PAPER *Special Section on Machine Vision and its Applications*

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

Romain GALLEN[†,††], ***Nonmember***, **Nicolas HAUTIÈRE**[††], ***Member***, ***and*** **Eric DUMONT**[††], ***Nonmember***

SUMMARY In this paper, we propose a new way to estimate fog extinction at night. 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 adaptative 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. Validation process has been conducted with experiments in a fog chamber, we present the results and discuss the method, its benefits and its limits.

key words: *fog, granulometry, camera, forward scattering, adaptative 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, e.g. [1, 2]. Among the sensors, camera is one of the most promising since it can be low cost one and suits different applications [3]. However, 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 [4]. First, the reliability of the systems is reduced because some visual aspects of the highway scenes are changed, so that the 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 the perturbations, rain is the one with higher occurrence in tempered climate. It has a great impact on friction [5] but also on visibility [6]. Recently, different camera-based systems have been proposed to detect rain on the windshield [7–9] as well as wet pavement [10, 11]. 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 [12].

Different methods were proposed to detect and characterize visibility in daytime fog by in-vehicle camera. [13] 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 [14]. 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 [15]. This method was later adapted to monocular vision [16]. Some methods restore the images grabbed in daytime fog [17, 18] and might be used in ADAS. Finally, it is proposed in [19] 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, [20] uses the attenuation of distant light sources to reconstruct the 3D structure of the scene. After extracting the halo of distant sources, [21] and [22] 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 [23] 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

Manuscript received November 6, 2009.
Manuscript revised January 1, 2010.
[†]UniverSud, LIVIC - INRETS/LCPC, 14, route de la minière, 78000 Versailles, France
[††]UPE, LEPSIS - INRETS/LCPC, 58, boulevard Lefebvre, 75015 Paris, France
DOI: 10.1587/transinf.E0.D.1

beam would be attenuated by 95%, then computing the equivalent attenuation for that slab of atmosphere with Beer-Lambert model [24]. 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 $< 500m$) 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 FS related to the fog granulometry. The method is assessed thanks to realistic photometrical simulations and validated experimentally by measurements in a fog chamber.

In section 2, we present a model light propagation in fog at night and a simulation software of foggy scenes. In section 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 section 4 we expose the validation process we used on simulated and real measurements in fog. In section 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

Eq. (1) relates the effects of nighttime fog on photometry from the linear system theory point of view [25]. The first part corresponds to Beer-Lambert's attenuation law for collimated beams, the second part expresses the frequential effect of the scattering of light by the particles in the medium.

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

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) [26].

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

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

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

Using the V_{met} for night fog characterization means using only the first part of Eq.(1), thus neglecting the scattering effect of light. We show in section 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 [27]. 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 $V_{met} \leq 500m$. 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 give tabulated phase functions and we need to set the extinction factor k of Beer-Lambert model. We have used two different sets of phase functions. One set uses Shettle-Fenn [28] drop size distributions (see Fig. 1). Those are denoted G_1 to G_4 (G_1 being the advection fog type and G_4 the radiation fog type). The other set uses real measurements of droplet size distributions made in the fog chamber presented in Sec. 4.2. Those are denoted ADV and RAD, ADV being composed of bigger particles and RAD composed of smaller droplets. The equivalent phase functions of all those distributions were computed according to Mie theory.

We are planing 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.

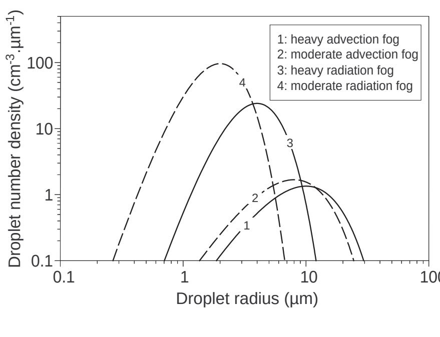

Fig. 1 Four distributions according to [28]

Fig. 2 Potential site and simulation of light sources at night

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.

