Object Detection for Autonomous Vehicles under Special Situations

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Background & Motivation

With the development of AI especially the neural network deep learning models, more and more autonomous vehicles are available and running in the public. Researchers forecast that by 2025 we'll see approximately 8 million autonomous or semi-autonomous vehicles on the road.[1] AI will become the main decision-making source for any self-driving cars that are at least at level 2 of autonomy [2] which leads to concern for the public's safety as the result of the uncertainty of AI. Autonomous vehicles replied on cameras, lasers, radar, and other sensors to gather information from the environment and process those data using a pre-trained neural network AI model to detect different objects. Although the state-of-art models have a high performance in object detection under a normal autonomous-driving environment, applying them under various special situations is another challenge such as bad weather, unexpected objects (such as plastic bags), and signals from other objects. The wrongful object detection under these special situations will lead to safety issues, which are accidents more than likely. For example, if the model detects a flying plastic bag in front of the car as a pedestrian it will slam the brake which may cause a crash if the car behind it thought it will keep driving. These difficulties and errors are mainly attributed to the lack of data for these special situations in the training dataset. Most datasets that the models are trained on are for normal objects such as cars, pedestrians, traffic lights, and traffic signals. There are not many datasets about the special situations mentioned above. Thus, I believe adding the new datasets to the training process can help the model learn about such situations and make the correct decision accordingly.

Central Hypothesis

I hypothesize that (1) detecting the false-positive object (False-positive object means that it will be detected, and AI will take action while it will not affect driving at all), (2) detecting the signal from other objects, and (3) detecting objects in bad weather would enhance the overall performance of object detection for autonomous vehicles and therefore, will increase the safety level and trustworthy level of the vehicle.

Summary of the overall approach

As shown in Figure 1, I will collect different data for each situation by conducting surveys and dataset reconstruction to establish different datasets for different situations. And then I will divide the dataset into 70/30 percent distribution for training and testing, respectively. The model that was pre-trained on the original dataset will be trained and tested on each dataset separately and evaluated by the accuracy of detection. Lastly, all datasets will be merged into the original test dataset to test the model and evaluate the difference between the accuracy. The model being used is the proposed system by Kim et al. [3] based on STDN. The evaluation will be conducted through an open-source simulator called VISTA2.0 [4]. The list of 3 aims is as follows:

Aim 1: Train the model with all kinds of possible scenarios in that a false-positive object interacts with the vehicles.

Aim 2: Train the model with all kinds of possible signals coming from other objects to enable the model to act accordingly.

Aim 3: Train the model with all kinds of possible bad weather to enable the model to detect objects in different bad weather conditions.

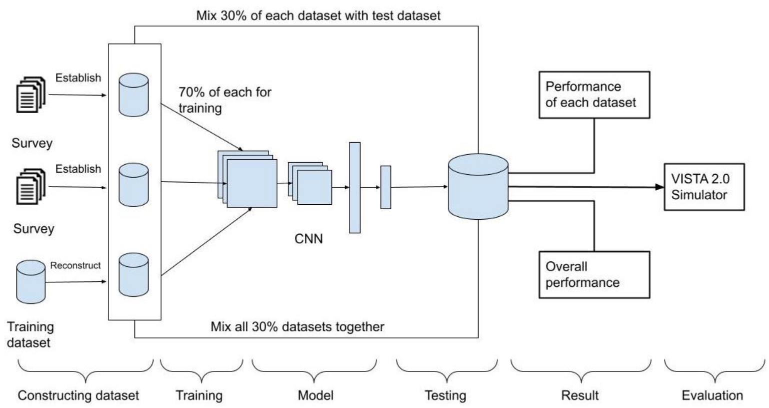

Figure 1: Overview of the methods

Aim 1

Method: To collect the data, I will first survey 100 drivers to list all the possible false-positive objects that will encounter during driving and their corresponding actions. The survey will be conducted on Amazon Mechanical Turk. The 100 drivers will be selected randomly based on their years of driving experience and separated into 5 groups evenly (20 for each), 1-5 years of experience, 5-10 years of experience, 10-15 years of experience, 15-20 years of experience, and 20+ years of experience. Each driver will be asked to list at least 5 possible false-positive objects and reactions to them such as ignore, bypass, and stop. After manual analysis, a final list of possible false-positive objects is built by including and excluding the survey results. Then a dataset will be established after collecting the data which will be manually labeled according to the final list. The dataset will be randomly divided into 70/30 for training and testing. Train the model on 70% of the dataset and mix the 30% with the original test dataset. Test the model on the mixed dataset to verify if a high performance has been produced before evaluation.

