Deep Learning for Multi-modal Sensor Data Fusion in Autonomous Vehicles

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1. Introduction to Autonomous Vehicles

Primarily, the design of a multi-modal sensor data fusion system for autonomous vehicles was determined by several key factors. A significant increase in traffic on highways and rural road traffic dictates the selection of efficient methodological solutions in road transport [1]. The variety of environmental conditions (which include not only atmospheric conditions but also light conditions, e.g. bright. insolation and unfriendly weather) impose significant conditional parameters in the field of sensory data processing. In order to ensure an adequate level of road safety the sensory outfit must function stably and efficiently regardless of particular environmental conditions. An almost ideal environment in which autonomous carriers should recognize surroundings refers among others to homogeneous, monochromatic surfaces, without reflections, with one intensity of lighting regardless of the time of day and which is not influenced by the weather. The determined research problem will be difficult to solve if the solution is supposed to provide an adequate smooth operation of a system when conditions do not deviate significantly from ideal, hypothetical conditions in the range of environmental conditions described above. Therefore, the influence of the following parameters should not be disregarded when creating a multi-modal sensor data fusion system for autonomous vehicles in the process of designing the system in order to use it in temporary, dynamic and changing conditions: frequent changes in light conditions, e.g. blackout, coming in and coming out of tunnels, both transition conditions and different weather phenomena such as snow, rain, fog or hail [2].

Noticeable progress has been observed in the field of advanced driver-assistance systems (ADAS) in recent years. The most significant progress is the appearance on the market of driverless cars (autonomous vehicles, AV) and electric cars. A panoramic view of car sensor outfit presented at the IAA enforces a conviction of the steps made in car sensor outfit from

sole vehicle control entities to even including interior sensors, which consider multifaceted conditions of a driver and passengers [3]. The advantages of autonomous vehicles (AVs) are numerous: firstly, AVs provide increased safety and reduced traffic congestion; in addition, AVs will reduce less congestion and reduced traffic oscillation (hence with less traffic jams and an improved environment). In order to operate vehicles autonomously and to react to situations on the road a relatively high amount of data must be processed based on the sensory input of the vehicle. The object of data processing and the counter object act as particular object of interest in the perceived environment of the vehicle.

1.1. Definition and Importance of Autonomous Vehicles

The relevance of multi-modal fusion in the autonomous vehicle domain is widely recognized and addressed by many researchers. As shown in figure 1, integrating information from multiple sensor sources is crucial to understanding the full picture of the driving environment [1]. In addition to the visual information from cameras, this can also include information from LiDAR scanners, where distance measurements are made based on laser ray travel times, and radar, where the distance between two objects is determined by the propagation time of the signals. In the context of autonomous vehicles, the fusion of information on different sensor sources is especially attractive due to the high dependability demands the autonomous vehicle environment has on the reliable detection and classification of objects.

Breakthroughs in the field of deep learning have led to a reassessment of the possibility of creating autonomous vehicles. The automotive industry is facing a revolution driven by sensors, data, and deep learning technology. Vision, radar and LiDAR are commonly used in the practical implementation of autonomous vehicles [4]. As these sensors capture complementary aspects of the vehicle's surroundings, deep learning on multi-modal sensor data fusion holds a big potential for effective perception. Instead of different sensor data being processed separately, the fusion of these different sources of information enables a holistic understanding of the vehicle's surroundings. Thus, we motivate more for investigating this promising but yet not well understood topic.

1.2. Challenges in Autonomous Driving

[5] At the time of writing this article, a significant part of the literature of multi-modal sensor data fusion and perception in autonomous driving (AD) was primarily based on handcrafted

