https://doi.org/10.2352/EI.2023.35.16.AVM-116

The Design and Validation of a Rain Model for a Simulated Automotive Environment

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Abstract

This paper presents the design of an accurate rain model for the commercially-available Anyverse automotive simulation environment. The model incorporates the physical properties of rain and a process to validate the model against real rain is proposed. Due to the high computational complexity of path tracing through a particle-based model, a second more computationally efficient model is also proposed. For the second model, the rain is modeled using a combination of a particle-based model and an attenuation field. The attenuation field is fine-tuned against the particle-only model to minimize the difference between the models.

Introduction

For safe, reliable, and continuous operation, automated vehicles need to be able to operate in adverse weather conditions. Cameras are perhaps the most important sensor which enable automated vehicles. Therefore, understanding the impact of rain on image quality is an important question in the context of autonomous vehicles and ADAS. However, accurately measuring image quality in an outdoor environment is a challenging problem due to calibration constraints and the number of overlapping environmental variables involved (lux level, sun position, etc.). A lack of control of weather conditions adds further complexity. Simulation is an attractive alternative that allows the impact of rain to be examined in an isolated, controllable manner. To fully characterize and understand the impact of rain, having an accurate, realistic, and validated rain model is an important initial step.

In most cases the effect of falling raindrops on image quality is minimal in comparison to the effects of raindrop adhesion on the lens, which leads to occlusion, and the effects of spray from puddles. However, within the context of sensor availability, due to the prevalence of rain, its effect on image quality needs to be properly characterized. For automotive applications, the impact of falling raindrops lies in particular in edge cases. Simulated rain is a useful approach for identifying and characterizing such edge cases that can lead to a system failure. There is currently a lack of publicly-available, open-source automotive datasets which include detailed weather labels. At best some datasets, such as BDD [1], contain very coarse labels (e.g. 'rain' and 'no rain'), which render the datasets unsuitable for accurately characterizing camera availability under rain conditions. An accurate rain model allows the creation of large-scale datasets with detailed weather labels.

Related Works

Broadly-speaking, simulated rain can be split into two categories, namely real rain simulation, where rain is replicated at an indoor testing facility, and virtually simulated rain, where rain is recreated in a virtual environment using a variety of physics-based models. Virtually simulated rain can also be added to an image in post-processing, as synthetic rain.

Physical real rain simulators or 'rain tunnels' try to mimic real rain by spraying water into a controlled environment. Water is typically sprayed into the environment through specialized nozzles which are calibrated to set the drop size distribution. The Cerema R&D Platform [2] is an example of a large-scale real rain simulator used for automotive applications. Duthon *et al.* used the Cerema rain simulator to validate a digital rain image simulator [3]. Smaller-scale real rain simulators can also be used. Hasirlioglu *et al.* designed a rain simulator to investigate the influence of rain on camera, LiDAR, and RADAR sensors [4]. The simulator consisted of several potential rain layers with the sensor under test placed at one end of the simulator and a target placed at the other. Physical rain simulators have the advantage of being relatively straightforward to implement, however, accurately recreating droplets of water that are similar to real raindrops is challenging as noted in [5].

Unlike real rain simulators, virtual rain simulators are typically created in a fully simulated environment. Many simulators are essentially game engines in their back end, such as Carla [6], while others such as SVL [7] and D-Space [8] are physics-based simulators that typically don't run in real-time but provide more accurate results based on larger mathematical models. The flexibility of virtual simulators is particularly useful for investigating the effects of a condition in terms of an application i.e. investigating the effects of rain on object detection performance in complex scenarios, whereas real rain simulators are better suited to characterizing the effect of a condition on the sensor itself. For example, Jeon *et al.* investigated the effect of heavy rain on lane detection [9] while Hasirlioglu *et al.* used their real rain simulator to look at sensor performance [4]. Many simulators come with prebuilt rain models, which are usually based on particle models, however, the degree to which these models have been validated is often unclear.

