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

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Abstract

In this paper, we propose a new way to estimate fog extinction at night using a 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. This method works in dense fogs (meteorological visibility distances < 400m) with a single image and three known light sources. The method is validated on synthetic images generated with a semi Monte-Carlo ray tracing software dedicated to fog simulation. We drove this study in simulated environment in order to help us designing a test site located outdoor.

1 Introduction

Car manufacturers and OEMs are interested in developing an in-vehicle camera based system that can detect and characterize poor visibility conditions due to fog at night. Dense fog is a major road safety issue, knowing the major importance of visual informations in the driving task. It is also an important information that can characterize the operational range of any camera-based system. In order to validate such a system, one needs to know the characteristics of the fogs we drive in. We have developed a simple static way of characterizing fog using a single image and three known light sources.

Previous works on nighttime fog detection and characterization with imagery are few. Using static imaging techniques, after extracting the halo of distant sources, [8] and [5] 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 light fog, whereas we also need a method that characterizes heavy to dense fogs (meteorological visibility $< 400m$) that may impact visual performances while driving.

In section 2, we present a model of night photometry in fog, and the simulation softwares we used to generate virtual scenes in dense fog. In section 3, we first propose a simplified model allowing to compute k, the extinction factor of Beer-Lambert's law, from a foggy image. We then discuss the limits of this model for light propagation in fog and show the need for a measure linked to the forward scattering of the particles in fog. Finally, we propose our model and show results on simulated scenes.

Our method presents different advantages such as the low cost, small size and multiple uses of cameras compared to transmissiometers or such measuring materials. It is easily extendable or adaptable to different ranges of meteorological visibilities. Our method also provides a measure denoted FS related to fog granulometry and thus to the visual effects of fog.

2 Modelling

2.1 Light Propagation in Fog

Eq. (1) relates the effects of fog on photometry from the linear filtering theory point of view [6]. It splits in two parts the different natures of fog effects on vision (extinction and halo effect) whereas Chandrasekhar's model for Radiative Transfert Equation does not [1]. The first part corresponds to Beer-Lambert's attenuation law for collimated beams, the second part is linked to single/multiple scattering of light by the particles in the medium.

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

where $L_s(0)$ is the luminance of the object, k the extinction coefficient, d the observation distance and M the frequential effect of fog on light propagation. 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)[3].

$$M(k, d) = M^{kd} \quad (2)$$

Beer-Lambert's extinction law is used in [7] in order to retrieve k, the extinction coefficient of fog. We show in section 3 that this model is somehow limited and can lead to bad estimations of k in case of fogs composed of big droplets because the forward scattering of the particles becomes non-negligible. This phenomenon also increases with the density of fog. The meteorological visibility distance V_{met} is a convenient unit and is related to the extinction coefficient k:

$$V_{met} = {}^{3}\!/_{k} \quad (3)$$

2.2 Fog Simulation

2.2.1 Semi Monte-Carlo Ray Tracing

PROF (Photometrical Rendering Of Fog), is a semi-Monte Carlo ray-tracing software designed for fog simulation [2]. It allows to simulate luminance images of an environment with multiple light sources in an homogeneous fog. Using PROF, we tried different configurations considering the number of light sources and their locations for $V_{met} \leq 500m$.

For the interactions of light with fog droplets, we can give the parameter denoted as g in Henyey-Greenstein's model (4) or tabulated phase functions, and we need to set the extinction factor k of Beer-Lambert's model. We used

$$P_{HG}(\mu, g) = \frac{1 - g^2}{(1 + g^2 - 2g\mu)^{3/2}} \tag{4}$$

where μ is the cosine of the angle between incidence light and scattered radiations and g is the asymmetry factor or also called *forward scattering parameter*.

We have used three different sets of phase functions. One set corresponds to the equivalent phase functions of fogs with Shettle-Fenn [9] drop size distributions computed with Mie theory. Those are denoted G_1 to G_4 (G_1 being the advection fog type and G_4 the radiation fog type). A second set corresponds to the equivalent phase function of fogs with real drop size distributions measured in a fog room. Those phase functions are denoted clfADV and clfRAD. We also used Henyey-Greenstein phase function in the validation process though it is a limited model for light propagation in fog [3]. We do not transform the luminance map of this virtual environment. It could be converted with a specific response function in order to simulate a camera or for display. Practically, we plan to adjust our camera settings so that the nearest source isn't saturated, and inverse the camera response function in order to get relative intensity perceived.

