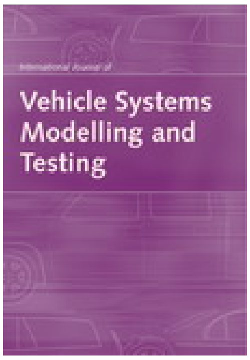

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Modelling and simulation of an autonomous vehicle based on Alexnet for traffic sign recognition

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Abstract: This paper presents a study on an autonomous vehicle system capable of recognising and responding to traffic signs. Using the virtual robot experimentation platform (V-REP) virtual simulation system, a training dataset is generated for traffic sign recognition (TSR), employing a pre-trained AlexNet network. The vehicle model, integrated with the trained network, operates within the V-REP environment, supported by a vision-based control system. Driving scenarios are designed to assess the system's ability to interpret and respond to traffic signs without human intervention. Experimental validation confirms the effectiveness and reliability of the proposed system, showcasing its potential for real-world applications in autonomous vehicles with TSR capabilities.

Keywords: autonomous vehicle; TSR; traffic sign recognition; V-REP virtual simulation system; AlexNet.

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1 Introduction

Autonomous vehicles are revolutionising the transportation industry, promising safer and more efficient mobility. Within this context, traffic sign recognition (TSR) plays a vital role in enabling these vehicles to interpret and respond to the information conveyed by traffic signs. Accurate and timely recognition of traffic signs is crucial for autonomous vehicles to navigate roads, comply with regulations, and ensure the safety of passengers and other road users.

Automating the process of TSR through computer vision and machine learning techniques offers the potential to enhance the capabilities of autonomous vehicles. By leveraging advanced algorithms and deep learning models, autonomous vehicles can effectively interpret traffic signs, including speed limits, stop signs, yield signs, and other regulatory signs. This allows the vehicles to make informed decisions, adjust their speed, plan manoeuvres, and ensure compliance with traffic rules. Bouaafia et al. (2021) introduced the deep convolutional neural network (CNN) and its architectures, such as, VGG16, VGG19, AlexNet, and Resnet50. An overview for the techniques and schemes used for road sign recognition is introduced. These networks have shown exceptional performance in road sign recognition. The techniques and schemes employed for road sign recognition are provided in an overview. Atif et al. (2022) employed ML-based classifiers to build a TSR system that analyses a sliding window of frames sampled by sensors on a vehicle. This system leverages machine learning algorithms to accurately identify and interpret traffic signs, contributing to the overall perception and decision-making capabilities of the autonomous vehicle. Zhou et al. (2018) combined with the idea of AlexNet and the residual network structure, and the optimised network model is used for road TSR. This hybrid model capitalises on the strengths of both architectures to achieve improved accuracy and efficiency in recognising traffic signs. Xie et al. (2021) provided a high-accuracy AlexNet model for an autonomous car in TSR.

The development of TSR systems for autonomous vehicles is driven by advancements in computer vision, image processing, and deep learning methodologies. Convolutional neural networks (CNNs) have emerged as a powerful tool for TSR in autonomous vehicles. These networks can automatically learn complex features from raw image data, enabling robust and accurate recognition of traffic signs across a wide range of scenarios and environmental conditions.A lightweight neural network architecture has been proposed for TSR, achieving high levels of accuracy and precision while utilising fewer trainable parameters (see Khan et al. (2023)). This approach emphasises efficiency without compromising performance. Fredj et al. (2023) used CNN to develop a Traffic and Road Sign recognition system. The performance of the proposed architecture is measured using a novel dataset, namely the Tunisian traffic signs dataset. These studies highlight the applicability and effectiveness of CNNs in real-world traffic sign recognition tasks. Niu and Li (2022) proposed a method based on YOLOv5s target detection and AlexNet image classification to detect and identify traffic lights. This approach combines the strengths of object detection and image classification techniques to improve traffic light recognition. Lim et al. (2023) provided a comprehensive overview of the latest advancements in TSR has been provided, covering various essential areas such as preprocessing techniques, feature extraction methods, classification techniques, datasets, and performance evaluation. This review consolidates the recent progress made in the field and offers insights into the current state-of-the-art approaches and their performance. The integration of computer vision and machine learning techniques, along with the utilisation of advanced deep learning models, showcases the potential for robust and accurate TSR in autonomous vehicles. Zheng et al. (2020) explores the role of activation functions in deep convolutional neural networks for image classification tasks. It compares and analyses the effects of different activation functions, providing valuable insights for the selection of activation functions in deep learning. Zheng et al. (2017) combines artificial features with deep convolutional activation features in fine-grained image classification to enhance accurate object classification in complex scenes.