The luminances measured on our luminance maps for a light source at 35m are shown on Fig. 3 for V_{met} between 66m and 200m.

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 fog granulometry and V_{met}. 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

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

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 the two 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 exitances $L_i(0)$ and $L_j(0)$ at different distances d_i and d_j, we can estimate k with Eq. (4) :

$$k_{ij} = \frac{\ln\left(\frac{L_i L_j(0)}{L_j L_i(0)}\right)}{d_j - d_i}\ ,\ L_i(0) = L_j(0) \Rightarrow k_{ij} = \frac{\ln\left({}^{L_i}/_{L_j}\right)}{d_j - d_i} \tag{5}$$

For example, with a pair of light sources at 80m and 200m, 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 $V_{met}\geq 100m$. 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,

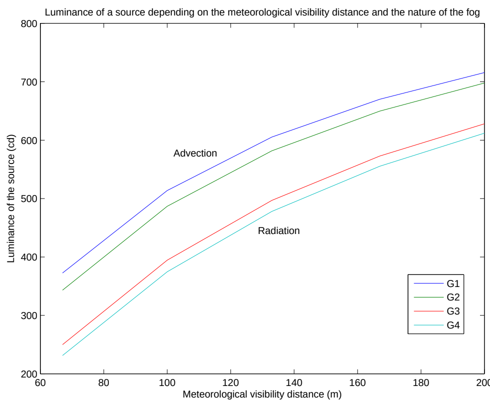

Fig. 3 Luminances of a source at 35m in four different fogs depending on the V_{met}

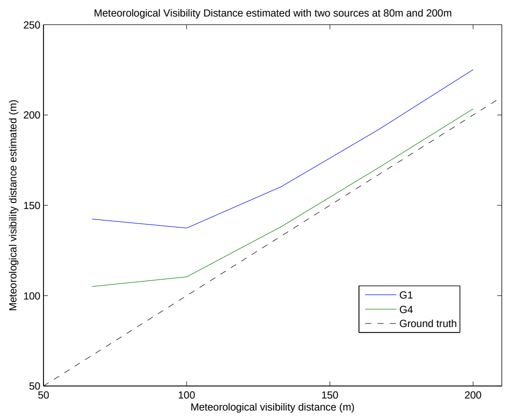

Fig. 4 Estimation of V_{met} using sources at 80m and 200m

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 $V_{met} \leq 100m$. 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 scattering of light.

3.2 Using n Sources

The range of fogs situations that can be studied depends on the placement of the light sources with the method exposed in subsection 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.

3.3 Sensitivity Composition

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 [29]:

$$\nu(k_{ij}) = \left(\frac{\partial k_{ij}}{\partial L_i}\right)^2 + \left(\frac{\partial k_{ij}}{\partial L_j}\right)^2 + \left(\frac{\partial k_{ij}}{\partial d_i}\right)^2 + \left(\frac{\partial k}{\partial d_j}\right)^2 \quad (6)$$

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

$$k = \frac{\sum \frac{k_{ij}}{\nu_{ij}}}{\sum \frac{1}{\nu_{ij}}} \quad (7)$$

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 35m, 80m and 200m we see in Tab. 1 different estimations of k and 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 ($V_{met} = 33m$) and lower for distant light 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

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 pair of light sources observed for different V_{met} in advection fog

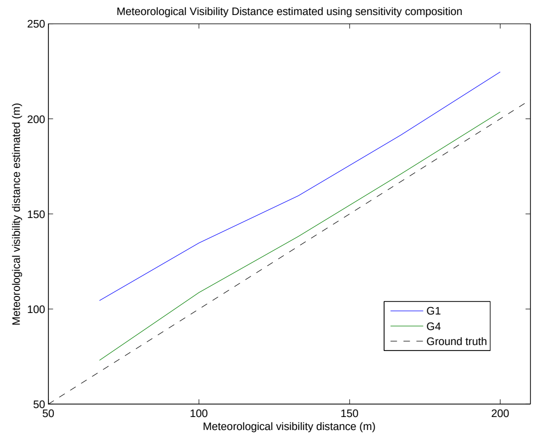

Fig. 5 Estimation of V_{met} using three light sources and sensitivity composition (7)

one particular pair among the three possible pairs. It works well for radiation fogs (see Fig. 5), but even with sensitivity composition and three light sources, some k values 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 several light sources at different distances from 30m to 400m or farther, we could address a large range of fog conditions.

