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Implementation of Distributed AI in an Autonomous Driving Application

K. Rahimunnisa

Department of Electronics and Communication Engineering, Easwari Engineering College, Chennai, Tamil Nadu, India

E-mail: krahimunnisa@gmail.com

Abstract

Vehicle driving is an art to be performed with maximum attention. A small distraction or error in the driving practice may lead to severe problem to the people and the vehicle. The autonomous driving systems are implemented partially in few applications to rectify such human errors through an Artificial Intelligence (AI) algorithm. The AI algorithms require certain peripheral units like camera and sensors for their operation and are very effective and fast compared to the manual process. The computational complexity of autonomous driving systems are very high than the other applications where it requires continuous monitoring and instantaneous processing. Therefore it requires a huge amount of memory space and heavy processors. To address such limitations, the recent year applications are implemented with a cloud communication system for processing the collected data in a remote place. However, security and communication concerns present in such models have led this proposed work to implement a distributed AI architecture for an autonomous driving system.

Keywords: Autonomous driving, distributed AI, cloud computing, source processing, local data storage

1. Introduction

Autonomous vehicles are developed to understand its surroundings without a human interruption. It is achieved by incorporating the vehicle engine and braking system with several sensors and camera units. The autonomous vehicles which are designed for taxi applications are programmed to move even without a human inside the car for taking passenger standing at a remote location [1, 2]. However, the vehicle engines are programmed to operate same as like of a human driver operating a traditional car. In general, the automated driving systems are ranged into 5 categories as shown below.

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- Level 1 – Driver Assistance
- Level 2 – Partial Automation
- Level 3 – Conditional Automation
- Level 4 – High Automation
- Level 5 – Full Automation

The level 1 and level 2 automation systems are operated with a human interruption to monitor the performances of the vehicle. Cruise control system is an example for level 1 automation where it assists the driver to maintain a constant speed as prescribed [2, 3]. The Advance Driver Assistance System (ADAS) is a sample for level 2 partial automation system that can able to control the steering operation of a vehicle along with the acceleration control process. Though, the level 2 system can be interrupted at any time based on the driver's requirement.

The conditional automation systems are considered as a level 3 automation system which allows an automated module to observe the environmental conditions of a vehicle. Traffic sign assist and high beam assist are the examples of a conditional automation system. The level 4 high automation systems are equipped with Geofencing modules to operate vehicle at an emergency situation. The conditional automated system can able park the vehicles in a safe manner at the critical times like driver emergencies. The fully automated vehicles are can perform the driving tasks with a zero human interaction in the movement [4-6]. Such models are considered as level 5 automation systems that can move the vehicle from one place to another place just by giving a destination place. Table 1 explores the observations of various robotic driving mechanisms.

Table 1. Differences among the driving mechanisms

Vehicle Type	**Autonomous**	**Automated**	**Self-Driving**
Driving Instruction	Not Required	Required	Up to human interruption
Human presence	Not Required	Required	Required
Application	Emergency Vehicle	Taxi and Public Transport	All Purposes

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1.1 Architecture of an Autonomous Vehicle

The autonomous vehicle systems are controlled through the signals received from sensors, actuators, and processing units [7, 8]. The recent year automated systems are equipped with a neural network based algorithms that requires a powerful processing unit for its operation. The sensor modules are incorporated in some cases with image processing and Geofencing modules for providing an additional security to an automated vehicle. The image processing algorithms are helpful in detecting the pedestrian movements and traffic signs. At the same time sensors and actuators are utilized to track the speed of the front and following vehicles on the road [9, 10]. The Geofencing systems are employed to observe the changes in the blind spot area of the vehicle. Figure 1 explores an architectural overview of an autonomous vehicle system.