Tian et al. (2019) utilises deep learning for the accurate prediction of electric vehicle charging demand and optimises the layout of charging stations to improve the efficiency of electric vehicle charging. Jiang et al. (2021) employs long short-term memory (LSTM) networks to predict PM2.5 concentrations. These advancements contribute significantly to enhancing the overall safety and efficiency of autonomous transportation systems.

This study utilises the virtual robot experimentation platform (V-REP) virtual simulation platform to establish a virtual physical model of an autonomous car. Within this model, a TSR system is designed based on the Alexnet network, enabling the car to navigate within a simulated traffic environment. Furthermore, a simplified road network is created within the simulation. The results of the simulation demonstrate that the designed sign recognition system accurately identifies common traffic signs on the road, thereby assisting the autonomous car in adhering to the detected signs and achieving self-driving capabilities.

This study employs modelling and simulation techniques to investigate a TSR system based on AlexNet. The primary objective is to validate the real-world applicability of deep learning models within autonomous driving systems. The research focuses on enhancing the perceptual and recognition capabilities of autonomous vehicles, specifically in the context of traffic sign identification. The overarching goal is to facilitate accurate TSR by autonomous vehicles across diverse road conditions, thereby ensuring adherence to road regulations and traffic sign directives.

2 Traffic sign recognition based on Alexnet

In this section, we present the TSR approach utilising the AlexNet model.

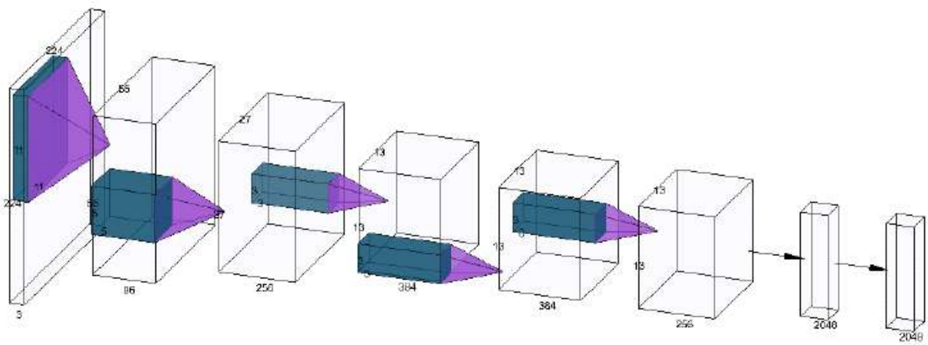
2.1 Brief introduction of AlexNet

AlexNet is a CNN architecture that was developed by Alex Krishevsky, Ilya Sutskever, and Geoffrey Hinton in 2012. AlexNet consists of eight layers, including five convolutional layers, followed by three fully connected layers. It operates on 2D images as input, see Yuan and Jun (2016).

The design of AlexNet excels in the aspect of image feature learning, and for autonomous vehicles, visual perception is of paramount importance. Therefore, the choice of AlexNet is based on its outstanding capability in image feature learning. Serving as a pre-trained model, AlexNet is highly suitable for transfer learning, significantly reducing the required samples, time, and computational resources for learning. AlexNet has undergone training on a large-scale dataset. In the task of autonomously recognising traffic signs for self-driving vehicles, utilising a pre-trained AlexNet facilitates faster convergence and superior performance. Furthermore, in comparison to certain state-of-the-art deep learning models, AlexNet's structure is relatively straightforward, making it more accessible for understanding and interpretation. This simplicity is advantageous for considering the interpretability of models in subsequent research, especially in critical domains like autonomous vehicles.

AlexNet's architecture encompasses eight layers, consisting of five convolutional layers and three fully connected layers (Figure 1). Its architectural choices, including the use of rectified linear unit (ReLU) activation functions, address the vanishing gradient problem and facilitate faster training.

Figure 1 AlexNet's architecture (see online version for colours)



Convolutional layers: The initial layers of AlexNet employ convolutional operations to extract low-level features from input images. These layers utilise a large number of learnable filters to capture various visual patterns.