3.4 The Forward Scattering Bias

3.4.1 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 part 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 :

$$L_i(0) = L_i(d)e^{kd_i} \quad (8)$$

We know the intrinsic luminance (without fog) and we compute the relative error in the estimation of the luminance using Eq. (8). We show on Fig. 6 the relative

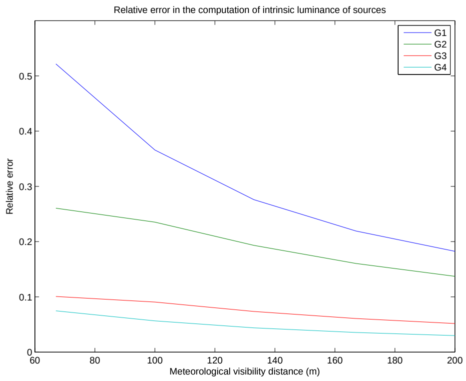

Fig. 6 Error in the computation of intrinsic luminance

error when computing the light sources luminance depending on V_{met} and distance. This relative error is independent of the intensity of the light source. Knowing this error and the estimated $V_{met_{est}}$, we can classify the type of fog with respect to its forward scattering properties. We computed a tabulated function of the relative error depending on the V_{met} and the granulometry (see Fig. 6). The granulometric distributions we used as references for the tabulated are those from Shettle-Fenn presented in Sec. 2.2 denoted G_1 to G_4.

3.4.2 a Forward Scattering Related Measure : FS

We define 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 reference error curves. Fogs G_4 to G_1 present increasing forward scattering. Our measure FS should be increasing with error, it 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. $FS = 1$ corresponds to an error like for G_4 fog. $FS = 4$ corresponds to an error like for G_1 fog, if the relative error estimation of L_0 is more important than what observed for G_1, FS is thresholded to 5. Intermediate values describe 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 Tab. 2. The measure FS should be seen as a classification measure that links the forward scattering of a fog to one of the reference fogs G_1 to G_4. Here, for a radiation type granulometric distribution RAD, $FS = 2.1$, 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 radiation type granulometric distribution RAD has $FS = 3.3$, meaning it is between G_2 and G_1 and is more the moderate advection fog than the heavy advection fog type.

Phase	$V_{met_{ref}}$	$V_{met_{est}}$	Rel. Err.	FS
RAD	100	100.6	0.117	2.1
ADV	100	102 .3	0.274	3.33

Table 2 Result of our forward scattering estimation with reference fogs G_1 to G_4

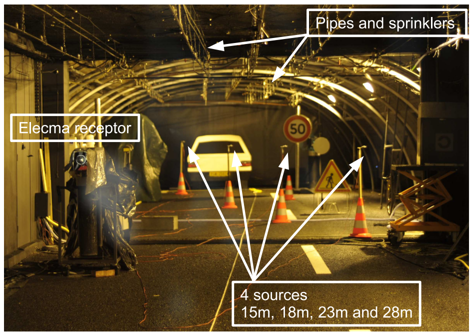

Fig. 7 Experimental Setting

4. Validation with Real Fog Experiments

4.1 Artificial Fog Chamber

After validating the method on simulated luminance maps, we set up an experiment in the fog chamber of Clermont-Ferrand [30]. It 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 $28m$. Granulometric distributions were measured with a Palas sensor. Fogs with different droplet size distributions can be produced. One fog is produced with tap water, containing minerals, which gives granulometric distributions with a mode around $1\mu m$ and droplets sizes distributed between $0.8\mu m$ and $8\mu m$, which is characteristic of radiation fog. The other granulometric distribution is obtained with the use of demineralized water, containing less condensation nuclei. This distribution is composed of larger droplets distributed between $0.4\mu m$ and $20\mu m$ and has a mean diameter being around $5\mu m$ which is characteristic of advection fog though it seems natural advection fogs may contain even bigger droplets [31, 32].