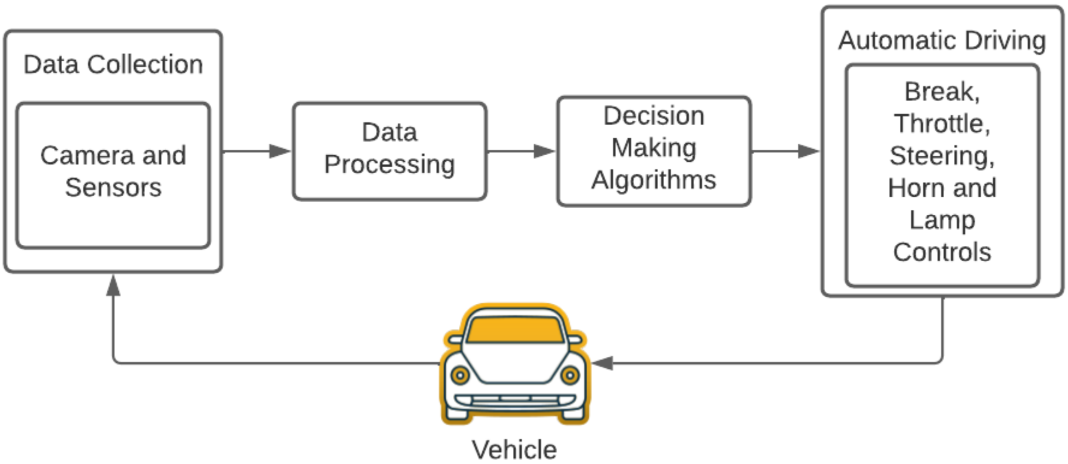

Figure 1. Architectural view of an autonomous vehicle system

2. Literature Work

An autonomous driving behavior model was developed using recurrent neural network. The model is split into three sections as recognition, planning and prediction where the recognition module is placed to reduce the redundant data collected from a real time scenario. A CNN based classification module was incorporated in the work for estimating the path planning. A RNN model is equipped in the process for providing the required driving patterns. A simulation experiment was conducted to prove the efficiency of the model in traffic and terrain areas and it achieves the accuracy of 97.72% in a light traffic areas [11]. A deep reinforcement learning model was developed to make an urban autonomous driving model. A latent process is incorporated in the work along with reinforcement learning for minimizing the computational complexity. A simulated experiment was conducted in the work with CARLA and it shown an acceptable learning rate [12]. A video surveillance system was developed using a fusion system based on CNN and SVM algorithms. The workflow was organized with a preprocessing step for compressing the video frames collected through the camera device. This gives a dimensionality reduction in the computational process and makes the model to be operated with more number of features. The accuracy attainments in the proposed model were showing betterment over the background subtraction method, CNN and SVM [13].

An intelligent transportation system was proposed to handle the traffic situations for manual and autonomous vehicles placed in 5G environment. The proposed model utilizes a long-term memory networks for giving input from two different datasets. A softmax function is included in the work for obtaining the algorithms intention from the probability matrix and it gives maximum accuracy of 91.58% on lane changing process [14]. A lane keep assistance system was designed using SVM approach on autonomous vehicle where the steering angle, camera image and vehicle speed references are considered as an input to the system. The experimental result explores a better accuracy rate of 94.2% in medium Gaussian SVM technique [15]. An electric wheelchair system was developed using PID controller and eye tracking algorithm. An image processing based algorithm was incorporated in the work to segment the pupil layer of the eye and its direction. Based on the direction of an eye a derivative control is determined in the proposed work and that controls the direction movement of a wheelchair with 90% accuracy [16].

A multi-model autonomous driving system was proposed to read both image and LiDAR signals. The experimental indicates a better prediction rate over the regular methods [17]. Apart from LiDAR, Li-Fi techniques are also implemented in the certain vehicles for making communication between vehicles. The transmission and processing of li-Fi signals are comparatively better over the traditional RF communications and that requires only simple amplifier model that too can be operated with minimum solar energy [18]. A CNN based system was developed to recognize the vehicle number plate using CNN. The experimental work utilizes a K-means clustering approach for number segmentation from the number plates and it achieves an average accuracy of 98.1% in different models [19].

A speed bum detection model was developed using deep learning and computer vision algorithms. A real time embedded model is made to verify the performances of the proposed model and found satisfied with its precision of 99.05% and accuracy of 98.54%. The speed regulation is corrected in the method by evaluating the object distance through a Raspberry Pi module [20]. An accident alert system is incorporated in most of the autonomous vehicle which leads to send the accident location to the rescue team by analyzing the accelerometer state of the vehicle. A false alarm switch is also included in the work for stopping the false emergency signal forwarded to the rescue team. The switch was designed to erase the signal once it is activated within 20seconds after the initial signal transmission [21]. An automated fair collection system for vehicles was proposed using a blockchain technology for providing privacy over the vehicle and driver information to the operating system [22].