Augmenting training data for machine learning algorithms with synthetic weather-degraded data is a popular technique, in an attempt to limit the algorithm's degradation in performance when presented with real-world weather-degraded data. Haldar *et al.*

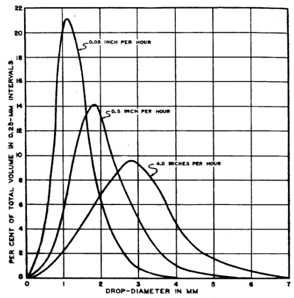

Figure 1. Raindrop diameter distributions for rain of varying intensities [18].

used a physics-based simulator to boost the performance of an object detection algorithm in rain [10]. Many synthetic rain generation techniques are deep learning-based and rely on the collection of rain and no-rain image pairs to use as training data [11, 12]. No matter what type of rain simulation is used, the importance of validating the model is crucial to avoid a domain mismatch. Hnewa and Radha noted that any inaccuracy in a simulated rain model is likely to lead to a domain mismatch when an algorithm is evaluated on real rain [13].

Rain Characteristics

In North-Western Europe the mean rainfall intensity, including periods of no rain, is between 0.05-0.3 mm/hr [14], while the total annual precipitation ranges from 100mm to 1300mm[14]. In Ireland, the average rainfall is between 1000mm and 1300mm per year [15], with rain falling on up to 300 days per year. The average rainfall intensity rate in Ireland is 2 mm/hour.

Several studies, investigating features of rain, have been published which indicate that raindrops are uniformly distributed in space [16, 17]. Unlike the spatial distribution of raindrops, drop size distribution is not uniform. Laws and Parsons noted that drop size distribution is correlated with rainfall intensity [18]. As the rainfall intensity increases, so too does the average drop size. This increase in drop size is also characterized as having a wider distribution meaning that as the rainfall intensity increases, so does the range of the droplet size distribution. Figure 2 shows the distribution of raindrop sizes for three different rainfall intensities. Typical drop sizes range in value from just above 0 mm to 6 mm for rain falling at 12.5 mm/hour (0.5 inches/hour).

Raindrop terminal velocity is related to raindrop size [19]. Several models for raindrop terminal velocity have been created [19, 20, 21, 22, 23, 24]. The results of these studies are summarised in Figure 1, with a high level of correlation demonstrated between the studies. Typical terminal velocities are in the range of 2 to 10 m/s.

The Anyverse Simulation Environment

The Anyverse simulation environment [26] is a commercially available simulator specializing in high-end simulated data for automotive applications. The proprietary simulator, which is physics based, uses hyperspectral path tracing to produce highly accurate simulated data. A sample image from the Anyverse simulator is shown in Figure 3.

All objects added to a scene are spectrally characterized for 256 different wavelengths, up to 780nm. Optical irradiance is simulated for each object in the scene and passed to the optical system to simulate the effect of a camera lens. Multiple optical models, including pinhole and thin lens, are available in the simulator. The optical irradiance is filtered by wavelength, to simulate the effect of an IR filter and a color filter array. The filtered irradiance is then passed to a simulated image sensor. Multiple image sensor models or custom configurations are available. Finally, the digital output from the image sensor is passed to an ISP pipeline for further processing.

Model Design

Particle Model

To capture the characteristics of rain a particle-based model is used. Each raindrop is modeled as a 3-dimensional sphere and added to the scene. The model has the following properties to capture the physical properties of rain accurately:

- Raindrops are evenly distributed in space.
- Raindrop diameter is between 0 and 6 mm and is randomly sampled from a Gaussian distribution.
- Raindrop terminal velocity is calculated based on drop size.
- Raindrop ‘streaks’ are captured using a 3D motion blur model which factors in exposure time and raindrop speed.

Raindrops are added to a scene that undergoes path tracing. Path tracing is used to accurately capture the effect of rain on optical irradiance in the scene. The principles of tracing are embedded in ray optics (geometric optics) which have been noted to have been suitable for modeling the effect of refraction due to raindrops [27].