4.2 Experimentation

We put light sources at $15m$, $18m$, $23m$ and $28m$ (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 the V_{met} values given by the TR30. As suspected, intensities perceived in the direction of the light source can be very high

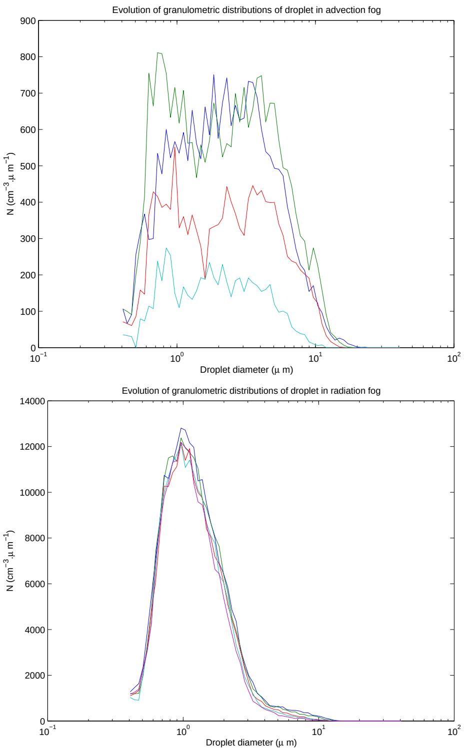

Fig. 8 Evolution of granulometric distributions during the experiments with advection (up) and radiation (down) fog

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 phenomenons, 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 luminances in advection fog than in radiation fog for equivalent values of V_{met}. As shown on Fig. 10, real luminances can be ten times greater in advection fog than in radiation fog. This effect is stronger than

Radiation	V_{met}						
$V_{met_{ref}}$	8	9	12	16	20	25	34
$V_{met_{est}}$	6.3	6.2	8.5	9.5	12.5	15.6	37.5
Advection	V_{met}						
$V_{met_{ref}}$	11	15.5	22	28	33	34	43
$V_{met_{est}}$	8.2	11.1	12.8	14.1	17.1	17.5	24.7

Table 3 Estimation of V_{met} with different natures of fog

showed in the simulation. This could come from the fact that we are currently dealing with very dense fogs. The relative luminance of a light in advection fog is 4 to 10 times that of the same light source in radiation fog for V_{met} comprised between 15m and 45m.

We now want to 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 Eq. (6) and Eq. (7). The results are shown in Tab. 3. We can see in Tab. 3 that the estimation of V_{met} is better achieved in radiation fog than in advection fog. That was also the case with simulated images. The sensitivity composition method was applied with the six possible pairs of light sources. 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 Sec. 3.4 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. It can be over 1000% for advection fogs. The computation of the measure FS using our tabulated errors as shown in Sec. 3.4 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

