Static Estimation of the Meteorological Visibility Distance in Night Fog with Imagery

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SUMMARY In this article, we propose a new way to estimate fog extinction at night with a camera. We also propose a method for the classification of fog depending on the forward scattering. We show that a characterization of fog based on the atmospheric extinction parameter only is not sufficient, specifically in the perspective of adaptive lighting for road safety. This method has been validated on synthetic images generated with a semi Monte-Carlo ray tracing software dedicated to fog simulation as well as with experiments in a fog chamber, we present the results and discuss the method, its potential applications and its limits.

key words: fog, granulometry, camera, forward scattering, adaptive lighting

1. Introduction

The development of Advanced Driver Assistance Systems (ADAS) is a very active field of research in the automotive industry. Some widespread systems rely on proprioceptive sensors and are installed on today’s cars like the Anti Blocking System (ABS) or the Electronic Stability Program (ESP). Others rely on exteroceptive sensors (LIDAR, RADAR, camera) such as Lane Departure Warning (LDW), Forward Collision Warning (FCW), Traffic Sign Recognition (TSR) or Adaptive Forward Lighting (AFL) systems.

Among the sensors, camera is one of the most promising since it can be low cost and suits different applications [1]. The reliability of camera-based systems is still not 100% guaranteed, which hinders their massive deployment in today’s cars. In particular, degraded weather conditions, such as rain or fog, are major concerns [2]. First, the reliability of the systems is reduced because some visual aspects of the highway scenes are changed, so that computer vision methods designed for clear weather conditions may not be relevant anymore. Second, adverse weather conditions directly affect the safety of the driver, since it can limit the visibility range of the driver or lower the friction.

Detecting, characterizing and mitigating the effects of adverse weather conditions using the signal of a single camera is thus a challenge for future camera-based ADAS. Among those perturbations, rain is the one with higher occurrence in tempered climate. It has a great impact on friction [3] but also on visibility [4]. Recently, different camera-based systems have been proposed to detect rain on the windshield [5], [6] as well as wet pavement [7]. Fog is known for its effects on visibility. Dense fog is an important road safety issue, given the major importance of visual informations in the driving task [8].

Different methods were proposed to detect and characterize visibility in daytime fog by in-vehicle camera. [9] estimates the visibility distance by measuring the contrast attenuation of lane markings at different distances in front of the vehicle. A monocular method using Koschmieder’s model allows estimation of the meteorological visibility distance [10]. A method based on stereo-vision computes the distance to the farthest point on the road surface with a contrast greater than 5% which gives the visibility distance [11]. This method was later adapted to monocular vision [12]. Some methods restore the images grabbed in daytime fog [13], [14] and might be used in ADAS. Finally, it is proposed in [15] to use the presence of daytime fog to segment the free space area ahead of the vehicle.

Previous works on nighttime fog detection and characterization with imagery are few. Using static imaging techniques, [16] uses the attenuation of distant light sources to reconstruct the 3D structure of the scene. After extracting the halo of distant sources, [17] and [18] look for the parameters of an atmospheric point spread function that fits the evolution of intensity of the halo. These methods exploit the single/multiple scattering properties of fog, and are relevant for haze and light fog. Kwon[19] proposed a static device made of a Near-IR camera, a retroreflective target placed a few meters ahead of the camera and illuminated by a Near-IR light source. This apparatus should be installed near the road on sites with a high potential of occurrence of fog events.

Though fog and its effects on energy transmission and visual performance have been studied for a long time, the authors do not agree on the proper models to use in order to characterize it. The standards of meteorological measurements for fog at night rely on the estimation of the distance at which a collimated beam would be attenuated by 95%, then computing the equivalent attenuation for that slab of atmosphere with Beer-Lambert model [20]. This suggests that the Beer-Lambert model and specifically the extinction coefficient is sufficient to describe the effects of fog on light propagation, which is questionable.

