Removing adverse weather impacts from autonomous vehicle camera systems with generative techniques

A Preprint

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1 Problem Statement and Motivation

This project seeks to use generative algorithms to mitigate adverse weather effects in autonomous vehicle camera feeds, enhancing object detection, classification, and localization. Autonomous systems combine various sensors, with cameras being cost-effective yet vulnerable to weather disturbances like light rain, heavy rain, smoke, fog, haze, snow, and contamination. Despite prior research in weather removal, modern generative techniques, such as denoising and in-painting, present novel solutions. This project will: (1) modify a generative model for driving scenarios under snow, rain, and combined rain-haze conditions; (2) assess the model's effectiveness on these datasets; and (3) determine its impact on object recognition algorithms. Although autonomous vehicle cameras record videos, this project limit the scope to images with adverse weather effects.

2 Previous and Related Work

Özdenizci et al.'s (2022) applied denoising diffusion models to adverse weather datasets that included desnowing, deraining, dehazing and raindrop removal and claim state of the art performance in weather-specific and multi-weather restoration [1]. Their technique can be applied to any arbitary sized image . However, their implementation takes 20 seconds to process a single 640 x 432 pixel image on one NVIDIA A40 GPU, which cannot be used on autonomous vehicles due to the real time constraints. Kawar et al. (2023), on the other hand, focused on general image restoration [2]. They suggest that many restoration tasks can be framed as linear inverse problems and introduce their Denoising Diffusion Restoration Models (DDRM) for super-resolution, deblurring, inpainting, and colorization in noisy conditions. Their technique is 5x faster than the nearest competitor. DDRM's speed could be promising for autonomous vehicle cameras systems. However, heavy rain or severe weather conditions, combining snow and fog, are expected to introduce non-linear distortions.

Besides the past work on Generative Diffusion Models, we also studied literatures on Generative Adversarial Networks (GAN). Yang et al. (2023) developed ViWS-Net using GANs to mitigate weather effects in videos. Their videos are processed at 224 x 224 pixels at five frames per second [3]. Training employed two NVIDIA RTX 3090 GPUs, with an inference time of 0.46 seconds—though the specifics of what was inferred and on which hardware aren't detailed. They note ViWS-Net's computational efficiency is on par with other methods but excels in multi-weather removal. Their evaluation used Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM) metrics. They do not assess whether their outputs improve downstream object detection or classification algorithms.

Additionally, we look into previous work on Transformer Models. Valanarasu et al. (2022) introduced TransWeather, a transformer technique with an encoder-decoder structure, boasting state-of-the-art performance across weather conditions [4]. It processes 256 x 256 pixel images in one second using an NVIDIA RTX 8000 GPU. However, TransWeather struggles with high-intensity rain in real-world datasets, aligning with Zhang et al.'s (2023) observation that most de-raining algorithms falter in dynamic scenes or with high rain rates [5].

3 Dataset

This project will examine three autonomous vehicle datasets with adverse weather conditions. The first is the IUPUI Driving Video/Image Benchmark [6], which offers in-car camera footage under varying illumination and road scenarios, that includes higher risk driving scenarios. It captures diverse adverse conditions like snow, rain, direct sunlight, dim light, reflections, and wet roads, among others. The second is the Snow100K [7] dataset which provides 100,000 synthesized snowy images alongside 1,329 realistic snowy counterparts. The third is the RainDrops [8] dataset, which presents paired images with identical backgrounds; one image is marred by raindrops, while its pair remains unaffected.

4 Methodology and Experiments

This project selects the DDRM generative model and tests the hypothesis that general image restoration models based on linear inverse problems are still effective for the adverse weather problem for autonomous vehicles even in the presence of non-linear distortions. There are four broad project phases to undertake: (1) Apply the DDRM model to weather impacted street scenes. Firstly on synthetic adverse weather images to confirm that the model pipelines are working as expected and then on real datasets. (2) Attempt to map adverse weather phenomenon to DDRM's predefined degradation operator, H in its linear inverse problem formulation. Explore more appropriate degradation operators if unsuccessful. (3) Investigate improvements to the DDRM model if the performance on the adverse datasets aren't comparable to adverse weather removal models that don't employ generative techniques. (4) Evaluate how DDRM's outputs affect downstream object detection, classification and localisaton qualitatively and quantitatively in autonomous vehicle scenes before and after adverse weather removal.

5 Evaluation

Evaluation will be both quantitative and qualitative: (1) Quantitative metrics of model performance such as PSNR, SSIM, KID (Kernel Inception Distance) and NFEs (Number of Function Evaluations), which are commonly used to evaluate denoising effectiveness. Also, the subjective evaluation, which requires manual inspection of the the adverse weather removal results. (2) Quantitative metrics for object detection such as accuracy, precision and F1 scores. On top of that, performing comparative studies to evaluate the current model on the same dataset against several competitive image denoising methods (DCP, KDDN, GDN, DuRN, FFA, and MSBDN [9]).

6 Team Contributions

Team members will individually apply the extended DRRM model to datasets from Section 3. They'll then jointly design an evaluation framework, selecting suitable metrics and a downstream object detection, classification, and localization algorithm. Specific tasks include: (1) Collaboratively modifying the DDRM repository for adverse weather image processing. (2) Individually selecting a dataset and testing the modified DDRM model, and designing degradation operators for specific weather conditions, e.g. dehazing or desnowing. (3) Collaboratively selecting evaluation metrics, considering accuracy, losses, and efficiency, and picking an appropriate downstream algorithm to assess the DRRM model's effects on adverse weather removal.

References

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