



FINAL PROJECT REPORT COMPUTATIONAL THINKING

TOPIC: OBJECT DETECTION IN ADVERSE WEATHER CONDITIONS

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CHAPTER 01. PROBLEM OVERVIEW

01.01 Introduction

Self-driving cars have been developed introduced with a number of automated features including lane keeping assist, queue assist in traffic jams, parking assist and collision avoidance. These self-driving vehicles and intelligent visual traffic monitoring systems largely depend on a system that combines cameras and sensors. Adverse weather conditions such as dense fog, rain, snow, and sandstorms are considered dangerous limitations to camera functionality that severely affect the performance of applied computer vision algorithms used for scene understanding, i.e. detecting, tracking and recognizing vehicles in traffic scenes. In addition, the vehicle detection and scene understanding algorithms are mostly evaluated using datasets containing real-world images with the addition of certain types of synthetic images. Therefore, it is uncertain how these algorithms will perform on dubious images obtained from nature, and how the process of these algorithms is normalized in the field.

Effectiveness of vehicle detection is generally considered a high priority in traffic monitoring or intelligent video surveillance. Self-driving vehicles need to accurately detect traffic objects (e.g. cars, cyclists, pedestrians, traffic lights, etc) in real-time to make appropriate decisions when driving. To detect such objects, sensors such as cameras and light detectors in different ranges are commonly used in autonomous vehicles. In these types of sensors, the image quality of the camera is greatly affected by adverse weather conditions such as dense fog, heavy rain, blizzard, dust explosion, and low light conditions, in which cases visibility is not sufficient for accurate detection of vehicles on the road, which may lead to traffic accidents. Clear visibility can be achieved by utilizing image enhancement methods to obtain better visuals or distinct features. Providing detection systems with clear images can improve vehicle detection and tracking performance in intelligent video surveillance systems and autonomous vehicle applications.

For these reasons, the development of object detectors in self-driving vehicles has been a research topic of great interest. Recent object detectors in self-driving vehicles have achieved high accuracy in normal weather conditions. However, in the cases where they encounter adverse weather conditions that create a limit in visibility, especially dense fogs, these detectors tend to have a decline in accuracy.

Object detectors based on Deep Convolutional Neural Network integrating different strategies have been extensively studied to take advantage of both types of deep learning categories and compensate for their specific disadvantages. Real-time detection is a requirement for traffic monitoring and self-driving applications in foggy weather conditions. Although, real-time detection speed is achieved in [1], but it can not be utilized effectively in adverse weather conditions due to its low detection accuracy. This signifies that previous strategies to trade off between accuracy and detection time are no longer adequate.

Therefore, finding solutions for automatic accurate object detection in adverse weather conditions for self-driving vehicles is a significant challenge that concerns many in the research community.

01.02 Problem Description

In the scope of our project, the problem of object detection in adverse weather conditions is described as follows:

- **Input:** An image taken from a car's dashcam (front view), the image resolution is 1920x1200, with foggy weather conditions



Figure 1.1: Input image of the problem

- **Output:** Locations and labels of the objects (car, truck, pedestrian, traffic light) in the image, which are represented by the coordinates of the vertices of the minimum bounding boxes that cover the entirety of the objects, each object has one respective bounding box and label

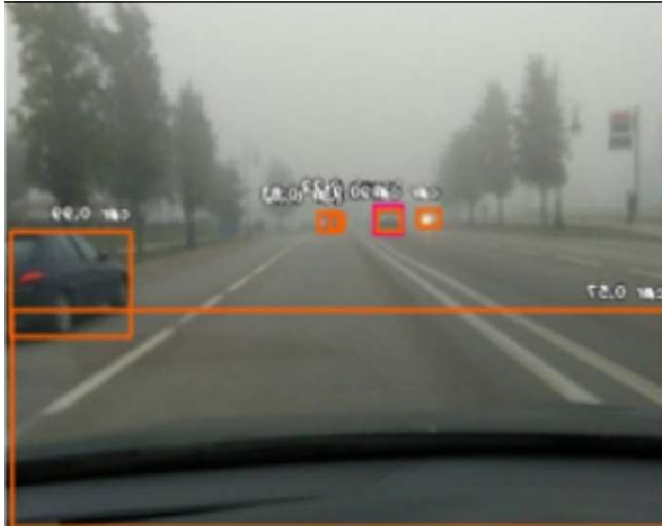


Figure 1.2: Output of the problem

CHAPTER 02. PROPOSED APPROACH

The problem of object detection in images with foggy weather conditions is divided into 2 main stages: (1) fog removal and details clarification in images, (2) detecting and classifying objects in images. To solve this problem, an DCNN-based (Deep Convolutional Neural Network) image adaptive object detection method named IA-YOLO was adopted.