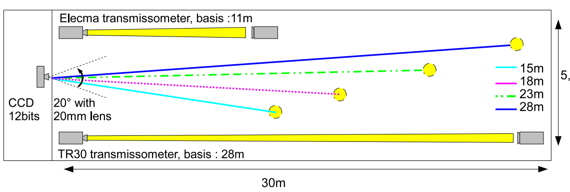

Fig. 9 Positioning of the light sources in the fog chamber

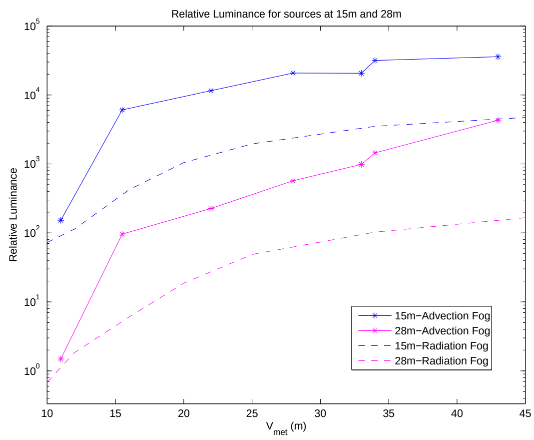

Fig. 10 Luminance of light sources at 15m and 28m in advection and radiation fog

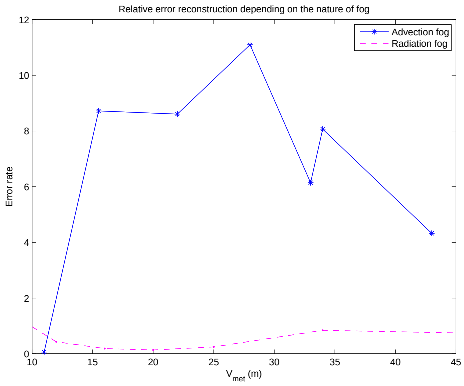

Fig. 11 Relative error estimation on L_0

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

It is a fact that 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 [33].

A first proposition in order to improve the safety in those situations would be to use two rear fog lights on cars, a minimum width separating back lights and it is also suggested that lowering the height of lights could lead to decreased distance estimations [34, 35].

New proposals are emerging since recent changes in law enforcement in Europe. Some of those changes concern the intensity of the front and rear lights of the car [36]. The future of adaptative lighting is to be able to cope with more complicated 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 [37]. 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 the V_{met} [38, 39]. We showed in 3 that an observer could perceive very different intensities from light sources at the same distance with the same V_{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 adaptative lighting could lead to wrong adaptation of the intensities of the lights.

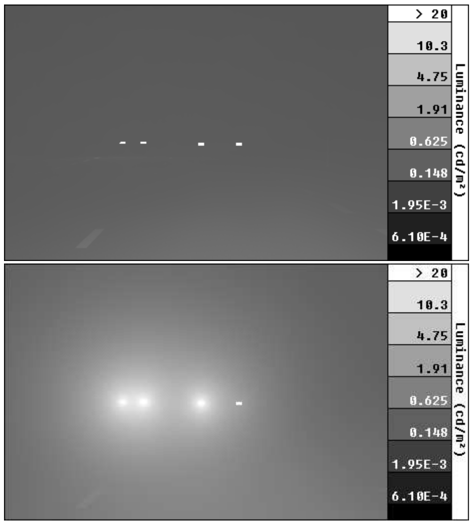

Fig. 12 Cars in radiation (up) and advection (down) fog with V_{met} of 100m

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_{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 have presented a new way of characterizing meteorological visibility distance with a camera that needs at least 1 image and three light sources of known distance and intensity. We showed that the method could be extended to any number of 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 have proposed a measure related to the forward scattering of the fog, an aspect of light propagation in fog at night that is linked to droplets granulometry and that strongly impacts on the appearance of light sources. We estimate our measure FS in reference to a tabulated function computed from simulation. The next step is to generalize this function with a 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 adaptative lighting. We also plan on testing our method on our site with real light sources and our onboard 14 bit CCD camera.

Acknowledgments

This work has been supported by the ANR DIVAS project. The authors would like to thank Michèle Colomb, Philippe Morange and Jean-Luc Bicard for their assistance during the experiments in the fog chamber.