In this article, we propose a computer vision method
that characterizes dense fogs in nighttime situations (meteorological visibility < 500 m) that may impact visual performances while driving. In this aim, we propose to use the presence of known light sources in the environment to compute the meteorological visibility distance as well as a new descriptor denoted $F S$ related to the droplet size distribution of fog. The method is assessed thanks to realistic photometrical simulations and validated experimentally by measurements in a fog chamber.

In Sect. 2, we present a model light propagation in fog at night and a simulation software of foggy scenes. In Sect. 3, we first propose a simplified method allowing to compute $k$, the extinction factor of Beer-Lambert’s law, from a foggy image. Then we discuss the limits of this model for light propagation in fog and show the need for a measure related to the forward scattering of the particles in fog. In Sect. 4 we expose the validation process we used on simulated and real measurements in fog. In Sect. 5 we show the needs in recent industrial applications and discuss the feasibility considering the state of the art.

2. Fog Model and Simulation

2.1 Light Propagation in Fog

Equation (1) relates the effects of nighttime fog on photometry from the linear system theory point of view [21]. The first part corresponds to Beer-Lambert’s attenuation law for collimated beams, the second part expresses the frequency effect of the scattering of light by the particles in the medium.

$$L_s(d) = L_s(0)e^{-kd} + L_s(0) * F^{-1}\{M^{kd} - e^{-kd}\}$$

where $L_s(0)$ is the luminance of the object, $k$ is the extinction coefficient, $d$ is the observation distance and $M$ characterizes the point spread function of fog. Using the analogy between a slab of fog and an optical filter, the Modulation Transfer Function (MTF) $M(k, d)$ of a homogeneous slab of fog of width $d$ and extinction coefficient $k$ can be derived from the MTF $M$ of a slab of unit optical depth, called the frequency contrast operator (FCO) [22].

$$M(k, d) = M^{kd}$$

In daytime fog a convenient and currently used unit is the meteorological visibility distance $V_{\text{met}}$. It is related to the extinction coefficient $k$ of Beer-Lambert that is also present in Eq. (1). $V_{\text{met}}$ is defined as:

$$V_{\text{met}} = \frac{3}{k}$$

Using $V_{\text{met}}$ for night fog characterization means using only the first part of Eq. (1), thus neglecting the scattering effect of light. We show in Sect. 3.1 that for light sources at night, this model is somehow limited in case of fogs composed of big droplets because the forward scattering of the particles becomes non-negligible. Forward scattering has a major impact on the appearance of light sources at night concerning the intensity perceived and the halo effect.

2.2 Fog Simulation by Semi Monte-Carlo Ray Tracing

PROF (Photometrical Rendering Of Fog), is a semi-Monte Carlo ray-tracing software designed for fog simulation [23]. We can produce luminance maps of an environment with several light sources in an homogeneous fog. Using PROF, we tried different configurations considering the number of light sources and their locations for $V_{\text{met}} \leq 500$ m. Depending on the number of rays used, there may be noise with variance proportional to the square root of the number of rays. We actually used $10^8$ rays, that is a common compromise between simulation time and noise. For the interactions of light with fog droplets, we provide PROF with tabulated phase functions and we set the extinction factor $k$ of Beer-Lambert model.

There exist different types of fog depending on the conditions which lead to their formation (valley fog, steam fog, upslope fog etc.). The nature of a particular fog is only relevant as far as different types of fog have different droplet size distributions. When it comes to the size of droplets, fog is usually classified as either advection or radiation fog. The sets of droplet size distributions that we use follow this classification. The first set is based on Shettle-Fenn droplet size distribution model illustrated in Fig. 1. $G_1$ and $G_2$ correspond to heavy and moderate advection fogs, $G_3$ and $G_4$ to heavy and moderate radiation fogs. The other set is based on measurements made in the artificial fog chamber presented in Sect. 4. ADV for big droplet distribution (advection fog type) and RAD for small droplet distribution (radiation fog type). The equivalent phase functions of all those distributions were computed according to Mie.