A deep learning based image recognition system was proposed for autonomous vehicle applications where the model was equipped with CNN algorithm for scene understanding and a back propagation signal was also incorporated in the work for fine tuning the operation [23]. An advanced driver assistance system was designed by incorporating deep learning algorithms and IoT sensors. The values observed from the IoT devices are considered as surrounding input and a MobileNet based deep learning model is included in the work analyzing the sensor values. A pulse rate sensor is also equipped in the work for receiving the status of the driver and a CC3200 chip is equipped in the work for sending signal to the rescue station for emergencies. The state of driver is also continuously monitored in the system using ESP8266 [24]. The Li-Fi technologies were also incorporated for vehicle to traffic signal communication for making the signals 'ON' at emergency situation. The Li-Fi receivers that are connected over the road lanes are collecting the information from the Li-Fi transmitter connected in the vehicles and forwarded it to the signal post through underground cable communication [25]. The literature study indicates that the image processing and data mining algorithms are performed in different applications of autonomous vehicles where the vehicle and driver information are saved using blockchain model. The fusion based techniques are found effective in such cases. However, its computational cost is very high over the regular algorithms. The following section explores the methodology followed in the proposed model on autonomous driving application.

3. Proposed Method

The proposed work aims to summarize the performance difference among the centralized and distributed AI systems on autonomous driving application. The work utilizes an openly available dataset [26] for the training and testing process. The dataset consists of various images taken on the road from a rooftop camera.

3.1 Centralized AI system

The centralized AI system of the proposed model utilizes a “Google Colab” platform for its analysis. The Colab allows to run the algorithms on Google could server with zero configuration and free access to its GPU space. Figure 2 explores the architectural view of a general centralized AI system where the information collected from the senor and camera are moved to a local data storage. In some cases a minor preprocessing algorithm will be incorporated into the local data storage module that removes the noisy and error data from the hard disc.

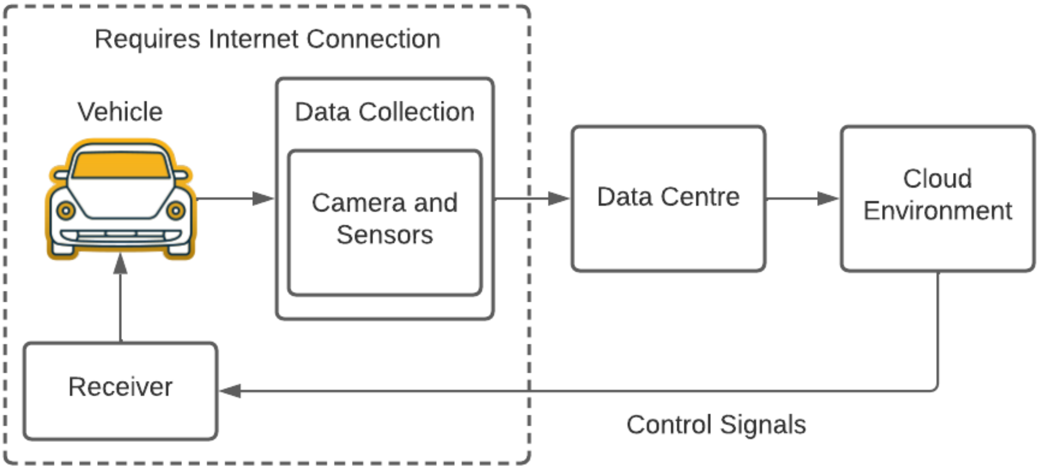

Figure 2. Architectural view of a centralized AI system

The internet connection given to the local storage system allows the collected data to forward over the remote data server and it permits the algorithm stored in the cloud server to access the information for the analytic process. A control signal will be forwarded to the vehicle from the cloud environment through a receiver connected to vehicle. The main limitation of the centralized AI system is the requirement of internet connection. Providing internet connection to all the road lines are practically difficult. The quality of the internet connection may get affected in some particular roadways due to environmental noise and industrial radiations. In the proposed work the traditional CNN and ANN algorithm were utilized for the analytic process.