ReLU activation: Rectified Linear Unit (ReLU) activation functions are used throughout AlexNet to introduce non-linearity, allowing the network to learn more complex representations. ReLU helps mitigate the vanishing gradient problem and accelerates training.

Pooling layers: After each set of convolutional layers, max-pooling layers are applied to reduce spatial dimensions while preserving important features. Pooling helps capture invariant properties and enhances translation invariance.

Local response normalisation: AlexNet incorporates local response normalisation, a normalisation technique that promotes competition between features within the same local neighbourhood. It enhances the network's ability to generalise and respond to various input variations.

Dropout: To prevent overfitting, AlexNet uses a technique called dropout during training. Dropout randomly drops out a fraction of the neurons, forcing the network to rely on different combinations of features and improving generalisation.

Fully connected layers: The last three layers of AlexNet are fully connected layers that process the high-level features learned by previous layers. These layers progressively reduce the dimensions and ultimately output class probabilities.

Softmax activation: The final layer employs the softmax activation function, which transforms the network's outputs into a probability distribution over different classes, enabling classification.

This architecture follows a typical pattern of alternating convolutional layers with ReLU activations, pooling layers for down-sampling, and fully connected layers for classification. Dropout layers are used to reduce overfitting, and cross-channel normalisation helps with local contrast normalisation. Softmax activation is applied to produce class probabilities, and the network is trained using cross-entropy loss.

AlexNet played a significant role in popularising deep learning, especially in the field of computer vision, and its architectural principles have influenced subsequent CNN designs.

2.2 Data collection and preparation

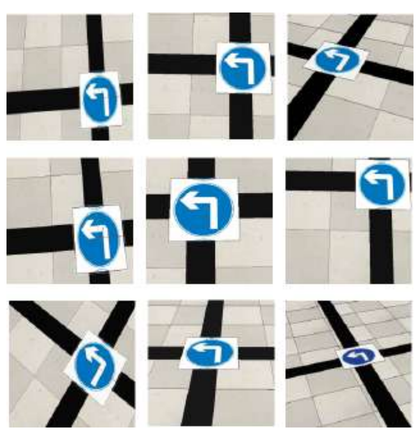
This study primarily focuses on the identification of left-turn signs, right-turn signs, stop signs and road without traffic signs (Figure 2).

Figure 2 Traffic signs in China (see online version for colours)

To increase the number of training samples, we employed the V-REP virtual simulation system to construct traffic signs positioned on the road. By simulating the perspective of traffic signs captured by an autonomous vehicle at various locations and using random camera positions, we obtained additional traffic sign images for learning purposes.

Since we utilised transfer learning with the pre-trained AlexNet model, the data requirement was not excessively high. Hence, we prepared about 20 sample images for each traffic sign, and some of these images are illustrated in Figures 3–5.

Figure 3 Sample set of left turn traffic signs (see online version for colours)



In addition, an image enhancement function is employed to generate an image data augmentation object capable of implementing a multitude of transformations on input images. These transformations encompass rotation, scaling, flipping, cropping, translation, shearing, as well as adjustments in brightness and contrast. The integration of these augmentations serves to enhance the diversity and variability of the training data, consequently fostering improved generalisation and robustness in deep learning models.

Figure 4 Sample set of right turn traffic signs (see online version for colours)

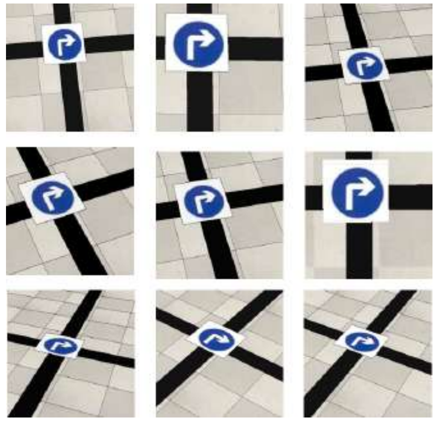


Figure 5 Sample set of stop traffic signs (see online version for colours)

2.3 Transfer learning with the pre-trained AlexNet

In this study, an AlexNet pre-trained network is employed, which has undergone training on an extensive dataset consisting of over one million images. This pre-trained network exhibits the capability to classify images across a vast range of 1000 object classes. Through this training process, the network has acquired a comprehensive and informative feature representation derived from the extensive image collection.