We are planning on using a potential site next to our facilities in order to experiment our methods in real fog. So our simulations should be compliant with the dimensions of this real site and its characteristics. We simulated a very simple scene compatible and close to our site consisting of a road of asphalt, light sources and fog. We have used a dark pavement (10% reflexion and Lambertian model) which is consistent with usual road surfaces (see Fig. 2). The luminances measured on our luminance maps for a light source at 35 m are shown on Fig. 3 for $V_{\text{met}}$ between 66 m and 200 m.

![Fig. 1 Four distributions according to [24].](image-url)
3. Night Fog Characterization

Our goal is to develop a camera based method able to characterize fog. We show that the $V_{met}$ (the extinction coefficient $k$) is biased depending on the droplet size distribution of fog and $V_{met}$ itself. We show that forward scattering, which is related to granulometry, has an important effect on the aspect of light sources and on the intensities perceived. So we develop a method that estimates $k$ but also gives information on the forward scattering of the particles.

3.1 Classical Approach with Two Light Sources

Neglecting the second part of Eq. (1), leads to the Beer-Lambert extinction model

$$L_s(d) = L_s(0)e^{-kd} \quad (4)$$

Beer-Lambert describes the first order of interaction between light and the atmosphere. But this is a limited model for two reasons, first of which, droplets are not absorbent, they scatter light. Since the albedo of water is nearly one and the size of some droplets can exceed ten times the wavelength of visible light, most energy is scattered forward when light “hits” droplets. Another bias between both models corresponds to the multiple scattering, but it is usually assumed to be negligible.

From Eq. (4), using two light sources $L_i$ and $L_j$ of existences $L_i(0)$ and $L_j(0)$ at different distances $d_i$ and $d_j$, we can estimate $k$ with Eq. (4):

$$k_{ij} = \ln \left( \frac{L_i(0)}{L_j(0)} \right) \frac{d_j}{d_j - d_i}.$$  

For example, with a pair of light sources at 80 m and 200 m, we see in Fig. 4 different estimations of $V_{met}$ depending on the nature of fog.

For radiation fog like $G_4$ (small particles, mode $\leq 2 \mu m$), the forward scattering is not too strong and extinction law is still valid for $V_{met} \geq 100 m$. In our example, this error on the estimation of $k$ is less than 10% with a peak at 50% for the highest density of fog (the relative error on $k$ equals the relative error on $V_{met}$). For advection fog like $G_1$ (big droplets, mode $\geq 3 \mu m$ or superior, more forward scattering) the error on the estimation of $k$ is greater than that of radiation fog and also depends on $k$, it strongly increases for $V_{met} \leq 100 m$. The error increases beyond 100% for small values of $V_{met}$. This shows that the estimation of $k$ is biased depending on the position of the sources and this bias comes from the forward scattering of light.

3.2 Using $n$ Sources with Sensitivity Composition

The range of fogs situations that can be studied depends on the placement of the light sources with the method exposed in Sect. 3.1. We may overcome this problem by placing several sources on a wide range of distance and exploiting the
most suitable pair among the possible.

Using three light sources, we compute three different estimations of \( k \) using the three possible pairs of sources. We propose a method to automatically extract the most reliable estimation of \( k \) based on the notion of sensitivity. Sensitivity is a blind way to estimate the variance of a computation, based on the partial derivatives of a function. Here, we want to know how reliable the estimations are depending on the positioning and the perceived intensity of the light sources. We take the sensitivity as the \( L_2 \) norm of partial derivatives [25]:

\[
\nu(k_{ij}) = \left( \frac{\partial k_{ij}}{\partial L_i} \right)^2 + \left( \frac{\partial k_{ij}}{\partial L_j} \right)^2 + \left( \frac{\partial k_{ij}}{\partial d_i} \right)^2 + \left( \frac{\partial k_{ij}}{\partial d_j} \right)^2
\]

We estimate \( k \) from the three estimations \( k_{12}, k_{13}, k_{23} \):

\[
k = \frac{\sum k_{ij} \nu_{ij}}{\sum \nu_{ij}}
\]

We can also estimate the sensitivity of \( V_{met} \) with the same principle and compose these values in the same manner. Using three light sources \( S_1, S_2, S_3 \) at 35 m, 80 m and 200 m we see in Table 1 for different values of \( V_{met} \) the sensitivities associated to these computations.