02.01 Fog removal and details clarification in images

The IA-YOLO model contains a fully differentiable image processing module (DIP module), the hyperparameters of which are adaptively learned by a small CNN-based parameter predictor (CNN-PP).

The CNN-PP uses downsampled images as input to train a model to predict the hyperparameters for the filters in the DIP module. High resolution input images are then processed by DIP's filters with the learned hyperparameters to remove fog and enhance the clarification of details. DIP module consists of six differentiable filters with adjustable hyperparameters, including *Defog*, *White Balance (WB)*, *Gamma*, *Contrast*, *Tone* and *Sharpen*. The color and tone filters, which are the *WB*, *Gamma*, *Contrast* and *Tone* are also expressed as Pixel-wise Filters. The *Defog* filter is specifically design for and only applied to foggy images. The *Sharpen* filter applies sharpening to the image, which can highlight the image details and make the objects in the image more detectable.

In addition, this method uses images in both normal and adverse weather conditions to train the proposed network. By taking advantage of the CNN-PP network, the method can adaptively deal with images affected by varying degrees of weather conditions.

02.02 Detecting and classifying objects in images

The object detection pipeline that is adopted in the IA-YOLO method is the YOLOv3 object detection network [...]. YOLOv3 is a one-stage detector that is widely used in many practical applications including image editing, security monitoring, crowd detection and autonomous driving [...]. It implements multi-scale training by making predictions on multi-scale feature maps, so as to further improve the detection accuracy, especially for small objects.

CHAPTER 03. APPLICATION OF COMPUTATIONAL THINKING

03.01 Decomposition

As stated in Chapter 2, the main problem – object detection in adverse weather conditions, can be decomposed into 2 sub-problems: (1) Fog removal and details clarification in images and (2) Detecting and classifying objects in images. Each subproblem is then divided into smaller subproblems, as depicted in the following diagram:

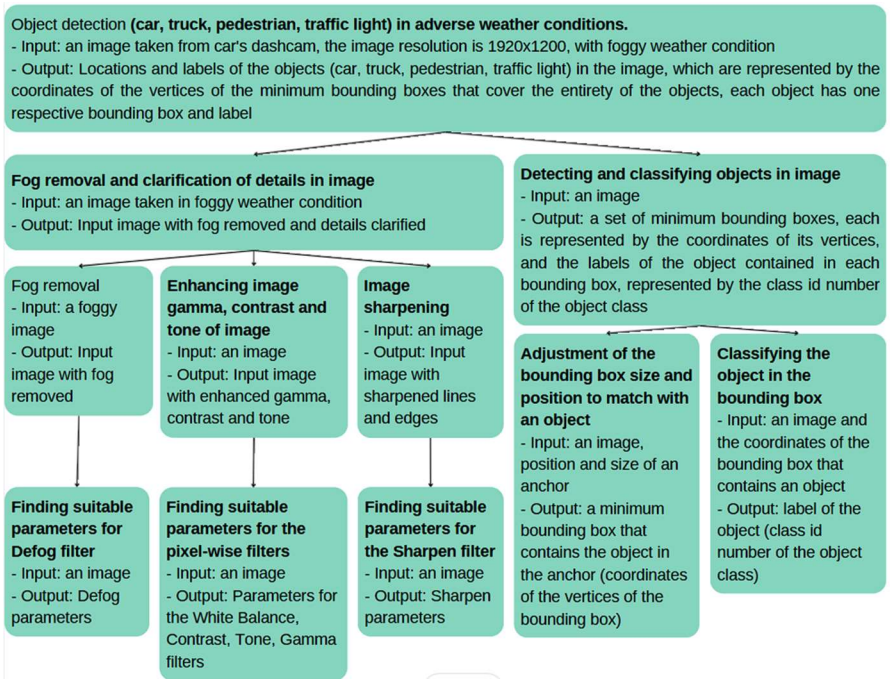


Diagram 3.1: the decomposition of the main problem

03.02 Pattern Recognition

In the main problem of the project, we analysed the 2 sub-problems and decomposed them further into smaller sub-problems:

- Regarding the subproblem of fog removal and clarification of details in image, we decomposed it into 3 sub-problems:
 - finding the suitable parameters for the *Defog* filter
 - finding the suitable parameters for the pixel-wise filter, e.g. the *White balance*, *Contrast* and *Tone* filter
 - finding the suitable parameters for the *Sharpen* filter

These 3 sub-problems all share a similar pattern, which is finding suitable parameters for the filters. Therefore, we grouped them into one single problem of finding image processing parameters,

which can be solved by using regression models, specifically the CNN-PP module in the IA-YOLO model.

