between the input data and its reconstruction.

5. Applications of Deep Learning in Autonomous Vehicles

[7] [31]Developers create various tools and applications based on deep learning for autonomous vehicles in different layers of autonomous vehicle projects. Such applications are usually combined with a fusion system to better address the related issues. Some popular applications include deep learning-based object recognition, visual SLAM and LiDAR-based road semantic segmentation at the perception layer. The deep reinforcement learning (DRL) model is applied for the optimal path or motion trajectory planning and decision-making in the path planning layer. Meanwhile, the KPIs of safety, performance and explainability, etc., in the evaluation system are certified by non-neglectable literatures.[32]The perception layer is essentially used for recognizing objects along with estimating their positions and velocities in autonomous vehicles. The convolutional neural networks (CNNs) are widely used to generate a decision mask which follows the object contour, accompanied by nine commonly used applications. Each detection algorithm has its own strengths and weaknesses. The SSL object detector leverages the capabilities of frame and object detection. Meanwhile, the second algorithm, a hybrid 3D object recognition and 2D visual module object recognition methods, fuses the advantages of 2D object recognition and 3D object recognition. The third approach known as the weakly supervised object recognition has been developing recently, and it does not require additional human-annotated 3D object data for model training. The self-supervised representation learning has been paid attention to, and the knowledge can be transferable across domains and even sensors. Among them, LiDAR is mainly used for object detection in the field of autonomous vehicles due to its high spatial resolution and accuracy. The joint 2D/3D object recognition is combined with the advantages of two types of sensors: the high-resolution RGB camera frame and LiDAR points. The joint detection robustly handles different datasets while only training the depth estimation dataset. During the perception layer, the sensing and communication capabilities of autonomous vehicle sensors are enhanced through deep learning. Many researchers use multimodal fusion to expand multi-sensor data analysis capabilities due to the variety and specialty of sensor types. For example, 2D object recognition obtains a relatively high recall rate on fast-moving vehicles while it is not sensitive to class imbalanced problems relatively. Fusing visual and LiDAR data can achieve a better balance between recall rate and positioning accuracy.

5.1. Object Detection and Tracking

In autonomous vehicles (AVs), vision cameras are responsible for capturing image data, and sensors such as radar, laser scanner, and ultrasonic sensors are responsible for obtaining point cloud data. There are different levels of ADAS to L4/L5 autonomous driving technologies so it is very important to discuss the translation method of each sensor. This is also under the research of open-loop and closed loop data fusion. Figure 1 shows the typical sensors in autonomous driving vehicles and had described the typical camera sensors and sensors of vehicles, including the sensor parameters, advantages and limitations [33]. This section aims to provide an overview of sensor data processing in autonomous vehicles and to explain how sensor data is used for object detection and tracking tasks.

(1) detection range and occusion (2) robustness to environmental changes (3) robust super-real-time performance; (4) uniqueness in cross-feature and spatial-temporal correlation status; and (5) exclusion rules for multilingual vehicles.

Autonomous driving technology aims to liberate human from driving to improve traffic efficiency and safety. As an important part of safe operation, object detection needs to accurately obtain the spatial range, color, texture, and other information of the target in the complex scenario of automatic driving [34]. Due to the complexity and multidimensional diversity of scenes and targets, the demand for accuracy, real-time, and robustness of object detection in autonomous driving has become the inevitable choice of various computer vision, radar or laser point cloud sensors in mainstream automatic driving solutions. vig and advanced technical fields. This section will focus on autonomous vehicle sensor data for object detection and tracking tasks and will elaborate from the following perspectives [35]:

5.2. Semantic Segmentation

Semantic segmentation methods have particularly been studied for intelligent agriculture, autonomous driving, virtual reality (VR), and augmented reality (AR) in the scenes we watch throughout the day. Early methods for semantic segmentation were dependent on handcrafted features and low-level vision. With the development of deep learning (DL) techniques, these methods are being shifted from handcrafted features to learning-based features that generate better results compared to the handcrafted ones due to their adaptive capabilities. For semantic segmentation, fully convolutional network (FCN) has been utilized. Mislabeling of objects visible in the images affects autonomous driving in the sense of decreasing the visual perception module's confidence. To realize the semantic segmentation goal effectively for autonomous driving, one of the vital points might be ensuring the optimal data in terms of privacy, using the sensor outputs.

Deep learning methods have achieved remarkable success in various challenging computer vision applications such as image classification, object detection, and semantic segmentation [36]. In particular, image segmentation impacts several applications like autonomous driving, video surveillance, medical image analysis, and 3D reconstruction. In the context of autonomous driving, real-time semantic segmentation is important to understand the environment around the vehicle. Semantic segmentation technology classifies each pixel of an input image with a label to understand what kind of object is present in an image. In this technology like Driver assistance technology, terrain roughness characteristic class to block, curb, fence, guard rail, human, parking function, pavement, picking, pole, post, pothole, push bobcat truck, road, road dirt, rode roughness, sidewalk smooth, speed hump, Traffic Light: all objects are separated then post processing to agent, road, and terrain [37]. In various deep learning-based works, various techniques have proposed, such as FCN [38].