Figure 1: Simulation of three point sources in fog (35m, 200m and 80m from left to right)

We simulated a very simple scene compatible and close to our site consisting of a road of asphalt, extended sources and the fog. We have put a dark ground (10% reflexion and lambertian model) which is consistent with usual road surfaces. We verified that the dark ground and that multiple scattering of sources has no influence on the intensity received from the directions of the sources.

2.2.2 Atmospheric MTF

Luminance maps of a scene in fog may also be computed by convoluting an extended image with the point spread function (PSF) of the atmosphere [3]. The PSF is the inverse Fourier transform of the MTF. It depends on the particle size distribution as well as on the transmittance $T = kd$ of the medium. The extended image is an image where the pixels not only have an intensity level but also a distance information (from the virtual cameras).

Knowing the intensity and distance of each pixel and the PSF of the medium, we can compute the appearance of the scene in the presence of fog.

3 Characterizing Fog

3.1 Classical Approach

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

$$L_s(d) = L_s(0)e^{-kd} \tag{5}$$

This is a limited model for two reasons, first of which, droplets are not absorbent. 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 the two models corresponds to the multiple scattering.

During nighttime, we may use any of those two phenomenons (extinction or single/multiple scattering) to extract informations about the nature of the fog. We use Eq. (5) in order to retrieve the extinction coefficient k. The luminances measured on our luminance maps for a source at 35m are shown on figure 2 for V_{met} between 66m and 200m.

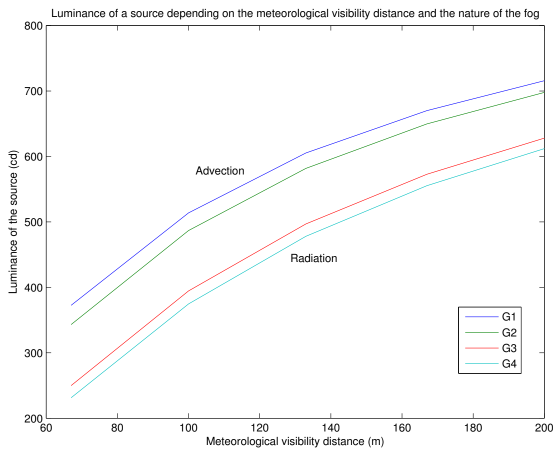

Figure 2: Luminances of a source at 35m in four different fogs depending on the V_{met}

3.2 A model with 2 Sources

From Eq. (5), using two light sources L_i and L_j of exitances $L_i(0)$ and $L_j(0)$ at different distances d_i and d_j, we can estimate k with Eq. (5) :

$$k = \frac{\ln\left(\frac{L_i L_j(0)}{L_j L_i(0)}\right)}{d_j - d_i} \ , \ L_i(0) = L_j(0) \Rightarrow k = \frac{\ln\left({L_i}/{L_j}\right)}{d_j - d_i} \tag{6}$$

For example, with a pair of sources at 80m and 200m, we see different estimations of k as a function of V_{met} on figure 3 :

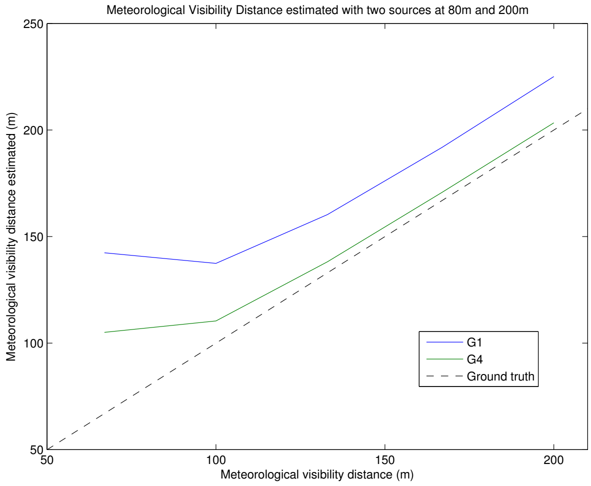

Figure 3: Estimation of V_{met} using pairs of sources at 80m and 200m

For radiation fog like G_4(small particles, mode $\leq 2\mu m$) the forward scattering isn't too strong and extinction law is still valid, given an error which depends on the transmittance of the atmosphere. In our example, this error is less than 10% with a peak at 50% for the highest density of fog.

For advection fog like G_1(big droplets, more forward scattering, mode $\geq 3\mu m$ or superior) the error on the estimation of k is greater than that of radiation fog, and also depends on T. In our example, the error increases beyond 100% for small V_{met}.

