Vehicle Classification in Inclement Weather Conditions Using Deep Learning

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Abstract: - In the past portion of 10 years, object discovery approaches given convolutional brain networks have been generally examined and effectively applied in numerous PC vision applications. In any case, identifying objects in harsh weather patterns stays a significant test in light of unfortunate permeability. In this paper, we address the item discovery issue within the sight of mist by presenting a novel double subnet network (DSNet) that can be prepared from start to finish and mutually learn three errands: permeability improvement, object grouping, and item restriction. DSNet achieves total execution improvement by including two subnetworks: the location subnet and the rebuilding subnet. We utilize RetinaNet as a spine organization (likewise called discovery subnet), which is liable for figuring out how to order and find objects. The reclamation subnet is planned by offering highlight extraction layers to the discovery subnet and embracing a component recuperation (FR) module for permeability upgrade. Exploratory outcomes show that our DSNet accomplished 50.84% mean normal accuracy (Guide) on an engineered hazy dataset that we created and 41.91% Guide on a public regular hazy dataset (Hazy Driving dataset), outflanking many cutting edge object locators and blend models among tease and discovery strategies while keeping a fast.

Key Words: ***RetinaNet, Double subnet network, Convolutional brain, Public regular hazy dataset.***

I. INTRODUCTION

In recent years, the development of intelligent autonomous vehicles (IAVs) has attracted considerable re- search attention since it has the potential to assist humans in their driving, reduce the number of traffic accidents, and change cityscapes. The design of a robust and dependable IAV necessitates the integration of many important functions, including but not limited to object detection [1], [2], tracking [3], [4], and human-machine interaction [5], [6].

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Object detection plays an essential role in IAVs because it not only determines the category, to which each object belongs and locates objects in a given image but also assists the system with safe navigation in complex driving environments. Numerous approaches and techniques for object detection have been introduced and have achieved impressive performances in recent years, especially methods using deep convolutional neural networks (CNNs) [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], ice crystals, dust, and other particles, which degrade the features extracted from these images for the purpose of object detection.

Traditionally, to improve object detection performance in the presence of haze, enhancing the visibility of hazy images has been used as a preprocessing step. Image dehazing can benefit both human visual perception for image quality and many systems that must operate under different weather conditions, such as traffic surveillance systems, intelligent vehicles, and outdoor object recognition systems. However, using images preprocessed by a better dehazing model in terms of restoration performance as an input of the object detector does not always guarantee improved object detection performance [19]. Furthermore, combining the models used by dehazing and detection methods can slow the detection speed because of the additional dehazing task. In this paper, we propose a novel object detection approach called dual-subnet network (DSNet), which is based on multi-task learning to cope with the problem of detecting objects in poor visibility conditions. To attain this objective, DSNet employs one of the best object detectors, namely, RetinaNet [15] as a backbone network (denoted as detection subnetwork) and proposes a feature recovery (FR) module to this base architecture to construct a restoration subnetwork for visibility enhancement, as shown in Fig. 1.

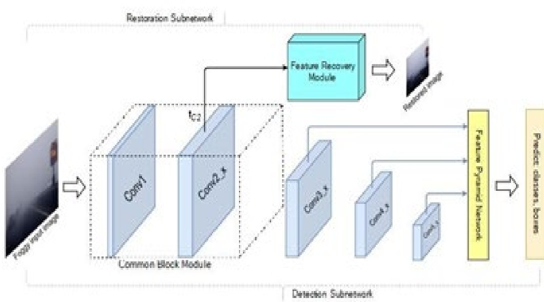


Fig.1. Base architecture to construct a restoration subnetwork for visibility enhancement

II. RELATED WORK

Many objects detection, image dehazing, and multi-task learning methods have been introduced in the literature. In this section, we briefly review some current methods and focus our attention on deep learning-based approaches that have demonstrated remarkable results in these fields.

1.1 Object detection

Object detection based on convolution neural networks (CNNs) has gained extensive interest to improve performance and can be divided into two main categories [20]:

- Region proposal-based approaches [7], [8], [9], [10] and
- Regression/classification-based approaches [11], [12], [13], [14], [15], [16], [17].

Under the methods belonging to the first category, region proposals with CNNs (R-CNN family) [7], [8], [9] and region-based fully convolution networks (R-FCN) [10] pro- posed approaches based on the region proposal method to create regions of interest (ROIs) for object detection. R-CNN [7] takes an input image and generates region proposals using an algorithm that calculates the hierarchical grouping of similar regions with respect to many compatible elements such as texture, colour, size, shape, and so on, which is known as selective search [21], then employs a CNN to extract features for each proposal, and finally adopts support vector machine (SVM) to perform classification. R-CNN showed dramatic performance improvement in object detection and semantic segmentation compared with previous methods [22], [23]. Although RCNN has achieved impressive accuracy, it still consumes a considerable amount of time during training and inference.

1.2 Image dehazing

The formation of a hazy image, as described by the atmospheric scattering model, was first introduced by the authors [28], and was subsequently improved by Nayar et al. [29] and Narasimhan et al. [30].

The atmospheric scattering model can be written as:

$I(x) = J(x)t(x) + \alpha(1 - t(x))$, (1) where $I(x)$ is the hazy image that is captured by the camera, $J(x)$ is the scene radiance that can be regarded as a haze-free image, α represents the global atmospheric light, and $t(x)$ represents the medium transmission, which is defined as: $t(x) = e{-}\beta d(x)$, (2) where β denotes the scattering coefficient of the atmosphere, and $d(x)$ denotes the scene depth.