- With the second sub-problem of detecting and classifying objects in image, there are 2 smaller sub-problems:
 - Adjustment of the bounding box size and position to match with an object, which seems has the the pattern of the object localization problem
 - Classifying the object detected in the bounding box, which has the pattern of the multi-class classification problem

Both of these sub-problems have patterns that are very popular topics in the field of machine learning and they can be and solved using existing DCNN-based object detection methods. Specifically, we use the YOLOv3 module in the IA-YOLO model to solve them.

03.03 Abstraction

The inputs and outputs of the object detection in adverse weather conditions problem and that of its sub-problems have been described elaborately in **Section 03.01**.

The first sub-problem can be viewed as a image processing problem. To solve this problem, the parameters of the DIP modules need to be find. This can be considered a regression problem. The input of this regression problem contains only images and the output is the parameters. The output of this sub-problem consists of the enhanced image that was processed by the DIP module.

The second sub-problem is considered an object detection problem, thus we don't need to take into account many specific information details of the input image other than the input image itself. Therefore, we can utilize any deep-learning-based object detection models to address this problem. The output of the detection models will give us the bounding boxes and labels of the objects.

03.04 Algorithm design

The algorithm the IA-YOLO method to solve our main problem is described in **Chart 3.1**.

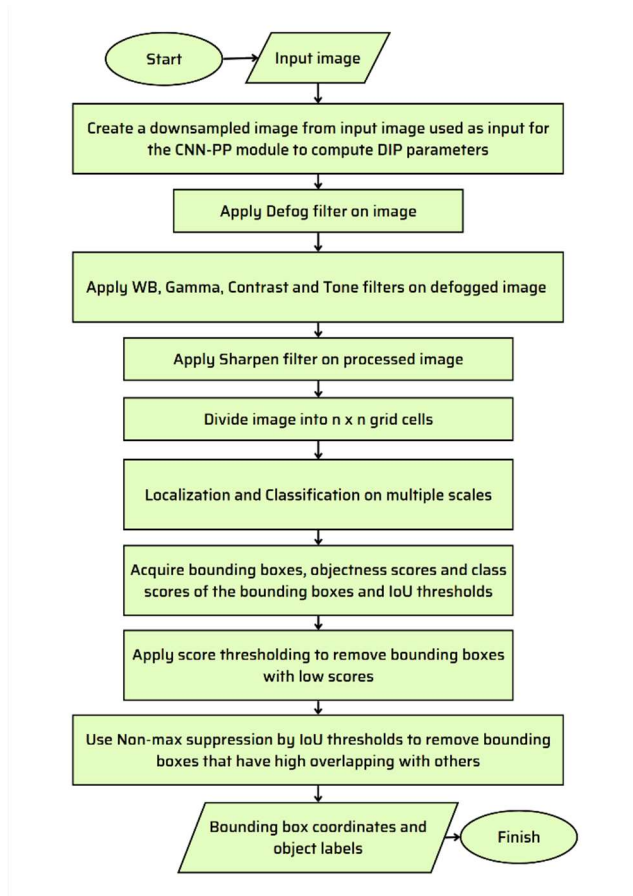


Chart 3.1: Algorithm of the IA-YOLO method to solve the object detection in adverse weather conditions problem

CHAPTER 04. CONCLUSION

With real-world foggy weather conditions, this method can create clearer output images with sharper edges around object boundaries and thus produce reliable detection results with higher confidence score and fewer missing cases, which are mainly caused by the interaction between weather-specific information and object information resulting in poor detection performance. **Figure 4.1** shows an example of object detection in foggy conditions. One can see that if images can be properly processed and enhanced according to weather conditions, more latent information about initially blurred objects and misidentified objects can be recovered. Therefore, we can see that this solution work much better than previous methods (namely the YOLO II baseline) in both foggy and low light situations.

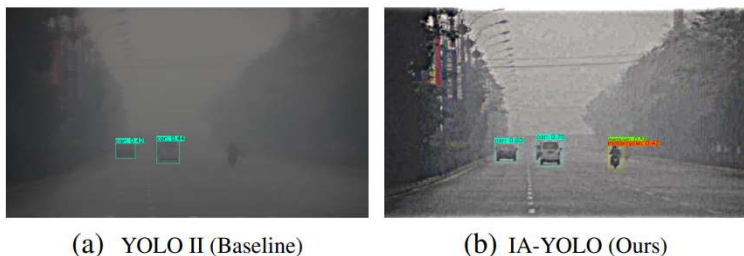


Figure 4.1: Example of object detection in foggy weather conditions

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