The main issue with using a particle model is the computation time associated with path tracing the scene once the rain has been added. Each raindrop has the potential to interact with light rays, in the form of either refraction or reflection. As more raindrops are added the number of interactions increases exponentially. The computational cost of path tracing becomes prohibitive as scenes get larger, especially if the rain model is used to render a large dataset suitable for training a machine learning algorithm.

Particle/Density Model

To address the computational complexity of the ‘Particle Model’ a more efficient two-stage model is proposed which uses a density-based attenuation field to approximate the effects of rain further from the camera. The model is split into two sections based on distance from the camera. The model leverages the fact that raindrops at different distances from a camera exhibit different behaviors on the image plane. Rain closest to the camera, referred to as ‘Near-Field’ (NF) rain, is clearly visible on the image plane and is prone to cause streaks in an image, due to motion blur. NF rain is modeled using the ‘Particle Model.’ Rain further

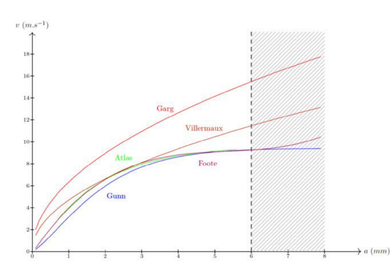

Figure 2. Raindrop terminal velocity models vs. drop radius [25].

Figure 3. *Sample Image from the Anyverse Simulator.*

from the camera, referred to as 'Far-Field' (FF) rain, is less visible on the image plane and causes a 'graying effect' on the image plane due to heavy dispersion and scattering of light. FF rain is modeled using an attenuation field.

Both models are set up using a cylindrical coordinate system with the camera at the origin. The coverage of both models is shown in Figure 4. There is no overlap between the coverage areas of the models. The radius of the NF rain section of the model is set so that raindrops are smaller than one pixel when projected onto the image plane. The radius length is specific to the camera setup and depends on a number of factors including focal length, pixel size, and sensor size. For a 70°field of view lens the radius of the NF rain is approximately 10m. The properties of NF and FF rain are summarised in Table 1. Figure 5 shows the output of each model on the image plane, with the 'Particle Model' on the left and the 'Particle/Density Model' on the right. Table 1 summarises the properties of NF and FF rain.

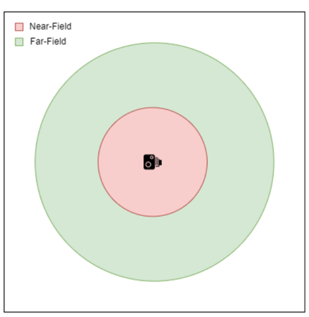

Figure 4. *Particle/Density Model Layout*

Validation Process

To ensure the accuracy of the two-stage model both the 'Particle Model' and 'Particle/Density Model' need to be validated against real rain in terms of image quality. To minimize the difference between the 'Particle/Density Model' and real rain, a three-step validation process is proposed:

1. Characterise the effect of real rain on the image plane.
2. Validate the particle model rendered in the simulator.
3. Calibrate the attenuation field to mimic the Particle Model.

To characterize the effect of rain on image quality both a short-distance and long-distance test are carried out. For the short-distance test an outdoor image quality scene is set up for long-term data collection. The scene consists of several industry standard image quality test charts, 2 mannequins, and a number of standard road signs. A picture of the scene is shown in Figure 6.

The outdoor scene is recorded using a 6.3MP FLIR Blackfly S camera, with a weather station recording the meteorological conditions and light levels at the scene. Image quality metrics for sharpness, such as MTF, contrast, and color accuracy can be measured from the charts. The charts are situated 13m from the camera making them suitable for characterizing the effects of NF rain.

For outdoor characterization over longer distances, the use of test targets becomes infeasible due to the required size of the targets. However, some metrics for sharpness, such as MTF [28], and contrast [29], can be approximated directly from a scene. The initial results from the long-range rain characterization are included in the Results Section of this paper.