The local AI system avoids the limitation of the internet connection on centralized AI system by having multiple local systems for the data processing. A high power processing unit with adequate GPU infrastructure is utilized in this model for processing the data collected from camera and sensor instantly.

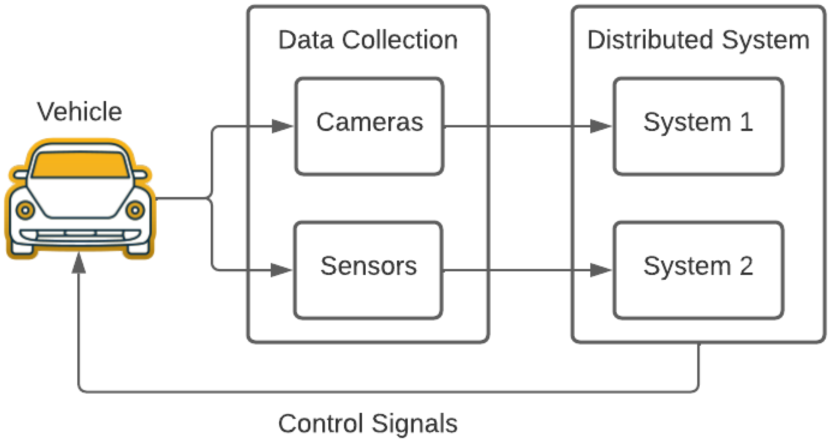

Figure 3. Architecture of a distributed AI system

The processing speed of the local AI system is limited to the range of rate of hardware provided to the system. In the distributed AI system, the local network is splitted into several modules where the data collected from camera can be given to one local system and the data collected from sensors can be forwarded to another local system. The algorithm included in the systems may get differ in respective to the application of the collected data. The application wise outcome is very efficient in the distributed AI systems. However, the system may get corrupted when there is any hardware damage or software malfunction.

4. Experimental Analysis

The distributed AI system of the proposed work is equipped with an 8GB RAM module of Intel core i7 processor. At the same time, the Google Colab module is equipped with 12GB RAM of Intel Xeon CPU. Table 2 explores the accuracy and precision differences among the CNN and ANN algorithms on both centralized and distributed AI models in different data ID and its average accuracy and precision range is projected in Figure 4.

Table 2. Accuracy and precision performance on different data ID

Algorithm	Data ID	Centralized AI System		Distributed AI System	
		Accuracy	Precision	Accuracy	Precision
CNN	1	75.6	74.3	75.2	73.9
	2	82.4	81.6	81.5	80.7

	3	78.1	77.5	80.3	79.6
	4	80.9	79.6	80.1	79.2
	5	74.5	73.4	73.9	73.1
	Average	78.3	77.28	78.2	77.3
ANN	1	88.4	87.5	90.2	89.7
	2	95.1	94.3	92.3	91.8
	3	91.1	90.7	88.7	87.4
	4	93.8	92.2	91.4	90.3
	5	87.7	86.1	85.9	85.1
	Average	91.22	90.16	89.7	88.86

The samples available in the dataset [26] are moved to their respective data ID from 1 to 5 and its performances were done separately on centralized and distributed system. The accuracy and precision projections between the two systems are not showing a huge difference on CNN algorithm. The average precision rate and accuracy estimation on ANN is showing a slight betterment in the ANN algorithm.