The training of AlexNet will be conducted on a Windows platform equipped with Core i5-8500, utilising the MATLAB Reinforcement Learning Toolbox. we employed the stochastic gradient descent (SGD) optimiser with a momentum parameter set to 0.9, facilitating rapid convergence during training. The initial learning rate was set to 0.001 and may be subject to a learning rate scheduling strategy, utilising a piecewise constant learning rate schedule, allowing for adaptive adjustments to the learning rate throughout the training process. To regulate the model's complexity, we introduced an L2 regularisation term with a weight set to 1e-4. The gradient threshold method opted for the L2 norm, and the gradient threshold was set to infinity, indicating an absence of constraints on the gradient threshold.The training process was configured with a maximum of 30 epochs, each consisting of small-batch training using 128 samples. Detailed information during the training process was displayed at a frequency of every 50 iterations. Additionally, the validation set was assessed every 50 iterations to monitor model performance and potential overfitting.

Initially, the dataset of sample images employed for training purposes is partitioned into two subsets. Randomly, 70% of the images are selected as the training set, while the remaining portion is designated as the test set. This division ensures a representative distribution of data for model training and subsequent evaluation.

Next, the pre-trained AlexNet network is loaded using the Matlab AlexNet function. Additionally, network-related parameters can be adjusted according to the specific requirements of the task at hand.Modifications to the network architecture can be made by adjusting the layers of the network. For instance, to change the number of output classes, you can replace the last few layers with new layers that match the desired number of classes.

Subsequently, the training options are established, and the AlexNet network is trained. Owing to the incorporation of pre-trained networks and transfer learning techniques, AlexNet demonstrates superior efficiency in training the learning of sample data, facilitating accelerated and significant performance enhancements.

Figure 6 illustrates the validation results of the trained model when applied to the validation image set containing traffic signs. The visualisation of these results indicates that the designed network exhibits improved accuracy in accurately classifying the traffic signs depicted in the images.

Figure 6 Validation results of the trained model (see online version for colours)

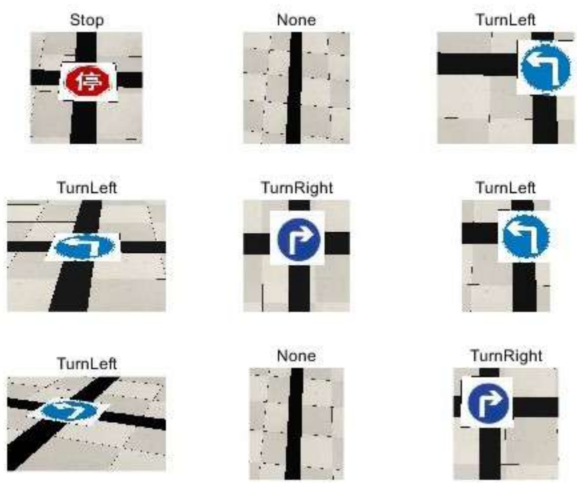
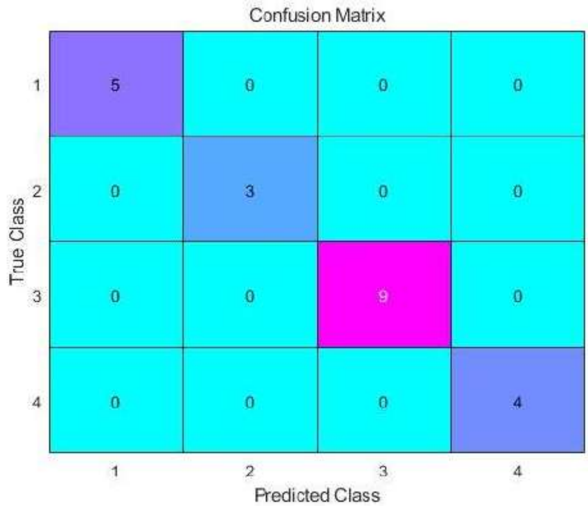


Figure 7 presents the confusion matrix of the trained model applied to the test samples. The matrix provides valuable insights into the model's performance in accurately recognising traffic signs and differentiating them from other signs, as well as correctly identifying cases where traffic signs are absent.