The effect of the 'Particle Model' on image quality is characterized in the simulator. As shown in Figure 5, image quality test charts for sharpness, contrast, and color accuracy are added to the scene. The model should be evaluated at different distances, so the test charts can be set up at varying distances from the camera in the scene. To ensure a fair comparison at each distance the charts need to be scaled to maintain a constant spatial resolution. The results are compared with the real rain characterization to ensure the accuracy of the 'Particle Model.'

Finally, the 'Particle/Density Model' needs to be evaluated and calibrated. Image quality is measured in the simulator in the same manner as the 'Particle Model.' As the density field approximates FF rain, the density field needs to be calibrated to match the already validated 'Particle Model'. Once calibrated, the computationally efficient 'Particle/Density Model' will produce a similar effect to real rain.

Results

This section presents the initial results from the long-distance rain characterization. An image of the same scene was captured in both rain and no rain conditions. Both images are displayed in Figure 7. Both images were processed using a minimal ISP pipeline, with no edge enhancement or denoising. The two images were captured 10 minutes apart and show the impact of

Near-Field Rain	Far-Field Rain
- Raindrops located near to the camera	- Raindrops located further from the camera
- Raindrops larger than 1 pixel on the image plane	- Raindrops smaller than 1 pixel on the image plane
- Individual raindrops are clearly visible on the image plane which leads to streaking and blurring	- Individual raindrops are not clearly visible on the image plane.
- Raindrops have less of an impact in terms of dispersion	- Raindrops cause heavy dispersion and scattering of light
- Modeled used a particle field	- Modeled using an attenuation field

Table 1: Properties of Near-Filed and Far-Field Rain.

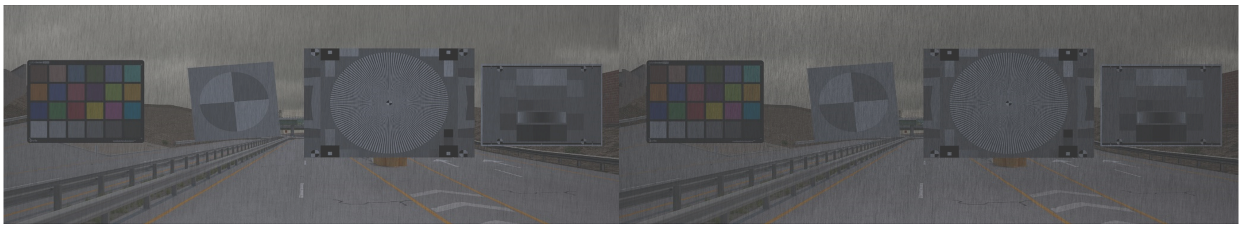

Figure 5. *The Particle Model and The Particle/Density Model.*

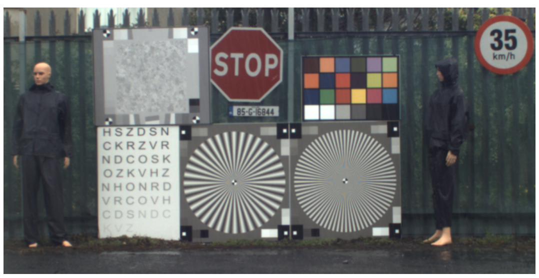

Figure 6. *Outdoor image quality test scene.*

rain on a typical scene. From a visual perspective, there appears to be less contrast in the rain image with the image appearing to be washed out and lacking highly saturated colors. The change in ambient light conditions is also evident with ambient light levels dropping in rain conditions. The rain in the right-hand image is clearly visible with the raindrops in the foreground easily distinguishable from the background scene. Due to a short exposure time, the effect of motion blur on the raindrops is limited and therefore long streaks of rain are not present in the image.

For each image, several different contrast metrics are measured and MTF is estimated from a slanted edge found in the scene. The distance between the camera and the target building is approximately 60m. To measure contrast several patches are selected from the pair images which correspond to different shades of gray: 60%, 35%, and 15% were selected from the scene. Figure 8 shows the regions, in red, that were selected from each image. The green box corresponds to the slanted edge used to measure NS-MTF (Natural Scene MTF). All patches selected were 100 x 100 pixels in size, with the contrast and NS-MTF measurements being taken from the luminance channel of the YCbCr colorspace.