3.3 A model with n sources

The range of fogs that can be studied depends on the placement of the sources with the method exposed in subsection 3.2. The main problem we met is on very small visibility distances, but in the field of road safety those are critical and need to be correctly estimated.

3.3.1 Sensitivity Composition

Using three light sources, we compute three different estimations of k. We propose a method to 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 are the estimations depending on the positioning and the perceived intensity of the sources. We take the sensitivity as the L_2 norm of partial derivatives [4]:

$$\nu(k) = \left(\frac{\partial k}{\partial L_i}\right)^2 + \left(\frac{\partial k}{\partial L_j}\right)^2 + \left(\frac{\partial k}{\partial d_i}\right)^2 + \left(\frac{\partial k}{\partial d_j}\right)^2 \quad (7)$$

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

$$k = \frac{\sum \frac{k_{ijest}}{\nu_{ij}}}{\sum \frac{1}{\nu_{ij}}} \quad (8)$$

We can also estimate the sensitivity of V_{met} with the same principle and compose these values in the same manner.

3.3.2 Results

Using three sources S_1, S_2, S_3 at 35m, 80m and 200m we see in tab. 1 different estimations of k and the sensitivities associated to these computations.

Adv.	ν		
$V_{met}(m)$	ν_{12}	ν_{23}	ν_{13}
33	14	464173	107805
100	517	56	459
200	8441	311	8732

Table 1: Sensitivity depending on the couple of sources observed for different V_{met} in advection fog

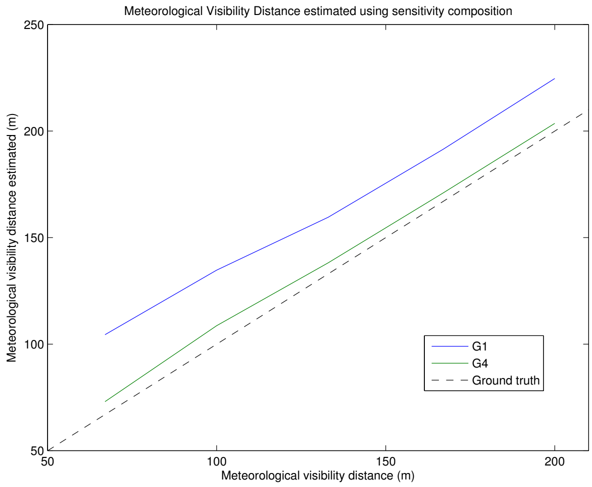

Figure 4: Estimation of V_{met} using three sources and sensitivity composition (8)

The sensitivity is well suited to our problem, we can see that it's lower for closer sources (1 and 2) in the heaviest fog ($V_{met} = 33m$) and lower for distant sources (2 and 3) when the fog is lighter ($V_{met} > 100m$). 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. 4), despite that even with the sensitivity composition and three sources some k's are badly estimated, particularly in advection fog.

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 numerous sources at different distances from 30m to 400m or farther, we could study very large range of fogs. We have tested it on noisy measurements generated using PROF and it greatly improves robustness to noise.

4 The Forward Scattering Bias

Depending on the size of the droplets, fog may have very different visual effects at night. It also impacts on the intensities perceived, specifically for light sources. The presence and size of halo around sources depends on the granulometry of fog and the intensity perceived from a source may differ from Beer-Lambert's extinction law depending on the transmittance as we've seen on fig. 2. This results in biased estimations of the atmospheric extinction parameter and an overestimation of the V_{met} (see part 3.2).

4.1 Impact of the Forward Scattering

We saw in fig. 2 that even sensitivity composition doesn't lead to accurate results in advection weather: 100% error in the worst case, the intensity perceived is 60% greater in the fog composed of the bigger droplets(G_1) than in the fog with smallest droplets(G_4). The V_{met} has also been overestimated by 55%.

Using this estimation, we overestimate the original intensity $L_i(0)$ of the sources if we compute it by reversing Eq. (5) following :

$$L_i(0) = L_i(d)e^{k_{est}d_i} \tag{9}$$

We know the real perceived intensity without fog and we compute the relative error in the estimation of the source intensity using Eq. (9). We show on fig. 5 the relative error when computing the sources intensity depending on the V_{met} and distance.