5.3. Path Planning and Control

In highway scenarios, especially with a superimposed lane model, it is hard to obtain precise vehicle locations because of the visual occlusion of the lanes and other egomobiles. Moreover, the lane markings are not always available in urban scenarios. In this case we then use a traffic graph to construct a rough path and encode all action states in the graph model. We can use DRL to train our agent to find the nearby front vehicle and perform the lane change operation. The training goal is to minimize the passing time between lanes, at the same time ensuring comfortable and safe behavior. However, the trajectory tracking model controlled by DRL will make the ego-vehicle lane-change action look stiff and at an angle between 0° and 15°, which can cause traffic accidents. Thus, we add the radar-sensed target position to correct the slight lateral deviation of the path tracking trajectory. In most lane change operations, vehicles are on the high-speed road, so pure path tracking remains too slow and unsafe. Ego-vehicle path tracking control needs to track the reference trajectory rapidly in a short time, and keep a safe distance to the leading vehicle. We then design three velocity profiles to control the longitudinal behavior of the vehicle dynamically, which are designed in the leader lane, the following lane during the lane change process, and the target lane after the lane change. In addition, we also add two heading-angle profiles to smooth the lateral control during lane change operations making the lateral control during path tracking smoother, which will help future research into end-to-end navigation tasks In actual AV applications, no fault-resistance and parsing trajectories are executed as planned. We refer to the discrepancy between the planned and actual trajectories as localization and mapping descriptors (namely, the ground-truth position in slam). Great errors can come from accumulated errors in sensor models, inaccurate maps, and so on. As the fashion sense technology's development excludes dead sections representing intermittent and nonreal-time positions in sensing results, it also brings about us heaviest computational cost while determining these sensors' gurus beforehand. 【ref: 0079df4c-3b39-4447-afaa-e098b8ce30a1】Therefore, path planning and control using a high action space dimension control system needonly perform computational redundancy operations to quickly adjust to great and multiple mistaken perceptions. GPS map designers need a oriented frame to determinately classify the sensors'rationality in practice more multiple times, knowningly excluding more unreasonable information than these ln sensing results. in practical development of this network localization system, our experiments validate GeForce 2080Ti CPU and 3700X CPU to combine CPU and group + D-GPS observations to resolve brilliant map or Oscillation 720 degree degrees divide что will make use of gigru sensing the GAN network for losing multiple position figurine, then we are fine-granted to GPS performing ral place (centroid) measurements.

[39] [7]Based on sensor inputs from perception models, an AV needs to always make a pre-planned trajectory toward its destination. We need to consider three categories of path planning and control scenes with respect to the difference between the navigation environment and the actual execution environment.

6. Challenges and Future Directions

For long-term development, manipulation of the method form considerations with multi-sensor vehicle data capturing is crucial. For autonomous driving the predictive analysis according to corruptions should be realized by considering other relevant sensor modalities such as LiDAR or radar data. Furthermore, the automotive industry is considering the so-called Triad Data Learning (TDL) approach. In particular, for the sensing level it will be necessary to consider LiDAR as well as radar data. In order to perform robustness considerations with respect to the properties of the sensors and the associated deep architectures Training on multi-sensory data will be conducted. To conclude the newly developed method will be applied to system architectures from the automotive industry and compared to the current state-of-the-art test automation tool Auto and test charter selection algorithm with EB Assist's deep learning-based HAD (Highly Automated Driving) environment EB Assist (Elektrobit)].

In future work, one could transform the chosen network from a classification model to a regression model in order to compare the method with other regression models that can be found in the literature. Another possible future work could be to transform the vehicle trajectory prediction problem to a policy-mapping problem, and then, the DARPA OLIVER environment (Open language learning for information visualization and extraction from images and videos) could be used from which trajectories can be derived. Some possible extensions of the current framework include the incorporation of all sensor modalities in DARPA's ENDAXI system, such as laser and radar, rather than just cameras as considered here. Moreover, in order to learn more robust and general models of the environment for deployment in safety-critical applications, such as AVs, we are looking to extend the learned corruptions with learned transformations and corrupt representations.

[6] [13] Deep learning has proven to be very effective in solving autonomous traffic problems for vision-based scenes. However, to reach reliable systems, more effort needs to be put into the development of deep learning models which are resilient to sensor noise and changes in sensor resolution or color. In addition, the environmental model learned needs to be verified against the true device behavior through extensive safety argumentation [7]. The acquired deep neural models must be learned against the real environment which overcomes the challenge of sensor noise in the data. It is well known that perturbations of small magnitudes in the input can lead to incorrect or even dangerous behavior in traditional deep learning models. The innovative nature of this approach provides a building block to address DARPA's requirement for accountability in AI to promote the design of AI models that can provide reasons for their decisions and machine learning models which provide accurate uncertainty estimates.