feature extraction and traditional machine learning algorithms. Here, we refer the reader to the previous literature review of that includes many works based on these techniques and presents a. few limited use cases of deep learning architectures for multi-modal AD perception. The work of gives a few selected examples of deep learning on single sensor data (camera data and LiDAR/ Laser Scan) which at that time were the most prevalent sensors used for perception in AD. The absence of a comprehensive review of the related literature motivated us to conduct this literature review article, which provides a deep and comprehensive insight into the primary research topics and directly compares the state-of-the-art AD perception systems based on multi-modal deep learning. The work highlights different popular architectures, compares and contrasts their performance in different AD sensing scenarios, introduces recent datasets and different simulators for AD research, and finally proposes a directional road map of the future vision of AD perception.[6] The active research area of self-driving cars is a complex problem platform that requires multimodal sensor integration. To accurately estimate the driving behavior, it is crucial to understand the scene from various perceptive modalities such as camera and LIDAR data. However, the main focus is often put on the fusion and integration of single modality, independent source of sensors, without considering the temporal dependencies within them, such as gate recurrent networks for multiple data fusion. In this work, we propose a novel method for recurrent multimodal data integration and show its effectiveness in performance measures and qualitative results. Temporal multimodal fusion between different source of sensor data was put in the spotlight as well as recurrent learning-based approaches._identifier The main idea of this paper is to guide the development of future research and set up a common playground for an inspirational perspective to apply deep learning and multimodal perception perception in autonomous driving.

2. Sensor Technologies in Autonomous Vehicles

Pathways to sensor fusion can be categorized under three sections: early fusion, intermediate fusion and late fusion. Conceptually, early fusion combines inputs very close to the sensor interfaces, effectively generating a single feature representation before passing the fused information through the other layers. However, the naive strategies to aggregate features at very early stages are not general and straightforward. For this reason, intermediate fusion strategies proposed to consider different modality expressions and to generate different features from different sensor data at an intermediate layer. Techniques generally consider to

pass through the input sensor specific layer and then obtain high level features and finally to combine them in one or more intermediate layer. On the other hand, late fusion sits at the top of the network, which takes as its input the independent representations generated for each modality before combining the final statistics into the meaningful results. However, canonical and other late fusion schemata cannot surpass the strength of LIDAR-only methods. Thus, sensor fusion algorithms are proposed to reduce this gap and achieve better results at the final endpoint [7].

[8]Since the introduction of the CMOS image sensor and the invention of the light detection and ranging (LiDAR) sensor, the sensors have continued to evolve. Both sensors are widely used in the current industry. These devices are complementary in nature and represent major components on many fully automated vehicles (Fahraz et al., 2019) [9]. LiDAR-based hardware captures a point-level representation of the surrounding area, while the relatively high-resolution camera provides detailed RGB data across the large field of view. However, the characteristics of sensor data (i.e., image data and point cloud data) are not directly comparable, yet they can compensate each other's shortcomings.

2.1. Types of Sensors Used in Autonomous Vehicles

All the sensors have their own individual strengths and weaknesses, so to use the strengths of each other and to overcome their weaknesses, semi-fused or fully-fused data from multiple sensors is used together. However, because of disparity in the nature or type of data from different sensors, it is difficult to achieve multi-modal sensor fusion. For example, to fuse the data from LiDAR-camera, clustering is done in the scene extracted from LiDAR and then a bounding box is created around the points that are extracted at same place. Then, these bounding boxes are projected on the camera image and the color of the scene is added to the bounding boxes. On the other hand, to fuse the data from LiDAR-radar, both LiDAR and radar provide the information in 2D form. Therefore, the radar data is only fused in the state of the vehicle and the LiDAR data is preferred over the radar's data to generate the distance along with the lanes. Let's now delve into the working of different sensors used for different purposes in autonomous vehicles.

To enable autonomous navigation, sensors like camera, LiDAR, and radar are used to acquire a wide range of information about the environment [10]. Cameras provide in-depth semantic information, e.g., types of cars, lane markings, and pedestrians. On the other hand, LiDARs

provide rich spatial information, i.e., 3D point clouds. Radars only provide velocity and distance. The main constraints are resolution for depth/semantic information [11]. Some important attributes of sensors for autonomous vehicles are as follows – performance in terms of resolution, range, temperature, interference, processing requirements, cost, weather conditions, datasets availability, illumination conditions, labeling, sensing range, resolution (spatial/temporal), power and size, and accuracy. If multiple sensors are used together, it can provide a better understanding of the environment by providing rich and complementary information [6]. The effectiveness and robustness of these systems can be ensured by integrating the data of all the sensors and to fuse them at different levels of abstraction.