Figure 7 Confusion matrix of the trained model (see online version for colours)



From the observed results, it is evident that the model exhibits a high level of accuracy in recognising traffic signs without misclassifying specific signs as other types. Additionally, the model demonstrates the ability to effectively identify instances that do not contain any traffic signs. These findings reflect the robustness and discriminative capabilities of the model in the context of TSR.

Figure 8 depicts the evolution of the model's classification accuracy throughout the training process. As the number of iterations increases, the model progressively learns to capture more refined features of traffic signs, resulting in improved prediction accuracy. The curve demonstrates a rapid initial improvement, eventually reaching a high plateau of accuracy. Moreover, the model exhibits faster convergence, showcasing its ability to converge quickly and effectively.

Figure 8 Accuracy of the trained model (see online version for colours)

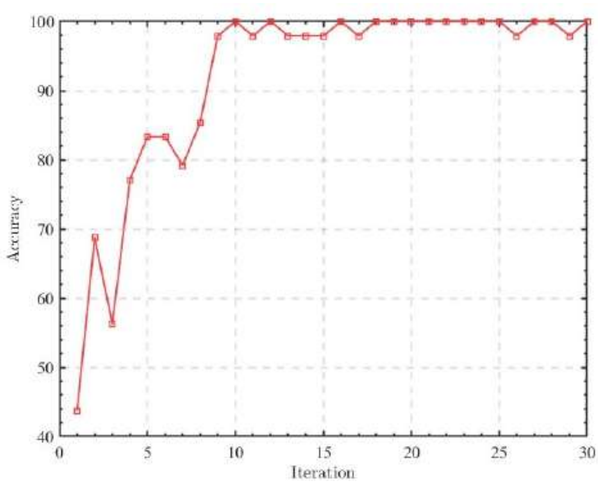
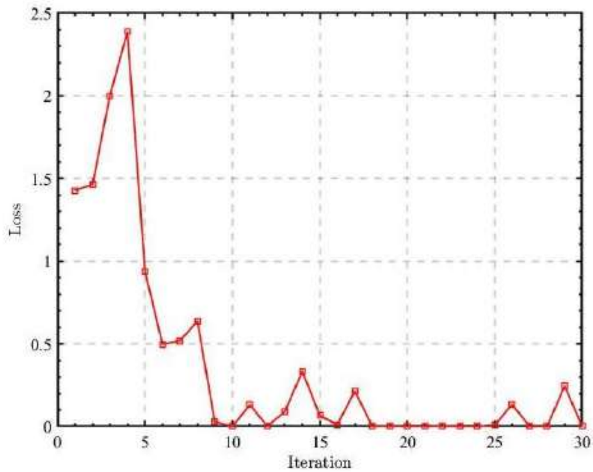


Figure 9 illustrates the variation of the model's loss value during training. The results indicate a lack of overfitting or underfitting, as the loss value demonstrates a stable pattern without significant fluctuations. This suggests that the model successfully captures the underlying patterns in the training data and generalises well to unseen examples, yielding reliable and consistent predictions.

Figure 9 Loss value of the trained model (see online version for colours)



3 Modelling of the autonomous vehicle

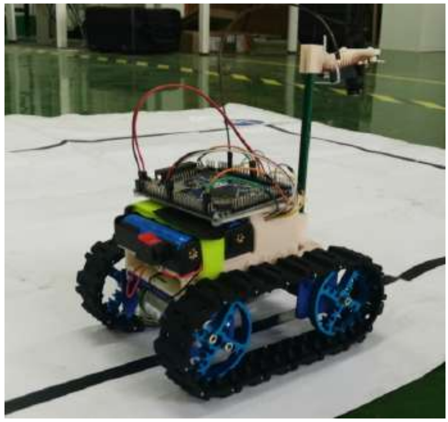
The fully developed AlexNet model exhibits commendable accuracy in classifying traffic signs and has been specifically tailored for integration into a self-driving car system. Its primary purpose is to evaluate the model's reliability and validity within the context of autonomous driving.

3.1 The autonomous vehicle

The autonomous vehicle (Figure 10) is equipped with OpenMV and STM32 microcontrollers. The OpenMV module is responsible for capturing ground traffic signs and detecting black guidance tracks. It then sends the recognition results to the STM32 control unit, which processes the information and generates corresponding control signals to drive the motors. This allows for precise control of the trolley's movements and navigation based on the detected signs and tracks.