Evaluation Plan: I will use an open-source simulator called VISTA2.0 [4] to evaluate the method. The trained model and mixed test dataset will be fed into the simulator. The simulator will run with different scenarios in 5 categories, starting with false-positive objects only, then more false-positive objects than normal objects, then an equal number of false-positive objects and normal objects, then fewer false-positive objects than normal objects, and ending with normal objects only. The detection accuracy of false-positive objects in different categories will be calculated and compared to measure the effectiveness of the method. The model in the simulator should be able to identify the false-positive objects with similar accuracy to normal objects. and while the false-positive objects are identified, less critical action or no action should be taken.

Aim 2

Method: To collect the data, I will first survey 100 operators of all other kinds of ground transportation other than cars to list all the possible signals that interact with vehicles such as turn signals from cyclists and stop signals from pedestrians, and corresponding actions from the cars. The survey will be conducted on Amazon Mechanical Turk. The 100 operators will be selected randomly based on methods of transportation and separated into 4 groups evenly (20 for each), bicycle, motorcycle, skateboarder, and walker. Each operator will be asked to list at least 5 possible interaction signals and reactions to them from the cars such as ignore, bypass, and stop. After manual analysis, a final list of possible interaction signals is built by including and excluding the survey results. Then a dataset will be established after collecting the data which will be manually labeled according to the final list. The dataset will be randomly divided into 70/30 for training and testing. Train the model on 70% of the dataset and mix the 30% with the original test dataset. Test the model on the mixed dataset to verify if a high performance has been produced before evaluation.

Evaluation Plan: I will use an open-source simulator called VISTA2.0 [4] to evaluate the method. The trained model and mixed test dataset will be fed into the simulator. The simulator will run with different scenarios in 5 categories, starting with different signals from objects only, then more interaction signals than normal objects, then an equal number of interaction signals and normal objects, then fewer interaction signals than normal objects, and ending with normal objects only. The detection accuracy of interaction signals in different categories will be calculated and compared to measure the effectiveness of the method. The model in the simulator should be able to identify the interaction signals from objects without a large impact on normal object detection. And while the interaction signals are identified, the corresponding action should be taken.

Aim 3

Method: The weather conditions can be classified into 5 phenomena: snow, frost, fog, light, and rain. For each phenomenon, there are 6 levels of severity, level 0 being normal, level 1 being light, level 2 being medium, level 3 being high, level 4 being large, and level 5 being extreme. Since level 0 normal does not affect the original dataset, it will not be taken into consideration. Then I will create the layers to represent each level of severity for each phenomenon that can be considered noise. Thus, a total of 25 layers will be created. And then for each data point in the training dataset, I will apply these 25 layers on it separately to produce a total of 26 data including the original data. Therefore, the original training dataset will be expended by 25 times. The model I am using is proposed by Kim [3] which has an adversarial mechanism. It will be able to detect the noise feature along with the normal feature. Thus, it can extract the noise and then conduct normal object detection. And then I will collect the natural data of the 5 phenomena with different severity levels up to 30% of the original training dataset and use it as the test dataset to mix with the original test dataset. Test the model on the mixed dataset to verify if a high performance has been produced before evaluation.

Evaluation Plan: I will use an open-source simulator called VISTA2.0 [4] to evaluate the method. The trained model and mixed test dataset will be fed into the simulator. The simulator will run with different scenarios in 5 categories, starting with different weather conditions only, then more different weather conditions than normal conditions, then an equal number of different weather conditions and normal conditions, then fewer different weather conditions than normal conditions, and ending with normal conditions only. The detection accuracy in different weather conditions in different categories will be calculated and compared to measure the effectiveness of the method. The model in the simulator should be able to detect objects in different weather conditions while still performing well on normal object detection.

Overall evaluation

Lastly, I will evaluate the overall performance of the model for each situation. I will use an open-source simulator called VISTA2.0 [4] to evaluate the overall performance. All the test datasets for each aim will be mixed with the original test dataset into the final test dataset. The trained model and final test dataset will be fed into the simulator. All scenarios that are mentioned above will be randomly tested. The detection accuracy will be compared to each aim and original model to determine the effectiveness of the methods.

Reference

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