References

[1] N. Barnes, A. Zelinsky, and L. Fletcher, "Real-time speed sign detection using the radial symmetry detector," IEEE Transactions on Intelligent Transportation Systems, vol.9, no.2, pp.322–332, 2008.
[2] T. Veit, J.P. Tarel, P. Nicolle, and P. Charbonnier, "Evaluation of road marking feature extraction," IEEE Conf. on Intelligent Transportation Systems, Beijing, China, pp.174–181, 2008.
[3] K. Takano, T. Monji, H. Kondo, and Y. Otsuka, "Environment recognition technologies for supporting safe driving," Hitachi Review, vol.53, no.4, pp.217–221, 2004.
[4] R. Kurata, H. Watanabe, M. Tohno, T. Ishii, and H. Oouchi, "Evaluation of the detection characteristics of road sensors under poor-visibility conditions," Proc. IEEE Intelligent Vehicles Symposium, 2004.
[5] Y. Delanne and M. Gothié, "Influence of road wetness on the skid resistance performance of tires," Bulletin des Laboratoires des Ponts et Chaussées, no.255, pp.23–34, 2005.
[6] N. Hautière, E. Dumont, R. Brémond, and V. Ledoux, "Review of the mechanisms of visibility reduction by rain and wet road," International Symposium on Automotive Lighting (ISAL'09), Darmstadt, Germany, pp.445–455, 2009.
[7] Y. Tanaka, A. Yamashita, T. Kaneko, and K. Miura., "Removal of adherent waterdrops from images acquired with a stereo camera system," IEICE Transactions on Information and Systems, vol.E89-D, no.7, pp.2021–2027, 2006.
[8] M. Roser and A. Geiger, "Video-based raindrop detection for improved image registration," IEEE Workshop on Video-Oriented Object and Event Classification (in conjunction with ICCV), Kyoto, Japan, September 2009.
[9] H. Kurihata, I. Ide, Y. Mekada, H. Murase, Y. Tamatsu, and T. Miyahara, "Rainy weather recognition from in-vehicle camera images for driver assistance," Proc. IEEE Intelligent Vehicles Symposium, 2005.
[10] M. Yamada, T. Oshima, K. Ueda, I. Horiba, and S. Yamamoto, "A study of the road surface condition detection technique for deployment on a vehicle," JSAE Review, vol.24, pp.183–188, 2003.
[11] T. Teshima, H. Saito, M. Shimizu, and A. Taguchi, "Classification of wet/dry area based on the mahalanobis distance of feature from time space image analysis," IAPR Conference on Machine Vision Applications (MVA'09), Yokohama, Japan, 2009.
[12] M. Sivak, "The information that drivers use: is it indeed 90% visual?," Perception, vol.26, pp.1081–1089, 1996.
[13] D. Pomerleau, "Visibility estimation from a moving vehicle using the RALPH vision system," IEEE Conf. Intelligent Transportation Systems, pp.906–911, 1997.
[14] N. Hautière, J.P. Tarel, J. Lavenant, and D. Aubert, "Automatic Fog Detection and Estimation of Visibility Distance through use of an Onboard Camera," Machine Vision and Applications Journal, vol.17, no.1, pp.8–20, 2006.
[15] N. Hautière, R. Labayrade, and D. Aubert, "Estimation of the visibility distance by stereovision: a generic approach," IEICE Transactions on Information and Systems, vol.E89-D, no.7, pp.2084–2091, 2006.
[16] C. Boussard, N. Hautière, and B. d'Andréa Novel, "Vehicle dynamics estimation for camera-based visibility range estimation," IEEE/RSJ International Conference on Intelligent RObots and Systems, Nice, France, 2008.
[17] K. He, J. Sun, and X. Tang, "Single image haze removal using dark channel prior," IEEE Conference on Computer Vision and Pattern Recognition, Miami, Florida, USA, 2009.
[18] J.P. Tarel and N. Hautière, "Fast visibility restoration from a single color or gray level image," IEEE International Conference on Computer Vision (ICCV'09), Kyoto, Japan, 2009.