2.2. Role of Sensors in Autonomous Driving

This section briefly describes the sensor data that are commonly used in autonomous driving that are relevant to the work reviewed in this survey. Environment perception and target detection in multiple sensor modalities are reviewed separately in later sections. Lidar, which works on the principle of active remote sensing, has become an increasingly critical sensor for the perception of the 3D environment for autonomous vehicles due to its natively high spatial resolution and precise depth measurements [12]. Lidar enables reliable 3D object detection and obstacle tracking in both daytime and nighttime scenarios, without being susceptible to the presence of strong ambient lights seen in passive sensors such as cameras. However, these systems are generally expensive, and there can be potentially issues due to telescoping, especially in inclement weather. Cameras are the most commonly used sensors for computer vision in non-autonomous systems. Cameras provide high-resolution images that provide rich semantic information as well as making a reliable 2D detection for the perception task and tracking. However, cameras are prone to nuisance factors such as varying lighting conditions, weather and occlusion. Also, the camera data may not accurately represent depth information, and cannot back-project 2D objects into 3D space as is possible with point-cloud data using lidar systems. Radars operate on the principle of active remote sensing to detect objects and scene understanding [10]. Radars excel in adverse weather conditions and are particularly robust in terms of occlusions, due to its non-line-of-sight object detection capability. These types of sensors are inexpensive and consume very little power; however, the data produced by these sensors by themselves may be typically less descriptive in terms of the semantics and types of detected objects. But, with advancements in deep learning and feature engineering, radars can be complementary sources of information for fusion-based

sensing. For example, radars can be used for obstruction detection, and is typically the first line of defense sensing, due to its robustness against weather conditions, and due to this it is often a prime candidate for utilization as a road safe sensor [13]. However, generally radars have a limited ability to discriminate between detected objects in diverse geometries or semantics. Also, the radar spatial resolution is lower than the mapping capabilities of LIDAR sensors when used alone with one or two rows. We refer to this as short range radar. Similarly, there is no intrinsic way for radar to estimate the ranging between it and the detected object and a set of items and can only estimate a bounded box. Long-range radar, cameras and lidar all have intrinsic ranging capabilities due to their distinct physics. As the number of sensor modalities increases, researchers in the community are paying significant attention to multimodal fusion of sensor data which can utilize the positive fonts and mitigate the weakness of each of the sensors. For example, passive cameras with multimodal radar transforms the raw detected points into estimates of the incoming points of each row of radar generating a pseudo imaging radar sensor. As mentioned earlier, cc: code wheel encoder can be considered a misaligned pair. One can argue that code wheel encoder is not considered a sensor after all but it embodies the decomposition of geometry to movement commands. In this sense in this review, we can say that we consider an autoencoder to be a sensor. It decomposes an input image to a set of two-dimensional pseudo curvilinear commands cm to move the object in the image plane to the target destination. We denote this facility to decompose by m to move the object by m as curvilinear sensor. In combination of a vision sensor and this curvilinear sensor, the df streams (1) provide a lower dimensional information to facilitate comparison of different positions of an object in image plan: it provides the pseudo sense of scale and orientation by help of this decomposition. (2) The input into the image sensor can be interpreted as the commands to move the object to different parts of the operational space. We denote the mapping from the pseudo commands to an object stream mo given by means of the operator Mmo. That is, m*(I) = M's. The multimodal transfer operator, T(mo,mv), id defined to relate mo to mv by the unimodal mapping given in (1) by the following simple composition: (=T(mo, mv) mo =Tmo;m*.)

3. Data Fusion in Autonomous Vehicles

AVs are equipped with multiple high-quality sensors such as cameras and Light Detection and Ranging (LiDAR) sensors. Each modality provides complementary information regarding the perception scene around the ego vehicle [7]. For instance, camera frames store

rich visual cues, but the ability to estimate precise 3D geometry is limited to the scale ambiguity. On the other hand, point cloud data generated by LiDAR sensors represent geometric cues (3D point locations in the camera frame of reference) and contain coarse 3D geometry information, but their visual quality is low. An effective fusion of all available sensing modalities is crucial for deploying multi-modal fusion algorithms for a critical sub-module such as, for example, object tracking for AVs. Consequently, the ability of deep learning (DL)-based multi-modal fusion techniques to better capitalize on insights from different sensing modalities promissory for holistic target tracking performance and reduction of the aforesaid model biases [1].

Deep learning (DL) technologies have become increasingly popular in recent research for autonomous vehicle (AV) perception and decision-making systems [4]. One of the applications of deep learning techniques has been in sensor data fusion for multi-modal perception in AVs. The key motivation behind using sensor fusion is that different sensors are sensitive to different cues. Each modality generates a set of signals that are spatially and/or temporally coherent. Therefore, by adopting a sensor fusion strategy that effectively combines the information from each sensor, we can lead to a more data-driven perception. In comparison to applying DL in the perception sub-system of an AV, it is shown that applying these techniques directly on sensor data, might offer some advantages such as low sensitivities to noise, particularly for low probability visual events, perspective distortion and occlusion.