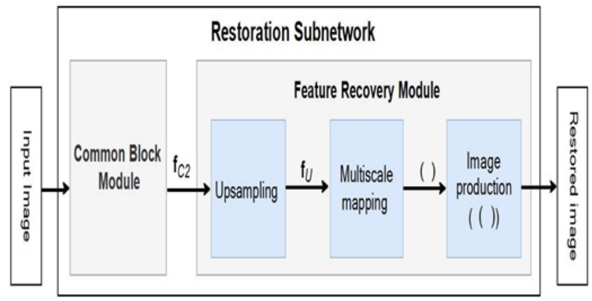
Based on the atmospheric scattering model, numerous dehazing approaches have been presented for visibility restoration of degraded images to improve the performance of systems that must perform under inclement weather conditions. Early dehazing methods often compute intermediate haze-relevant features based on many techniques, including, but not limited to, dark channel prior [31], [32], maximum contrast [33], colour attenuation [34], and hue disparity [35], to accomplish haze removal. More recently, given the power and success of deep CNN in computer vision tasks, dehazing approaches with deep CNN have been introduced to enhance haze removal performance. To avoid inaccurately estimating the physical parameter from a single image, DehazeNet [36] restores the visibility of hazy images by presenting an endto-end CNN to produce a medium transmission map from an entire image, which is then applied to the atmospheric scatter-ing model to retrieve haze-free images. MSCNN [37] pro- posed using two CNNs that have similar architectures called coarse-scale net and fine-scale net. Both these networks contain four components including convolution, max-pooling, up-sampling and linear combination for restoring the visibility of hazy images.

1.3 Multi-task learning

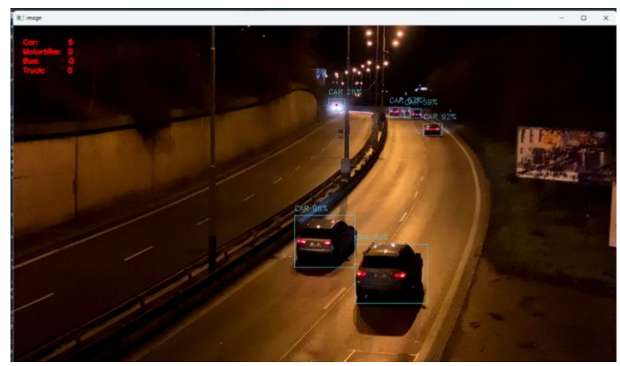
Multi-task literacy is concerned with multiple affiliated tasks that are learned, contemporaneously in which what's learned from one task can be salutary to the other tasks (41). Numerous multi-task learning styles have been proposed and proven to be effective for colorful deep literacy operations in the computer vision field. Kendall etal. (42) introduced a system that weighs multiple loss functions by considering the homoscedastic query of each task to perform common logic on three tasks, including depth retrogression, semantic, and case segmentation.(43) presented a convolutional neural network for learning semantic segmentation and bracket at the same time to enhance scene understanding in robotics operations. In (44), the authors applied multi-task learning successfully in a real- time independent driving operation, wherein bracket, discovery, and semantic segmentation tasks are incorporated into a model called MultiNet that uses three subnetworks. The approaches used by Lin etal. (15) and Kokkinos(45) have also been explored to contemporaneously learn retrogression and bracket tasks within a single armature for object discovery.

III. Proposed System

In this section, we introduce a new binary- subnet network (DSNet) that can significantly ameliorate the delicacy of object discovery in tempestuous rainfall conditions while maintaining fast vaticination running time. Our approach accomplishes this thing by concertedly learning three tasks, videlicet, visibility improvement, object bracket, and object localization.
The proposed DSNet consists of two subnetworks 1) a discovery subnet and 2) a restoration subnet. The discovery subnet is employed by exercising a CNN, videlicet, RetinaNet(15), which shares a common block(CB) module with the restoration subnet and is responsible for object bracket and object localization. The restoration subnet is designed by attaching a proposed point recovery (FR) module to the CB module for visibility improvement, . These two subnetworks partake the CB module to ensure pc = 1 − p else, (4) that the clean features (fC2) produced in this module can be used in both subnetworks during common literacy.
DSNet can be trained end- to- end and objects can be prognosticated by using the discovery subnet.



IV. Result



You-Tube Link - https://youtu.be/4WUTKcqV708
The above image shows the object detection in inclement weather conditions with object percentage.

Vehicle	Percentage	Timing
Car	98%	0.6
Car	99%	0.5
Car	96%	0.8
Car	94%	1.0

The above percentage show the screenshot the weather conditions in a night time.

V. Conclusion

In this paper, we presented a new approach to ameliorate object discovery performance in tempestuous rainfall conditions. Our DSNet model, which can be trained end to end for common literacy of visibility improvement, object bracket and object localization, is composed of two subnetworks, videlicet, the discovery and restoration subnets. The discovery subnet is introduced using RetinaNet, and the restoration subnet is designed by attaching the FR module to the last point birth subcaste of the third residual block of the discovery network. The experimental results on both synthetic and natural foggy datasets indicate that our proposed approach attained the most satisfactory discovery performance. Qualitative and quantitative evaluations of the compared styles prove that our DSNet is significantly more accurate than the other models while maintaining a high speed.

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