To validate the efficacy of the autonomous vehicle , we initially constructed a virtual physical model of the trolley within a simulation platform. This virtual model served as a representative replica of the actual physical system. Subsequently, we seamlessly integrated the designed TSR system into the virtual physical model. By doing so, we aimed to assess the reliability and effectiveness of the designed system in a controlled and virtual environment. This approach allowed us to conduct extensive testing, analyse the system's performance, and validate its functionality before deploying it in real-world scenarios.

Figure 10 The real autonomous vehicle (see online version for colours)



3.2 The autonomous vehicle in the V-REP

Virtual robot experimentation platform (V-REP) is a widely used robotics simulation software. It provides a comprehensive platform for simulating and visualising complex robotic systems in a virtual environment, see Rohmer et al. (2013).

The autonomous vehicle components are accurately replicated in a 1 : 1 scale within the V-REP simulation environment, matching the dimensions of the actual car. These replicated components are then meticulously assembled, employing suitable couplings and connections, to create a unified entity. This approach ensures that the virtual representation of the car faithfully mirrors its physical counterpart, encompassing precise proportions and structural details. By faithfully recreating the car's components and their interactions in the virtual realm, it facilitates realistic simulation and thorough testing of the car's behaviour and performance before its implementation in real-world scenarios.

In V-REP, the four wheels of a car, much like in a real vehicle, are linked to the body through four motors known as revolute joints (Figure 11). These revolute joints can be effectively operated using control commands within V-REP, enabling users to modify the car's position and attitude. By manipulating these joints, users can replicate the rotational movement of the wheels, thereby controlling the overall motion and behaviour of the simulated car.

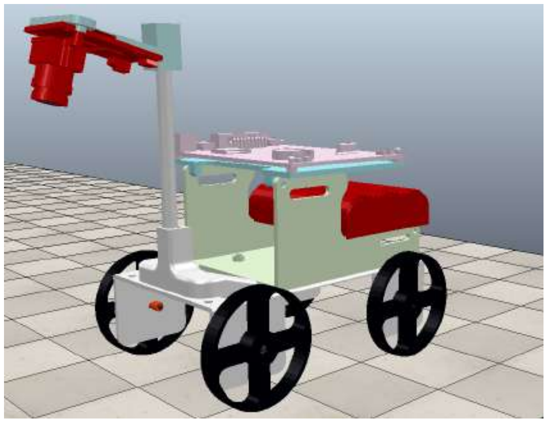
Furthermore, in the virtual model, V-REP incorporates a camera module instead of OpenMV's vision module. This camera module allows for the capture of environmental images within the V-REP virtual environment. By utilising this camera module, users can gather visual data that emulates the real-world perception of the car, enabling the simulation to incorporate visual inputs and potentially implement vision-based algorithms or tasks.

3.3 Control of the autonomous vehicle

When simplifying the actual traffic situations encountered by the autonomous vehicle, its tasks can be categorised into four distinct actions. Firstly, if the camera captures a left turn sign on the ground, the trolley is programmed to make a left turn accordingly. Similarly, if a right turn sign is detected by the camera, the trolley will execute a right turn. In the presence of a stop sign within the camera's view, the trolley will come to a complete stop. Lastly, in instances where no traffic signs are detected by the trolley's camera, it is required to autonomously follow a predetermined black guide track. These task categories provide a simplified framework for the autonomous vehicle's behaviour within its environment.

The tasks performed by the autonomous vehicle can be effectively composed of these four distinct working modes.

Figure 11 The virtual model of the autonomous vehicle (see online version for colours)



During operation, the control of each task mode of the autonomous vehicle is accomplished by independently controlling the speed of the four-wheel drive motors. This approach allows for precise manipulation of the autonomous vehicle's movement and enables it to execute the desired actions for each task mode. By adjusting the speed of the individual motors, the trolley can accurately navigate through turns, come to a halt, or follow the guide track as required by the specific task mode. This independent control mechanism ensures the autonomous vehicle's responsiveness and adaptability to different scenarios encountered during its operation.