3.1. Definition and Importance of Data Fusion

Envy-worthy accuracy results have been obtained using camera data in actual light conditions, whereas the alignment of neighboring frames has been the most challenging part in changing environments. LiDAR data can provide a very stable representation of nearby objects regardless of the light conditions. However, the sensor's high energy consumption, higher price and noise, especially in defective weather conditions, make it less desirable. Therefore, it is beneficial to integrate both of these outputs into the target environment [10]. It is necessary to use LiDAR and camera data together for successful results in order to make up for the weaknesses of these sensors In 2002, a simpler version of the idea of this study was explained by the fact that camera data can be used for 2D desk perception and semantic information, object detection, while 3D depth perception is possible with LiDAR scan inputs.

The authors have given information on the latest transformer architecture in the region by combining camera and LiDAR data [14].

Sensor data fusion has become one of the most demanding research topics among autonomous-driving studies. A variety of sensors including camera, LiDAR and radar have been integrated into a specific vehicle for the purpose of robust perception outputs. multi-modal sensor data fusion in autonomous vehicle applications, with a focus on deep learning studies on object detection and semantic segmentation. The authors elaborate on the most contemporary work in the new sensor data fusion systems that mainly integrate camera and LiDAR data. In addition, potential alternatives and future research opportunities are also presented in this review paper [5]. The study also aims to provide novel insight into implementing deep learning networks in order to gather the correct sensor representation efficiently and aims to provide a step-by-step guideline to the researchers for the future work in simulation models.

3.2. Challenges in Data Fusion for Autonomous Vehicles

Processing this rich sensor data in complex and dynamic scenarios has become more difficult with the advancement of higher level cognition tasks. In addition to the autonomous vehicles' ability to perform perception from diverse sensors, the ability to understand traffic scenes has become a main focus in the develop- ment of autonomous driving. However, the accurate perception by the autonomous vehicles of diverse traffic scenes in 3D, the ability to understand these scenes robustly and in detail, and the capacity to make high-level decisions still pose problems due to the unreasonable complexity of handling real-world driving scenes, and believe that is particularly vulnerable in scenarios where there are multiple vulnerable road users, i.e., pedestrians and cyclists, present in the environment. For these reasons, the object detection researchers have now started to turn their way to multimodal sensor fusion for overcoming these challenges. Consequently, sensor fusion can be generally categorized as single modality or multi modality based and we are in a transition phase, in which convolutional neural networks (CNN) based single modality sensors fusion and transformer-based multimodal sensor fusion algorithms are particularly popular and favored.

[15] [4]The recently-growing capabilities of sensors have provided even more spatial/visual information for sensor fusion with the development of the 3D object detection field of view in autonomous driving. The 3D object detection encompasses diverse aspects such as detecting

the object in 3D space, providing the position of the objects and their classification in 3D with a high detection rate, and categorizing the objects in various types. Especially, due to the rapid developments in the deep learning and computer vision areas, great progress has been achieved in object detection. For instance, pollatom et al. proposed a CNN based regionbased detector model Faster-RCNN for 3D object detection. Stereo-RCNN presents a pipeline by enabling the fusion of the lidar point clouds with the stero images for 3D object detection.

4. Deep Learning Fundamentals

The backdrop of our work is an adaptive regulation approach, initiated by an adaptive molecular switch (α-CCR5). The protein is up or down regulated according to the imminent decrease or increase of attached R5-specific gp120 envelope proteins of non-treated GagPol-instructed viruses. Additionally, the folding dynamics is also directly affected if an internal regularization by flipped local energy maxima is physically inscribed. Here, we use a refined model of minimal players, R, a prime amount of gp120 molecules, and T, total CCR5 at the surface of a target cell, which can sterically block other co-receptors thus impairing effective entry.