Figure 9 displays the histograms for each patch (different gray values) under rain and no rain conditions. Both the light gray (1) and mid-gray (2) patches show a significant change in the value of the luminance channel between both conditions. Under rain conditions, there is approximately a 50% decrease in luminance value for both patches. The dark gray patch (3) shows little change in luminance value under the two conditions, with a minor increase in luminance under rain conditions.

	Patch 1 vs Patch 2		Patch 1 vs Patch 3		Patch 2 vs Patch 3	
	Rain	No Rain	Rain	No Rain	Rain	No Rain
CNR	14.774	13.786	11.005	38.257	-2.9343	13.862
Michelson Contrast	0.4078	0.2577	0.3028	0.5939	-0. 1198	0.3970
Weber Contrast	0.6942	0.7558	0.8686	2.9252	-0.2140	1.3168

Table 2: Contrast Results

Table 2 displays the results of the relative contrasts between each patch in the same image under rain and no rain conditions. Patch 1 vs. Patch 3 demonstrates the expected result where there is a clear decrease in relative contrast across an image in rain conditions. The decrease, in contrast, is reflected in all three contrast metrics (CNR, Weber, and Michelson). A similar result is evident between Patch 2 and Patch 3 with contrast falling across all three metrics. The negative contrasts displayed in the results are due to the fact that in rain conditions Patch 2 and Patch 3 display differing behaviors. The value of Patch 2 significantly decreases in rain, while Patch 3 remains almost constant. The negative metric values arise due to the mean value of the luminance channel of Patch 2 falling below that of Patch 3 in rain conditions. The Patch 1 vs Patch 2 metrics show a minor increase in contrast under rain conditions. Both patches behave similarly under rain conditions with a substantial decrease in the luminance values across each patch. As both patches behave similarly the relative contrast between the patches remains almost identical.

Future Work

The design and validation of the rain model is part of a long-term project investigating the impact of rain on image quality and the subsequent effect on machine learning performance. The effects of NF and FF rain are being characterized in terms of image quality. Once characterized, the 'Particle Model' needs to be validated against real rain. Given that the 'Particle Model' is based on the physical properties of rain, the model should have a similar effect on image quality as real rain. The 'Particle/Density Model' will be calibrated by comparing the model with the 'Particle Model' in terms of each model's effect on image quality.

Figure 7. Long Distance Rain Characterisation Scene.

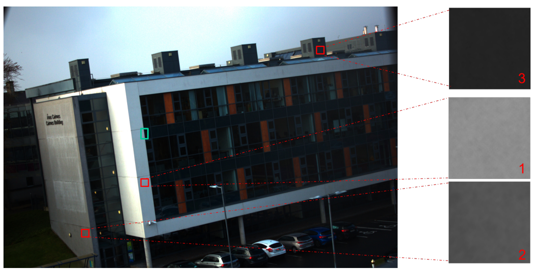

Figure 8. Long Distance Rain Characterisation Scene.

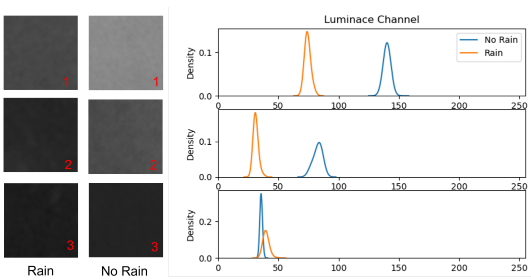

Figure 9. Histograms showing the profile of the luminance of channel of each patch under rain and no rain conditions.

Acknowledgments

This work was supported, in part, by Science Foundation Ireland grants 13/RC/2094 P2 and 18/SP/5942 co-funded under the European Regional Development Fund through the Southern & Eastern Regional Operational Programme to Lero - the Science Foundation Ireland Research Centre for Software (www.lero.iewww.lero.ie), and by Valeo Vision Systems.

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