Turn left and right: The autonomous vehicle's turning can be controlled by modulating the speed difference between its wheels. By adjusting the speeds of the wheels on either side of the autonomous vehicle, a differential drive system can be utilised to achieve turning manoeuvres. When the trolley needs to make a left turn, the wheels on the right side can be slowed down or stopped while the wheels on the left side continue to move at a normal speed or vice versa for a right turn. This speed difference creates a rotational effect, causing the trolley to turn in the desired direction. This method allows for agile and precise turning control without the need for additional steering mechanisms.

Stop: The autonomous vehicle can be brought to a stop by ensuring that all four wheels have ceased turning. By monitoring the rotational speed of each wheel, the autonomous vehicle's control system can detect when all four wheels have come to a halt. Once this condition is met, appropriate control commands can be sent to the wheel drive motors to stop their rotation completely. This ensures that the trolley remains stationary and is effectively stopped.

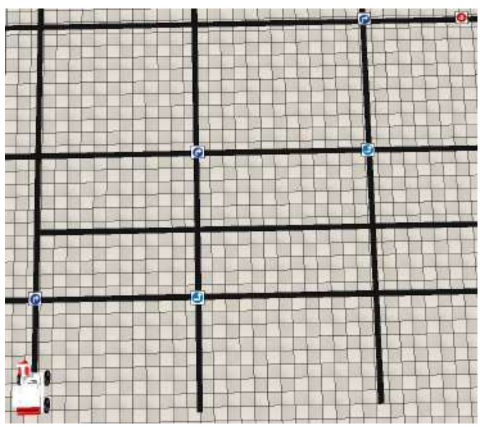
Straight forward: When the autonomous vehicle is travelling in a straight line, it is essential to continuously adjust its own attitude based on the straight line path information obtained from the image. This adjustment is necessary to maintain alignment with the predetermined trajectory. By analysing the image data captured by the camera, the autonomous vehicle's control system can extract relevant information about the straight line path and compare it with the desired trajectory.

4 Simulation and experiment

4.1 Virtual simulation

To validate the functionality of the autonomous vehicle's ability to autonomously recognise traffic signs and adhere to traffic rules in an unattended manner, driving scenarios were created within V-REP (Figure 12). These scenarios include various relevant traffic signs and pre-defined trajectories. By incorporating these elements into the simulation environment, it allows for comprehensive testing and evaluation of the self-driving car's performance.

Figure 12 Driving scenarios in V-REP (see online version for colours)



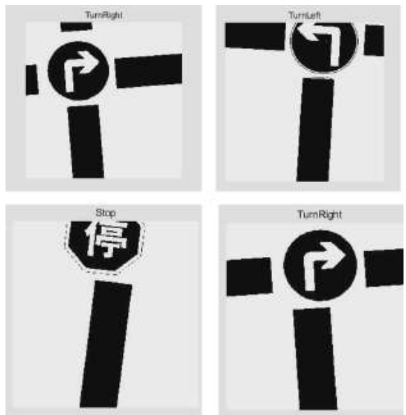
In the simulation scenario, the autonomous vehicle starts from a designated starting point and follows a predetermined trajectory. The car utilises its camera to recognise the black pre-defined trajectory on the road, enabling it to accurately stay within the designated path. Additionally, the car's camera system identifies the presence of traffic signs at road intersections.

By analysing the captured images, the autonomous vehicle's control system recognises the various traffic signs and interprets their corresponding meanings. Based on this information, the car adjusts its behaviour and adheres to traffic rules, ensuring it operates on the road in a compliant and safe manner. For example, when the camera detects a stop sign, the car will come to a complete stop. Similarly, when it identifies a left or right turn sign, the car will execute the corresponding manoeuvre accordingly.

By integrating the camera-based perception system and the control system, the autonomous vehicle car successfully recognises the pre-defined road trajectory and accurately interprets traffic signs to navigate the road following traffic rules. This simulation scenario allows for comprehensive testing and validation of the autonomous vehicle's ability to autonomously respond to the environment and demonstrate its adherence to traffic regulations.

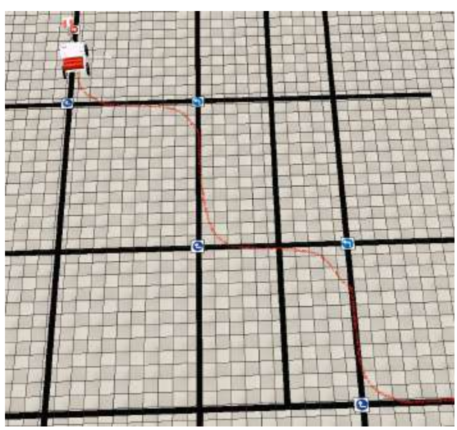
In Figure 13, the results of the on-board AlexNet TSR are presented. In the established simulation environment, six crucial traffic signs, which indicate the direction of the trolley's travel, were successfully identified. Furthermore, the vehicle seamlessly transitioned to the corresponding control system, accurately adjusting its steering, forward motion, and stopping actions based on the obtained image results.