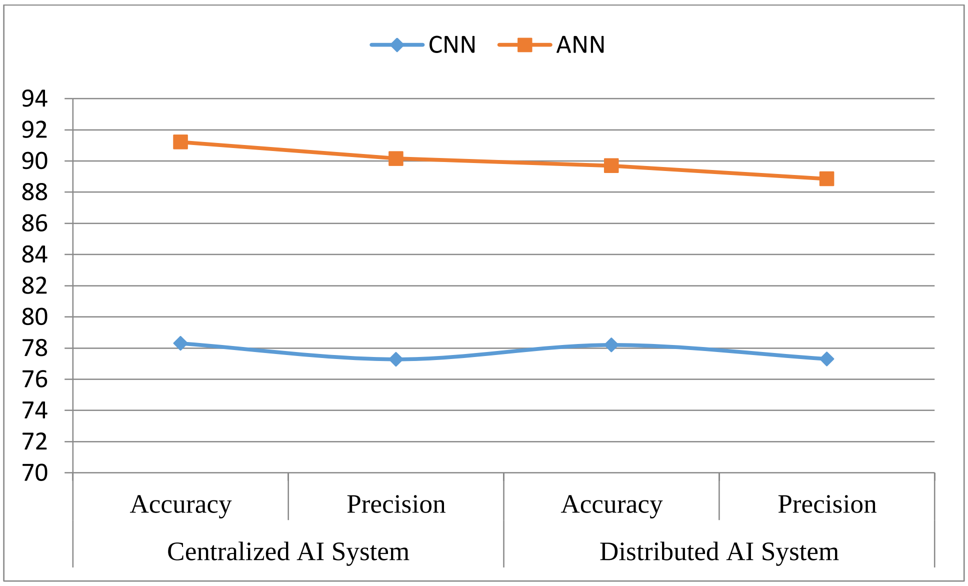

Figure 4. Performance difference among the centralized and distributed AI systems

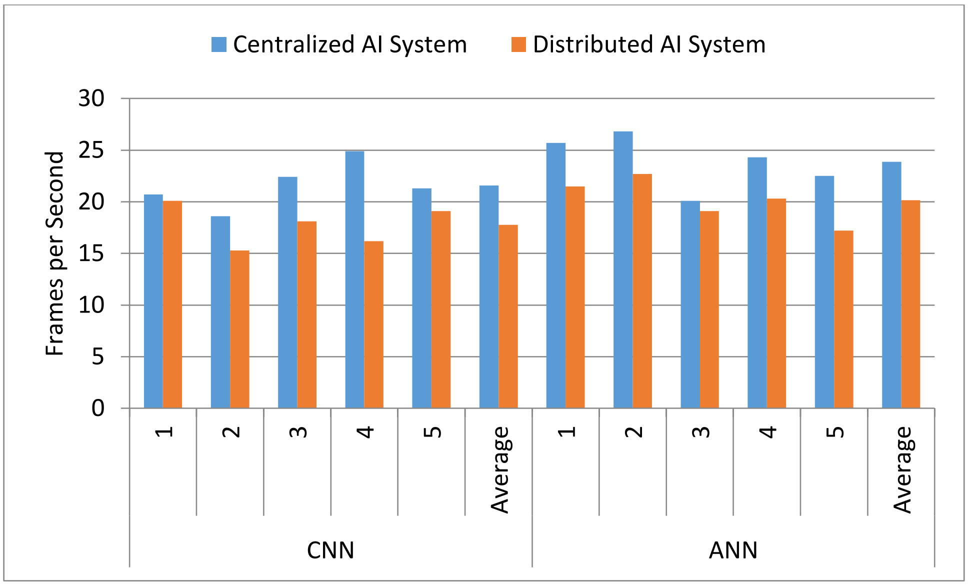

Figure 5. Computational effectiveness among the distributed and centralized AI systems

The computational betterment of the centralized AI system over the distributed AI system is shown in Figure 5. The average frame/second difference on the CNN and ANN algorithm is reached to 3.82 and 3.72 respectively. This difference can be matched by the distributed AI system by having a better range of RAM unit, preferably 16GB.

5. Conclusion

Effectiveness of a distributed AI system is verified in the proposed work over a centralized AI system with an autonomous driving dataset. The experimental work indicates a slight betterment on the centralized AI system accuracy with 0.1% on CNN and 1.52% on ANN algorithm. Similarly the processing speed of the centralized AI system shows a significant improvement over the distributed AI system. The distributed AI systems are efficient in terms of security but it lags when the hardware units are equipped with regular devices. The experimental work also identifies that a hardware unit assigned separately for the specific task may improve the performances of the distributed AI system.

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Author's biography

K. Rahimunnisa works as a Professor in the Department of Electronics and Communication Engineering at Easwari Engineering College, Chennai, Tamil Nadu, India. Her area of research includes VLSI architecture design, Image processing and crypto systems.