The sensitivity is well suited to our problem, we can see that it is lower for closer light sources (1 and 2) in the heaviest fog (\( V_{met} = 33 \) m) and lower for distant light sources (2 and 3) when the fog is lighter (\( V_{met} > 100 \) m). In any case, we know we can rely more on the information of one particular pair among the three possible pairs. It works well for radiation fogs (see Fig. 5), but even with sensitivity composition some \( k \) values are badly estimated, particularly in advection fog.

### Table 1: Sensitivity depending on the pair of light sources observed for different \( V_{met} \) in advection fog.

| \( V_{met} \) (m) | \( \nu_{12} \) | \( \nu_{23} \) | \( \nu_{13} \) |
|------------------|---------------|---------------|---------------|
| 33               | 14            | 464173        | 107805        |
| 100              | 517           | 56            | 459           |
| 200              | 8441          | 311           | 8732          |

The sensitivity composition of the estimates of \( k \) (or \( V_{met} \)) can be used with any number of lights at any distances. Supposing we had several light sources at different distances from 30 m to 400 m or farther, we could address a large range of fog conditions.

### 3.3 The Forward Scattering Bias

#### 3.3.1 Impact of the Forward Scattering

Depending on the size of the droplets, fog may have very different visual effects at night. The presence and size of halo around light sources depends on the granulometry of fog and the intensity perceived from a light source may differ from Beer-Lambert’s extinction law as we have seen on Fig. 3. This results in biased estimations of the atmospheric extinction parameter and an overestimation of the \( V_{met} \) (see Sect. 3.1).

We saw in Fig. 3 that even sensitivity composition does not lead to accurate results in advection weather: 100% error on the estimation of \( V_{met} \) in the worst case. The luminance perceived is 60% greater in the fog composed of the bigger droplets (\( G_1 \)) than in the fog with smallest droplets (\( G_4 \)). As a consequence, \( V_{met} \) is also overestimated by 55%. Using this estimation, we overestimate the original intensity \( L_i(0) \) of the light sources if we compute it by reversing Eq. (4) following:

\[
L_i(0) = L_i(d) e^{kd_i}
\]

Knowing the intrinsic luminance (without fog), we compute the relative error in the estimation of \( L_0 \) using Eq. (8). We show on Fig. 6 the relative error when computing the light sources luminance depending on \( V_{met} \) and distance. We computed tabulated functions of this error depending on \( V_{met} \) for four droplet size distributions (see Fig. 6). Those references from Shettle-Fenn presented in Sect. 2.2 are denoted \( G_1 \) to \( G_4 \). This relative error is independent of the intensity of the light source. Using this error and the estimated \( V_{met} \), we can compute a measure related to the forward scattering properties of fog.
Table 2  Result of our forward scattering estimation with reference fogs $G_1$ to $G_4$.  

| Phase | $V_{\text{met}_{in}}$ | $V_{\text{met}_{est}}$ | Rel. Err. | $FS$ |
|-------|-------------------|------------------|--------|-----|
| RAD   | 100               | 100.6            | 0.117  | 2.1 |
| ADV   | 100               | 102.3            | 0.274  | 3.33 |

Fig. 7  Evolution of granulometric distributions during two dissipations with advection (up) and radiation (down) fog.

3.3.2  A Forward Scattering Related Measure: $FS$

We define a measure linked to the forward scattering parameter: $FS \in [0; 5]$, the more there is forward scattering, the higher is $FS$. We compute the relative error estimation of $L_0$ and locate it with respect to the four reference error curves for a given $V_{\text{met}_{in}}$. Fogs $G_4$ to $G_1$ present increasing forward scattering. Our measure $FS$ is more important for $G_1$ fog than for $G_4$ fog. $FS = 0$ corresponds to the theoretical case of Beer-Lambert’s extinction law. $FS \leq 2$ corresponds to radiation fogs like $G_3$ or $G_4$. $FS \geq 3$ corresponds to advection fogs like $G_1$ or $G_2$. If the relative error estimation of $L_0$ is more important than what observed for $G_1$, $FS$ is thresholded to 5. Intermediate values of $FS$ relate the distance to the two nearest reference curves.