Figure 13 On-board Alexnet recognition of traffic signs



The trajectory of the centre of mass of the autonomous vehicle is depicted as the red path in Figure 14. This trajectory illustrates the trolley's ability to recognise traffic signs at specific locations and execute precise movements in accordance with the recognised signs. This capability ensures the successful completion of the task at hand.

Figure 14 Trajectory of the autonomous vehicle (see online version for colours)



4.2 *Experiment*

During the experimental session, the trained Alexnet was installed on the cart, which was tasked with autonomously navigating by identifying traffic signs on the ground and accurately following the predetermined black trajectory without any external intervention (Figures 15 and 16).

Figure 15 Driving scenarios in real (see online version for colours)

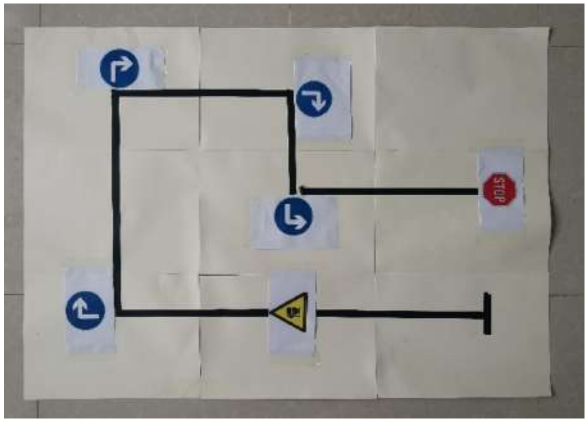
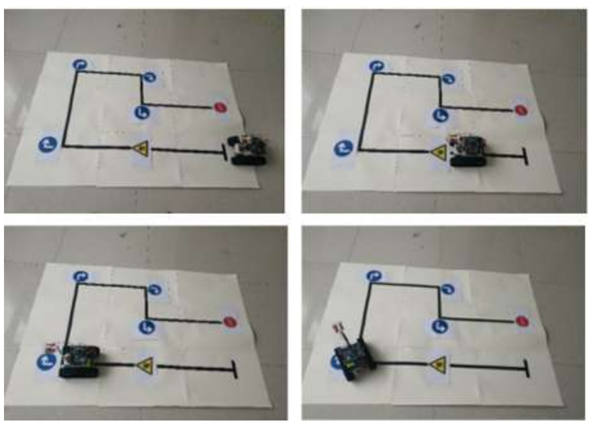


Figure 16 Experiment result of the autonomous vehicle (see online version for colours)



The experimental findings reveal that the cart exhibits enhanced reliance on vision control technology to track the predefined ground trajectory, and it can seamlessly transition between control systems based on the recognised traffic signs and corresponding traffic rules, thereby accomplishing automated driving.

5 Conclusion

This paper presents a study focused on autonomous vehicle capable of recognising traffic signs. The researchers utilised the V-REP virtual simulation system to generate a training dataset for TSR. For this purpose, a pre-trained AlexNet network was employed to achieve accurate recognition of traffic signs. Within the V-REP virtual simulation system, a vehicle was created and equipped with the trained network. Additionally, a vision-based control system was developed to facilitate autonomous operation of the vehicle.

To evaluate the functionality of the designed autonomous vehicle in responding to traffic signs without human intervention, driving scenarios were carefully designed and implemented within the V-REP virtual simulation system. These scenarios aimed to assess the autonomous vehicle's ability to operate in accordance with recognised traffic signs. By simulating various traffic scenarios, the researchers could validate the system's effectiveness and reliability in real-world-like situations.

Through experimental validation, the paper ultimately verifies the effectiveness and reliability of the proposed system. The results obtained from the experiments demonstrate the system's capability to recognise and appropriately respond to traffic signs, paving the way for potential real-world applications of autonomous vehicle with TSR capabilities.

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