Furthermore, and importantly for automotive and automation scenarios, the learned semantic representations are shared among sensor modalities, leading to a holistic understanding: Cameras, with their high resolution and color information, provide accurate localization of objects; Radars are especially relevant for localization in adverse weather conditions; Lidar excels for 3D object localization with applications like scene segmentation and also object tracking; and Ultrasonic sensors, which are frequently used in smart parking and adaptive cruise control solutions. A multitude of popular networks like ResNets and DenseNets have been used in automotive applications, either for holistic scene understanding or for object detection and tracking tasks. Although CNNs help integrating data from different sensors, research on using them for fusion of multi-modal streams over time is much more scarce compared to the other parts of the sensing pipeline. It is the focus of this paper. [13] Mostly quality control, stimuli, and parameter setting are the targets of hybrid systems generated by our brain. These targets are reached with the parameters of fluctuation inside a narrow stability band. For this end, the continuous updating of stimuli occurring under the influence of an ever-changing environment is compensated by an ongoing adaptation of the stored internal model. Through this, a panoply of stabilizing and destabilizing pathways is analyzed.

Close to the deterministic limit, the corroboration of the theoretical concept leads to a homogeneous semi-analytical approach comprising several parameter and stability studies, and a coincidence analysis with data from patients under antiretroviral therapy. Besides destabilizing areas, also 'whitelisting boundaries' can be achieved by safe therapy settings. Also, additional, multiple attractor ranges can emerge which—if properly stimulated—may lead to stabilization.

[16] Three main approaches of integrating data from different sensors can be distinguished in autonomous systems: (a) rule-based fusion, (b) feature-level fusion, and (c) decision-level fusion. Advances in deep learning in recent years, especially using convolutional neural networks (CNNs) for image and video processing have had a significant impact on all three stages of the sensor fusion pipeline. Besides the obvious benefits like improved accuracy and robust object detection, sensor fusion methods leveraging deep learning excel because they do not require often challenging and time-consuming manual feature designing.

4.1. Introduction to Neural Networks

At present, the deep learning neural network is known for its distinctive learning performance in computer vision technology. During a deep learning process, the hierarchical structures of data representations can be learnt automatically. It is known as the most advanced means in the field of image processing and pattern recognition. In addition, more convolutional neural network models have been improved gradually. In particular, the real-time processing performances of SSD-MobilenetV2 and YOLO-V3 are good. Nowadays, deep learning has become a mature and robust intelligent underlying technique. Compared to the traditional algorithm, Unicode deep learning requires a large amount of data usage to reach a high level of performance. At the same time, multi-modal sensor information can complement each other, further enlarge and strengthen the recognition and interpretation of the vehicle's features. Therefore, integrated multiple sensor data fusion methods are now a popular research topic both domestically and internationally [8].

A deep learning based sensor fusion framework has been proposed for detection of autonomous vehicles. A Convolutional Neural Network (CNN) processes and fuses multi-zoom LiDAR data and visual data. With the development of the driverless vehicle industry, the intelligent transportation system (ITS) is a hot topic and has gained widespread attention. This technique can sense the driving environment with multiple sensors and this is an

important step in the effectiveness of autonomous vehicles on various transportation tasks such as path planning, behavior decision making, vehicle control, and automatic driving assistance. It is a key technology for enhancing driving safety, improving work efficiency, and reducing vehicle accidents and casualties. In recent years, the demand for intelligent driving and unmanned driving has progressively increased, leading to the need for vehicle detection under various driving conditions [1].

4.2. Types of Deep Learning Architectures

In the standard configuration, HMMs with two or several outputs are used. However, for example in slicing, the sensor fusion can be possibly not only between signs of the color fashionable signals to the situation with two outputs and which marks the direction (freely transformable to two independent HMMs,) but also independently of their future conduct with expectations and preparations with a single output board. An output with a tray is a general sensor fusion problem to the mode with a single output. In "clipping" and "slicing", resulting HMM will have a number of outputs smaller than in original HMMs. Inputs of this HMM are transmitted from outputs of original HMMs, and the example from section 3 is given with similar sensor fusion of different speeding signals. Therefore, the configuration "slicing" and "clipping" can also be observed as a more general input sensor fusion technique. The bigger the loss, the easier parsing of resulting HMM, at practical check, will be thus more effective, however, it will be more serious the possible influence of the noise. Pragmatic auxiliary values must be well and at the same way very difficult to cause, for example, in mathematical mode, a knowledge about chess on the model board—namely capture of information from the side, which no undergo propagation. A problem of keeping as maximal magnitudes as possible less important information concerns the problem in the knowledge engineering of the max entropy as entropy value of the beginning of the simulation way with used decision strategies. That least important will be so numerous Plant input/output sensor fusion procedurals. Finally decision strategies will be also reduced. [17]

The purpose of the sensor data fusion is to maintain the output as similar as possible to the data origin from all sensors, regardless of the situation. The sensor data fusion refers to its ability to represent the structural HMM from the environment in a lossless form. It should also discharge every information less important for driving of the HMM, and it should to unify all information necessary for correct decision making of the ATM.