We have tested our measure of the forward scattering of the particles with noisy simulations generated with PROF. We show the results of $FS$ computation with real advection and radiation phase functions ADV and RAD in Table 2.

The measure $FS$ gives information on forward scattering with reference to fogs with droplet size distributions $G_1$ to $G_4$ as shown on Fig. 6. For a fog with droplet size distribution RAD typical of radiation type fog (see lower image on Fig. 7), relative error is 0.117 for $V_{\text{met}_{in}} = 100.6$ m, $FS = 2.1$, meaning it has forward scattering as $G_3$ (see Fig. 6) and is a moderate advection fog according to Shettle-Fenn (see Fig. 1). The fog with droplet size distribution ADV typical of advection type fog (see upper image on Fig. 7) has $FS = 3.3$, meaning its droplet size distribution is closer of $G_2$ and $G_1$ fogs and is more the moderate advection fog than the heavy advection fog type.

4.  Validation with Real Fog Experiments

We set up an experiment in a fog chamber in order to verify the important difference observed in simulation between fogs with different droplet size distributions (see Fig. 8).

4.1  Artificial Fog Chamber

The fog chamber of Clermont-Ferrand [26] is 30 meters long, 5.5 m wide and 2.7 m high and consists of a small-scale climatic chamber in which we can sprinkle water droplets until the air is saturated with fog. The evolution of density of the fog is permanently monitored by a TR30 transmissometers from Degreane Horizon with a base of 28 m. Granulometric distributions were measured with a Palas sensor. Using tap water produces droplet size distribution with a mode around $1 \mu$m and droplets sizes distributed between $0.8 \mu$m and $8 \mu$m, typical of radiation fog. Using demineralized water produces wider droplet size distribution with a mean diameter around $5 \mu$m and droplets sizes distributed between $0.4 \mu$m and $20 \mu$m, typical of advection fog.

4.2  Experimentation

We put light sources at 15 m, 18 m, 23 m and 28 m (see Fig. 9). The light sources were positioned so as to not interact with each other. The experiments consist in taking pictures with a video-luminancemeter LMK Color 98-4 with a 12 bit CCD sensor while the fog dissipates. We recorded simultaneously $V_{\text{met}}$ values given by the TR30. As suspected, intensities perceived in the direction of the light source can be very high when there is no fog. Even with the lowest integration time, the video-luminancemeter was saturated.
We used a neutral density filter in order to estimate the luminance of those light sources in clear weather.

During the experiments, the fog density was raised to its maximum by saturating the chamber with droplets. Then we let the fog dissipate naturally. It dissipates by two phenomena, heavier droplets fall to the ground and other water droplets aggregate and eventually fall. Because of the nature of the dissipation, fog is stratified, so all the optical instruments and light sources had to be placed at the same height.

4.3 Results

The simulated images generated with PROF showed greater luminance values with bigger droplets than with smaller droplets for equivalent values of $V_{\text{met}}$. As shown on Fig. 10, observed luminance values can be ten times greater in advection fog than in radiation fog. This effect is stronger than in the simulation. This could come from the fact that we are dealing with very dense fogs. The relative luminance of a light source in advection fog is 4 to 10 times that of the same light source in radiation fog for $V_{\text{met}}$ comprised between 15 m and 45 m.

We will now apply the method developed on synthetic luminance maps. Using pairs of light sources in order to estimate $k$ (see Eq. (5)) and composing the estimations using Eqs. (6) and (7). The results are shown in Table 3. The estimation of $V_{\text{met}}$ is better achieved in radiation fog than in advection fog. Like in the results obtained with simulated images. The sensitivity composition method was applied with the six possible pairs of light sources but the error is still important. The mean error is about 50% in radiation fog, the mean error is about 72% in advection fog. It is therefore logical that computation of the intrinsic luminance of sources using the method exposed in Sect. 3.3 leads to more error for advection fogs than for radiation fogs.