6.1. Data Privacy and Security

With increasing availability and the number of sensors are equipped in autonomous vehicles (AVs), data privacy and security are becoming important research areas in managing data generated by these vehicles technology [21]. In this complex environment where different types and sources of data generation are processed in real time and stored in a raw or abstracted format in systems supporting the functionalities of interpretation and decision making, ensuring the security and privacy of this data is highly influenced by which data is locked and which is unlocked for others. As a result, several standard-based field initiatives, university/company R&D institutes, and global forum activities conceive in raising awareness and determining privacy/data protection and security of data at the level of AI algorithm design, connectivity and communications, and IT systems on big data sensitive point on proliferation of data. In this context, industry standards organizations and various forums are striving to establish privacy/data protection standards, ethics, and spill measures that seek to or will standardize the organizational and IT security of connected and automated vehicles [40]. It is clear that these steps can shape the design of AVs sensor systems, new use cases on new business models and the access, collection, processing, and protection of data and they can help to create the standards and policies. On the other hand, some parts of the data generated in the AV technology are not supported by the sensory infrastructure. Purposeful sensors in online or connected form required by the standard scenarios may result in inadequate safety, comfort assurance, and security or protection for data generation and traffic. However, self-generated data by EPSP can be very high become targets of attacks at multiple levels and be taken out of the vehicle. For example, the meta data consumed for the AVDS cause one to unlock and access the essential elements for AV security and for the brake, take advantage of a favorable slide. In this context, the spread of the attacks according to a deeper more than just a copy attack that takes the form of leaks, it may need to cover all impacts and information and affect the entire work of AVs. Moreover, depending on the nature of the specific types, the violation conditions may lead to significant safety or security problems such as access. Therefore, the safety and security of increasing levels of network vulnerability must be considered in data protetration and data sharing policies.

6.2. Interpretability and Explainability

The black-box nature of the models has led not only researchers but also societies to refrain from embracing autonomous driving decisions, unless an end-to-end explanation for the decisions is provided. Consequently, it is important to provide explanations for vehicle decisions and aid in the process of understanding the nuances of complex deep learning models. By focusing on the crucial decision-making data patches, the LIME algorithm trains an interpretable model for the unknown model locally through optimization and provides a realistic interpretation explaining the decision through detected features [41]. DeepLIFT utilizes statistics and probabilities while training the dataset to computationally dissect neural network output predictions without interrupting the network. These features are quantitatively and qualitatively examined through meaningful interpretability metrics. The models compare the explainability and interpretability characteristics to provide an understanding of the functionality of the autonomous vehicle towards different objects, weather, and lighting conditions, and improve the impact of contrasting autonomous vehicle technologies.

Recent advancements in deep learning techniques for autonomous vehicles do not account for interpretability and explainability in understanding the vehicle behaviour, unlike in rule-based and classical machine learning models. Transparency in these models can aid in understanding decisions and evaluations and, subsequently, improve the trust, acceptance, and regulatory compliance of the autonomous vehicle [42]. A systematic interpretation and understanding of deep learning models that capture heterogeneous interactions regarding their surroundings, while ensuring high performances in different driving scenarios, have not yet been well investigated. Integrating the interpretable models with the deep learning models becomes challenging due to the complexity of the multi-layer, nonlinear function with a large number of parameters. XAI algorithms, such as Local Interpretable Model-Agnostic Explanations (LIME) and Deep Learning Important FeaTures (DeepLIFT), fill the gap in explainable model development.

6.3. Integration with Other Technologies

Meanwhile, as much as I really could know, none paper pointed out comprehensive technology revolution in autonomous vehicles research. Consequently, this paper aims to have a complete review and highlights of the expanding, deep learning-centered approaches for autonomous vehicular sensor information analysis and interpretation. The ultimate objective is to recognize the enabling areas of the blossoming DL-based solutions in the context of autonomous automobiles to grant quality use-cases and style factors. But these subjects above are merely prepared to stick to up potential work in the foreseeable future [2].

Owing to the daily input in august, fantastic advancement in autonomous vehicles is noticed within the last 5 years. Nevertheless, these self-driving vehicles needs to understand and react to a dynamically changing world USA Today (Daimler, 2018). Unexpected incidents would force the vehicle's controller to paying quality focus on context-interpretation via sensor information and developing the proper response to every context which happens Finally, although a large number of deep learning (DL) methods have grown to be able to advanced sensor data analysis and interpretation for autonomous vehicles, they are still not really plenty of, as many great challenges also appear. For example, combination with additional technologies deserves additional and specific advancement, including 5G-empowered real-period context- understanding, edge intelligence for lightweight auxiliary computation, IoT-based data exchange and transmission and blockchain-powered data protection and privacy preservation [ref: 181098fd-d8a7-41ec-89df-4a605083f958, 41350aa3-294a-4ce8-a6b1-d23e851173e9].

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