5. Deep Learning for Sensor Data Fusion

Many deep learning-based fusion algorithms have been proposed and their performances are at least comparable to traditional probability-based Bayesian fusion due to the power of deep learning for extracting high-level features indicative of the class of objects to detect. As a baseline, the Multi-Level Fusion Network (MLFN) for information fusion on autonomous vehicles extracts and learns features from single LiDAR and single monocular cameras, as shown in Figure 1. Then features representing global property are fused into a feature in a global fusion branch. Features from the LiDAR and the camera are successively fused in the pixel-wise and the global feature spaces learning different kinds of object information. By using pixel-wise and global feature fusion, each sensor modality cannot only perform feature extraction on their own data but also exploit existing global information to enhance learned features [18].

Fusing multi-modal sensor data in autonomous vehicles and industrial robotics is an essential task [1]. The best choices for multi-modal sensor fusion in autonomous driving are multiple range sensors, including cameras and LiDARs, due to the complementary strengths of each sensor. However, these kinds of multi-modal sensor data have different characteristics and it is a major challenge how to fuse them in an efficient manner [4]. This is because visual images contain rich color information and are well-suited to detect and localize pedestrians (among others), while LiDAR has the ability to accurately measure distances and form precise three-dimensional (3D) shape structures of detected objects. In order to overcome the complementary limitations of these sensors, sensor data fusion has been an active field of research in recent years.

5.1. Applications of Deep Learning in Sensor Data Fusion

Autonomous Vehicle: Autonomous vehicles are equipped with a variety of sensors, such as cameras, radars, laser rangefinders, and maps, which can acquire real-time driving information from multiple perspectives. However, these sensors are sensitive to different environmental conditions and possess different strengths and weaknesses, including variations in range, resolution, and accuracy. Combining data from multiple sensors can provide complementary information, thereby improving situational awareness, and control performance. For example, radar is robust to most severe weather conditions and low light illumination in which cameras may fail. Cameras can provide rich details and texture

information of the object's shape and material, while one of their biggest disadvantages is that they are more sensitive to ambient light and weather conditions, particularly when it comes to low visibility scenarios such as during nighttime and fog or when the reflection of the camera lens obscures the scene of interest. The main goal of developing these networks is to complement the perception capabilities of each individual sensor with the improved situational awareness and robustness of multi-modal sensor fusion (MMSF) that only occurs when using the representation stacks from all the sensors. Reference - [4]

5.2. Advantages of Deep Learning in Data Fusion

Deep learning has been widely used in data fusion, which has shown many benefits. One major advantage is that the decision-making process can reach a high level of accuracy [16]. In the autonomous driving domain, data fusion is essential for making intelligent scene understanding, so high-level accuracy is crucial. Another advantage of deep learning in data fusion is the data integration of different sensors (LiDAR, camera, and radar) [10]. With deep learning, the OOD (out-of-distribution) samples of the sensor will not harm the prediction model. Combining the strengths of different sensors is important for multi-sensor data fusion as each sensor has its own strengths and limitations. For example, LiDAR information provides 3D shape and depth, while the camera sensor provides rich color and semantic information. Combining these multiple sensor data will build an accurate and strong semantic and spatial information [19]. With increasing technology advancement of vehicle sensors, deep learning has played a significant role in sensor fusion.

6. Case Studies and Research in Autonomous Vehicles

To overcome the limitations of using only LiDAR and image data, in this section, we investigate the fusion of all four sensor modalities on autonomous vehicles. Based on the spectral and temporal characteristics of the data, deep learning methods were developed for simulating sensor fusion in cross-sensor embedding learning for the fusion of various combination of multi-modalness. In this section, we use neural network-based deep fusion as a case study and study its effectiveness on both unmanned vehicle cross-modal object recognition and language image/audio understanding applications. AI and multi-sensor data fusion are two technical directions for digital vehicles. AI is the core technology of car brain and multi-sensory fusion is the physical basis of car brain. Deep learning makes it possible to realize multi-sensor fusion of complex, high-level and spatial-temporal correlation data with

low error rate for the first time. The study of multi-modal object recognition and temporal-spatial fusion object tracking provides theoretical guidance for safe driving applications where learning ability is critical to reflect diverse traffic information in unknown driving scenarios.