We can see that the relative error in the estimation of $L_0$ of the sources is less than 100% for radiation fogs (see Fig. 11). It can be over 1000% for advection fogs. The computation of the measure $FS$ using our tabulated errors as shown in Sect. 3.3 is not satisfactory. All measures give more error than the $G_1$ fog in simulation, leading to $FS = 5$. This could come from the fact that the experiments were conducted in very dense fogs and that the tabulated function were computed with sources at different distances in simulation and in the fog chamber. The tabulated functions of relative error on the computation of $L_0$ we got from simulation are not suited for real fogs. But the computation of a relative error on the estimation of $L_0$ seems to be relevant to differentiate fogs with much forward scattering and fogs with less forward scattering.

5. Applications

Drivers suffer visual impairment in fog at night, specifically in dense fog environments or when visual cues are few. It is believed that drivers may change their behavior in fog, they may use shorter following distances in foggy conditions as compared with clear weather [27].

Road operators may have great interest in being able to characterize fog with static cameras. Moreover since they have numerous cameras at their disposal along the road. It has been shown in Sect. 3 that highway visibility cannot be...
assessed with $V_{\text{met}}$ information only and that droplet size distribution of fog impacts on the perception of drivers. Using a static estimation such as proposed in this paper may help them propose relevant speed advisement depending on the visibility conditions.

New ADAS are emerging since recent changes in law enforcement in Europe. Some of those changes concern the intensity of rear lights of the car [28]. Adaptive lighting aims at being able to cope with more complex situations than day or night differentiation, tunnel outing or some highly contrasted scenes that could lower the visual performance of lights. Technical propositions consists in adapting the intensity and the lighted area of lights.

Solutions proposed nowadays concern adapting the intensity of rear lights to reduced conditions of visibility in order to improve perception by keeping the intensity perceived constant at some distance [29]. They propose to use the meteorological visibility distance, derived of the parameter $k$ of Beer-Lambert model in order to compensate for the attenuation of light. In-car experiments exist, they use lidar technology to estimate $k$, thus $V_{\text{met}}$ [30], [31]. We showed in Sect. 3 that an observer could perceive very different intensities from light sources at the same distance with the same $V_{\text{met}}$ depending on the granulometry of the droplets composing the fog. This leads to the conclusion that using only Beer-Lambert model of light propagation in adaptive lighting could lead to wrong adaptation of the intensities of the lights.

We showed the needs to take into account granulometry in active lighting systems working at night. Cameras or lidars estimation of the density of fog at night should give a granulometry related parameter in complement to $V_{\text{met}}$, that is not sufficient to describe the visual effect of fog on perception (see Fig. 12). We believe that recent developments in cameras (high definition, but more importantly for our applications high dynamic), could lead to develop such a method.

6. Conclusion and Outlook

We presented a new way of characterizing meteorological visibility distance in night fog with a camera that needs at least one image and three light sources of known distance and intensity. We showed that the method can be extended to any number of light sources and that it could increase the range and confidence on the estimation of the extinction coefficient $k$. This method improves previous results, particularly in the case of dense fogs. But still, a bias exists that is related to the scattering of light by droplets. We showed the needs for a more complete model than classic Beer-Lambert’s extinction law for light propagation in fog at night. We proposed a measure related to the forward scattering of fog, an aspect of light propagation in fog at night that is linked to droplet size distribution and that strongly impacts on the appearance of light sources. We estimate our measure $FS$ in reference to tabulated functions computed from simulation. The next step is to generalize those functions with functional description instead of a tabulated one and make reference to real observations through a calibration process. We showed that forward scattering should not be neglected, particularly with regard to recent evolutions in road safety transportation systems such as adaptive lighting.

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