[19] N. Hautière, J.P. Tarel, and D. Aubert, "Free space detection for autonomous navigation in daytime foggy weather," IAPR Conference on Machine Vision Applications (MVA'09), Yokohama, Japan, May 20-22 2009.
[20] S.G. Narasimhan and S.K. Nayar, "Vision and the atmosphere," International Journal of Computer Vision, vol.48, no.3, pp.233–254, 2002.
[21] S.G. Narasimhan and S.K. Nayar, "Shedding light on the weather," Proc. IEEE Conference on Computer Vision and Pattern Recognition, 2003.
[22] S. Metari and F. Deschênes, "A new convolution kernel for atmospheric point spread function applied to computer vision," Proceedings of the IEEE International Conference on Computer Vision, Rio de Janeiro, Brazil, October 2007.
[23] T.M. Kwon, "Atmospheric visibility measurements using video cameras: Relative visibility," tech. rep., University of Minnesota Duluth, July 2004.
[24] International lighting vocabulary, Commission Internationale de l'Éclairage, 1987.
[25] N. Nameda, "Fog modulation transfer function and signal lighting," Lighting Research & Technology, vol.24, no.2, pp.103–106, 1992.
[26] E. Dumont and V. Cavallo, "Extended photometric model of fog effects on road vision," Transport Research Records, no.1862, pp.77–81, 2004.
[27] E. Dumont, "Semi-monte-carlo light tracing for the study of road visibility in fog," Monte Carlo and Quasi-Monte Carlo Methods 1998, Berlin, pp.177–187, Springer-Verlag, 1999.
[28] E.P. Shettle and R.W. Fenn, "Models for the aerosols of the lower atmosphere and the effectsof humidity variations on their optical properties," AFGL-TR 79-0214, Air Force Geophysics Laboratory, Hanscom Air Force Base, MA, 1979.
[29] N. Hautière, D. Aubert, E. Dumont, and J.P. Tarel, "Experimental validation of dedicated methods to in-vehicle estimation of atmospheric visibility," IEEE Transactions on Instrumentation and Measurement, vol.57, no.10, pp.2218–2225, October 2008.
[30] M. Colomb, K. Hirech, P. Andre, J. Boreux, P. Lacote, and J. Dufour, "An innovative artificial fog production device improved in the european project FOG," Atmospheric Research, vol.87, pp.242–251, 2008.
[31] I. Gultepe and J. Milbrandt, "Microphysical observations and mesoscale model simulation of a warm fog case during fram project," Pure and Applied Geophysics, vol.164, pp.1161–1178, 2007.
[32] T. Okuda, K. Tomine, F. Kobayashi, and H. Sugawara, "Visibility and fog drop size spectra at misawa air base," Journal of the Meteorological Society of Japan, vol.86, No. 6, pp.901–917, 2008.
[33] S. Caro, V. Cavallo, C. Marendaz, E. Boer, and V. F.,

"Can headway reduction in fog be explained by impaired perception of relative motion?," Human factors, vol.51 (3), pp.378–392, 2009.

[34] V. Cavallo, M. Colomb, and J. Doré, "Distance perception of vehicle rear lights in fog," Human Factors, vol.43, pp.442–451, 2001.

[35] A. Buchner, M. Brandt, and J. Bell, R. andWeise, "Car backlight position and fog density bias observer-car distance estimates and time-to-collision judgments," Human Factors, vol.48, No.2, pp.300–317, 2006.

[36] Type-approval requirements for the general safety of motor vehicles, Add. 37, Rev. 2, Amend. 2, Rear fog lamps, United Nations Economic Commission for Europe, 2007.

[37] T. Luce, "Intelligent rear lamps - a breakthrough for safety and comfort," Proceedings of the SPIE, 2005.

[38] J.D. Klett, "Stable analytical inversion solution for processing lidar returns," Applied Optics, vol.20, No. 2, pp.211–220, 1981.

[39] L. Pirodda, "Enhancing visibility through fog," Optics and Laser Technology, vol.39, No. 6, pp.293–299, 1997.