[20] [1]Artificial intelligence (AI) and multi-sensor data fusion [8], are two main technical directions of autonomous vehicles. The typical multi-sensor fusion on autonomous vehicles are the fusion of LiDAR and image sensors. Multi-sensor fusion significantly improves the robustness of autonomous driving systems in dealing with complex driving environments. Multi-sensor fusion has the potential to be a key enabling technology for the deployment of driverless vehicles in the next five to ten years. Multi-modal learned representations can provide orthogonal information useful for a variety of recognition tasks and are also helpful for large-scale, highly variable multimodal recognition applications.

6.1. Recent Advances in Sensor Data Fusion Research

The data fusion approach should be repeated on different stages of the data processing pipeline, before multimodal data are combined into a single integrated information stream. Here distributions of latent feature spaces and decision spaces for each sensing modality are expected to be different and only mode-agnostic processes should be conducted afterwards. Transfer learning is a useful tool in adapting such generative or discriminative models when quantities of data collection are imbalanced for different sensing modalities. Each sensing modality has its own specific properties, such as its resolution, sensitivity, and field of view. In the meantime, the information of different modalities of similar format can complement and help each other when used together, e.g., sound and vision data collected from often overlapped positions.

This study mainly discusses the recent advance in deep learning based multi-modal sensor data fusion in autonomous driving. Besides, given the high-level abstraction of the unit data, the fusion can be processed at multiple levels and form various strategies for different applications. For example, methods like deep-image features and then lead to multi-scale LiDAR point cloud, which are not easily fused at the raw sensor data level. ThereImplementing multisensory sensor data fusion is of particular scientific challenge, yet also of utmost practical importance for autonomous or semi-autonomous vehicles, agricultural robots, augmented reality and many others instances. The objective of data fusion

is to integrate sensory information from different interconnected sensors devoted to several kinds of sensory channels (e.g. visual, auditory, haptic) and/or to different types of physical phenomena (e.g., cameras capturing images, radars recording echoes or reflected waves, laser scanning systems performing measurements of those echoes).

[6] In recent years, deep learning has been widely used in multiple domains due to its superior performance in handling multi-modal sensor data, such as image data from cameras and point cloud data from LiDAR and radar sensors. And the success of deep learning has also encouraged further efforts to fuse different sensors for robot applications such as autonomous navigation on road, application is to fuse different sensors and perceive the environment for fast localisation and mapping, as well as safe navigation in autonomous cars. Even though different sensors provide complementary information, e.g., different texture feature from images and distance from the LiDAR, hi fuse different sensors for robot applications such as autonomous navigation on road, multiple sensor data have different data formats and high-level semantics. It is still a challenging task to discover their correlations and fuse them seamlessly and efficiently.

6.2. Real-world Applications of Deep Learning in Autonomous Vehicles

Even though fixed number of sensors and fixed sensor type concept explanations are well-tuned for related tasks, real-world applications do not create respect to such constraints in general. Therefore, whenever forming AV perception blocks in the design transfer function, obstacle detection and recognition authors need to consider these natural requirements. Nevertheless, the main sentence of the design document for these perception building blocks must be problem definition (e.g., various sensor combination-based multi-modal AV perception or unstructured building environment compatible object detection) and any relative problem-based sub-scopes. Thus, in this multi-modal object detection literature, the content was discussed together with this discipline in which the scope was determined [4].

The main sensor type currently used in the backbone of autonomous vehicles are monocular, stereo, and even multi-camera systems [21]. Even such scenario capture the visual characteristics and cues with intensive information that will help the further computer vision-related tasks, one important issue is the nature of lighting and weather changes to camera captured imagery. Remembering that multi-sensor-based detection results are more comprehensive and better informed, and also keeping in mind that these equipments have

obstacle penetration capability, these two sensor types (LiDAR and Radar) are preferred options for object detection on an autonomous vehicle platform. We also refer to the multi-modal sensor fusion guide to gain insights about these AV perception building blocks and to elaborate how robustly can be designed by the usage of machine and deep learning algorithms within this framework [3].