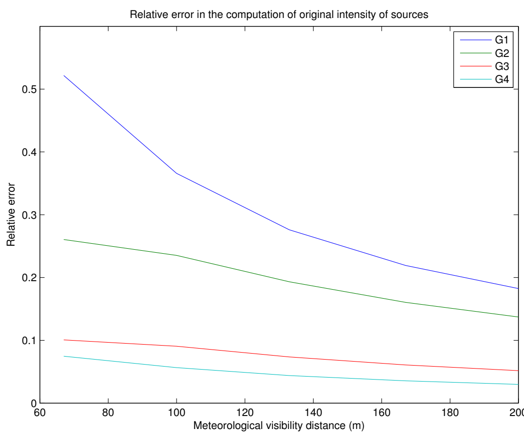

Figure 5: Error in the computation of sources intensity

This relative error is independent of the intensity of the source. Knowing this error and the meteorological visibility distance estimated $V_{met_{est}}$ we can classify the type of fog due to its forward scattering properties. We computed a tabulated function of the relative error depending on the transmittance and the granulometry (see fig. 5).

We propose a measure linked to the forward scattering parameter $FS \in [0;5]$. For a given $V_{met_{est}}$, we compute the error and locate it with respect to the four error curves. Fogs G_4 to G_1 present increasing forward scattering. Our measure FS should be more important for G_1 fog than for G_4 fog. $FS = 0$ corresponds to the theoretical case of Beer-Lambert's extinction law. If the error is greater than the error of G_1, it is thresholded at 5. Intermediate values relate the importance of the forward scattering in the fog.

4.2 Results

We have tested our measure of the forward scattering of the particles with noisy simulations generated with PROF. We chose to study the measure with our advection and radiation real phase functions and with two Henyey-Greenstein phase functions with forward scattering parameter of 0.95 (corresponding to an advection fog) and 0.55 (radiation fog).

Phase	$V_{met_{ref}}$	$V_{met_{est}}$	Rel. Err.	FS
HG g=0.55	100	99.5	0.041	0.71
HG g=0.95	100	102	0.228	2.95
clf-RAD	100	100.6	0.117	2.1
clf-ADV	100	102 .3	0.274	3.33

Table 2: Result of our forward scattering estimation with different natures of fog

5 Conclusion and outlook

We have presented a new way of characterizing meteorological visibility distance that needs at least 1 image and three sources of known distance and intensity. This method has been tested on synthetic images in order to design our test site. This method improves previous results, particularly in the case of dense fogs. It also provides a measure related to the forward scattering of the fog, a phenomenon linked to droplets granulometry and that strongly impacts on the appearance of light sources in fog at night. We showed the needs for a more complete model than classic Beer-Lambert's extinction law for light propagation in fog. We estimate our measure FS from a tabulated function. The next step is to generalize this function with a functional description instead of a tabulated one. The method has been tested and validated in simulation. The goal is now to test it on a road site with real sources.

Acknowledgment

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References

[1] Chandrasekhar, S. :"Radiative Transfer", *Dover Publications*, 1960.

[2] Dumont, E.:"Semi-Monte Carlo light tracing applied to the study of road visibility in fog", In *Monte Carlo and Quasi-Monte Carlo Methods 1998*, pp.177-187, Berlin, 1999, Springer-Verlag.

[3] Dumont, E. and Cavallo, V.:"Extended photometric model of fog effects on road vision" *Journal of the TRB*, no.1862, pp.77-81, 2004.

[4] Hautière N., Aubert D., Dumont E. and Tarel J.-P. :"Experimental Validation of Dedicated Methods to In-Vehicle Estimation of Atmospheric Visibility Distance" *IEEE T Instrum Meas*, vol.57(10), pp.2218-2225, 2008.

[5] Metari, S. and Deschênes, F. :"A New Convolution Kernel for Atmospheric Point Spread Function Applied to Computer Vision", *Proc. IEEE ICCV '07*, pp.1-8, 2007

[6] Nameda, N. : "Fog Modulation Transfer Function and Signal Lighting", *Lighting Research and Technology*, vol.24, no.2, pp.103-106, 1992.

[7] Narasimhan, S.G. and Nayar, S.K. :"Vision and the Atmosphere", *Int J Comput Vision*, vol.48, no.3, pp.233-254, 2002.

[8] Narasimhan, S.G. and Nayar, S.K. :"Shedding light on the weather" *Proc. IEEE CVPR '03*, pp.665-672, 2003.

[9] Shettle, E.P. and Fenn, R.W. :"Models for the Aerosols of the Lower Atmosphere and the Effects on Humidity Variations on Their Optical Properties" *Environ Res*, AFGL-TR-79-0214, 1979.