7. Challenges and Future Directions

[11]One of the future trends of autonomous driving sensor fusion is developing methods that can be trained with edge data [19]. In the modern Internet of Things environment, it is inevitable to perform several data fusion tasks on edge devices (e.g., head-light cameras, infotainment systems, ECUs). These edge devices are memory- and power-constrained. Such devices require energy efficient and lightweight network architectures. Additionally, manufacturers often rely on semi-proprietary and platform-dependent inference frameworks. For this reason, recent research increasingly explores the challenges associated with efficient deep learning algorithms and architectures for sensor fusion in edge devices. In some applications, 3D convolutions enable 3D spatial features. However, in many other fusion-related circumstances it is meaningful to employ structured topologies (like temporal, graph or kernel-predicate pyramids). Combining these attributes with efficient architectures and deep learning networks can provide the required contextual information and capture the global dependencies among sensory modalities which are spread across the input space.[3]In deep learning, hardware inefficient computations (like convolutions, multiplications, and the associated memory/stored weights) are expensive in terms of both energy usage and memory, and traversing the prediction gradients back and forward leads to an overfitting of the network. Due to their inherent complexity, successful fusion requires the proper fusion operation in view of cost-effectiveness both in terms of computation and storage. Since fusing sensor modalities across all layers of the network is not possible in reasonable time and cost, only a suitable fusion level should be chosen. For example, it has been shown that middle fusion is suitable for controlling and decision-making tasks since it consolidates the information from all layers of the sensor-specific shared part. On a different note, the end level fusion can be considered for sensor specific semantic detection tasks like object detection and part-based detection as it consolidates the sensor specific spatial information containing the object semi-transparent or extensive parts of detected object parts.

7.1. Ethical and Safety Concerns in Autonomous Vehicles

Physical and physiological health would have to improve to some extent if the highly riskless age of autonomous driving were to arrive. Even if the driving system is replaced by an autonomous driving system to improve physical health care in a highly riskless age, there would not be the development effect expected in the present case. RV-VPers come into routine behavior in the morning in order to perform physical health care . In the development society and the highly riskless age, physical health care would have to perform another behavior in addition to vehicles guidance. 1) The Autonomous Vehicle (AV) sent their own state, the surrounding state of the travel route, and the state that they could see (on-road, in-vehicle) to the DP Center. 2) The DP Center determines the highest weight for the associated behavior-pattern group of states by applying the fusion strategy of the CV and the recognition value is used to assign an importance rank to it [8].

Several real-world issues have been identified in the use of autonomous vehicles such as ethical and safety concerns, online learning, sensor data fusion, hardware-in-the-loop, and emotional AVs . The possibility of a fatal accident is expected to decrease when autonomous driving AI systems are well trained using multi-modal information. Consequently, it becomes possible to examine whether a serious impediment to the spread of autonomous vehicles can be overcome by developing a fusion technology of various types of sensors attached to autonomous vehicles: camera, LiDAR, radar, ultrasonic sensor, GPS, IMU, speed sensor, wheel speed sensors . We can obtain the benefits of each sensor with this technique without being affected by the limitations of each sensor. In addition, when the vision capture information of different vehicles is combined using stereo cameras, fusion of this information is easily employed to improve autonomous vehicles driving support by eliminating exceptions under ambiguous conditions [22].

7.2. Potential Research Areas for Future Development

Multi-modal sensor fusion is the key to understand the ego vehicle's surrounding better and make more precise decisions in an autonomous vehicle design. One key issue is to establish the correspondence between different modalities and construct their relationships over time to recognize the similarities and differences for better association of modalities. The other concern of sensor fusion in autonomous vehicle design is to model the environment information from sensors so as to provide an accurate description for the decisions made in

the vehicle. Therefore, improving the performance of sensor fusion in autonomous vehicle design in term of multimodal inputs, the correspondence between the modalities, and the inference of environment phenomena will not only provide a more accurate and reliable description percepts in the vehicle control in uncertain decision-making [4].

In this chapter the path to driver–vehicle cooperation in terms of controlled multi-sensor multi-modal vehicle-software data buses is proposed and described. The trace of what has been done and the steps left before the proposed scenario takes place are presented. Finally, the potential research areas for future development are compiled [22], [6].

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