# Artificial Perception under Adverse Conditions: the Case of the Visibility Range 

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#### Abstract

Many factors can alter the quality of the signal resulting from an optical sensor mounted onboard an automotive vehicle. To be able to detect and quantify these degraded operation conditions while relying only on the signals resulting from sensors themselves is a challenge for the future driver assistances. In this paper, an approach dealing with daytime fog conditions is presented. First of all, daytime fog is modelled and new visibility distances fitting well with daytime fog driving conditions are defined. Then, two methods for computing the visibility range are proposed. Finally, several applications are derived: enhancement of driver assistances, automation of fog beams and intelligent speed alert. Finally, some perspectives for future research directions are indicated.


Keywords Intelligent transportation systems; Advanced driver assistance; Onboard vision; Camera; Atmospheric visibility measurement; Fog detection; Contrast impairment.

## 1. Introduction

Many factors can alter the quality of the signal resulting from an optical sensor mounted onboard an automotive vehicle (camera, laser, etc.): the fog, the rain, the sun at grazing angle, the reflections on the pavement, the presence of stains on the windshield, the glare due to the headlights of other vehicles, the strong gradients of brightness at the entrance and exit of tunnels, etc. To be able to detect and quantify these degraded operation conditions while relying only on the signals resulting from sensors themselves is a challenge for the future driver assistances relying on optical sensors.

First, it is one of the keys to obtain a very important level of reliability of the sensor unit and associated signal processing. Indeed, whatever its intrinsic qualities, a processing will produce the awaited answers only if the input signal has a sufficient level of quality. Detecting and quantifying the degradations of this signal, even identifying the causes of these degradations, should make it possible to estimate an index of confidence on the operation of the system and thus constitute a kind of self-diagnosis system. In parallel, it can be possible to adapt the operation of the sensor, to improve the quality of the signal and/or to dynamically adjust some parameters in the processing.
Second, it is a means of carrying out new driver assistances, e.g. the automation of the fog lamps. This is also a means of gathering within the same sensor (in particular a camera) a set of functions that are already present in the vehicle (rain sensor, light level sensor) or that are going to come (automatic fog lamps, automatic demisting, automatic cleaning of the stains for example). Such a reduction of the number of sensors would make it possible to decrease the volume and the total cost of the system.

Third, some of the causes of the degradation of the signal quality are also causes of road accidents (e.g. rain, fog, sun at grazing angle, etc.). Thus, by establishing a mapping function between the vision of the driver and the vision of the sensor, in particular in terms of dynamic range, resolution and sensitivity, such algorithms can make it possible to generate relevant alarms for the driver in the event of behaviours unsuited to the traffic conditions.
Until now, this approach has been followed for the computation of the visibility range, which constitutes a relevant and illustrative case study. Starting from existing works on fog modelling, two complementary methods have been developed aiming at estimating the visibility range using respectively one or two in-vehicle cameras. Both methods are based on the definition of the meteorological visibility distance. The first technique, using a model of atmospheric scattering, detects and estimates the density of daytime fog by using a single camera. The second technique, using a generic property of the atmosphere, is able to estimate the visibility range under all meteorological conditions both in daytime and in night time by using a stereoscopic sensor. In a near future, these methods are likely to be used to provide drivers an appropriate speed with respect to the visibility range, to enhance obstacle detection techniques or to automate the fog lamps.
This paper is organized as follows. First, it deals with the general problem of artificial perception under adverse weather conditions. Second, two approaches computing the visibility range are presented and validated thanks to actual images and video sequences grabbed under various situations on the test track of Versailles Satory. Finally, some applications are presented and some ideas for future researches are indicated.

## 2. Visibility Range Computation under Adverse Weather Conditions

The literature on the interaction of light with the atmosphere has been written over more than two centuries (Bouguer, 1729) (Allard, 1876). Different reviews on the topic have been available in the literature (Middleton, 1952) (Minnaert, 1954) for half a century and still serve as reference for recent works in computer vision.

### 2.1 Fog Modelling

In the atmosphere, visible light is mainly attenuated by the scattering phenomenon characterized by an extinction coefficient k . The phenomenon is particularly strong in fog and causes a luminous veil which impairs visibility in daytime (Paulmier, 2004). In 1924, Koschmieder (Middleton, 1952) established a simple relationship between the apparent luminance $L$ of an object at a distance $d$, and its intrinsic luminance $L_{0}$ :
$\mathrm{L}=\mathrm{L}_{0} \mathrm{e}^{-\mathrm{kd}}+\mathrm{L}_{\mathrm{f}}\left(1-\mathrm{e}^{-\mathrm{kd}}\right)$
where $L_{f}$ denotes the luminance of background sky. Based on these results, Duntley (Middleton, 1952) derived a law for the atmospheric attenuation of contrasts:
$C=\frac{\left|L-L_{f}\right|}{L_{f}}=C_{0} e^{-k d}$
where C designates the apparent contrast at distance d and $\mathrm{C}_{0}$ the intrinsic contrast of the object against the sky. The Commission Internationale de l'Eclairage (CIE, 1987) adopted a contrast threshold of $5 \%$ to define $\mathrm{V}_{\text {met }}$, the meteorological visibility distance, defined as the greatest distance at which a black object ( $\mathrm{C}_{0}=1$ ) of suitable dimensions can be recognized by day against the horizon sky:

$$
\begin{equation*}
\mathrm{V}_{\mathrm{met}}=-\frac{1}{\mathrm{k}} \log (0.05) \approx \frac{3}{\mathrm{k}} \tag{3}
\end{equation*}
$$

### 2.2 New Visibility Range Definitions

The mobilized visibility distance $\mathrm{V}_{\text {mob }}$ is now defined as the distance to the most distant visible object on the road surface, which is assumed to be black or at least dark. $\mathrm{V}_{\text {mob }}$ has to be compared with $\mathrm{V}_{\max }$, the mobilizable visibility distance: the maximum distance at which a potential object on the road surface would be visible. $\mathrm{V}_{\text {max }}$ can be expressed as a function of $\mathrm{V}_{\text {met }}$ and the contrast threshold $\mathrm{C}_{\mathrm{BW}}$ between a "white" object and a "black" object. Using (1) and (2), the following relationship has been shown (Hautière, 2007b):

$$
\begin{equation*}
\mathrm{V}_{\max }=-\frac{\mathrm{V}_{\mathrm{met}}}{3} \log \left(\frac{\mathrm{C}_{\mathrm{BW}}}{1+\mathrm{C}_{\mathrm{BW}}}\right) \tag{4}
\end{equation*}
$$

The value $\tilde{\mathrm{C}}_{\mathrm{BW}}$ so that $\mathrm{V}_{\text {max }}=\mathrm{V}_{\text {met }}$ is easily obtained:
$\tilde{\mathrm{C}}_{\text {BW }}=\frac{1}{\mathrm{e}^{3}-1} \approx 5 \%$
Thus, by using this $5 \%$ contrast threshold value, $\mathrm{V}_{\text {max }}$ is very close to $\mathrm{V}_{\text {met }}$. It follows the following relationship between mobilized, mobilizable and meteorological visibility distances in daytime fog:

$$
\begin{equation*}
\mathrm{V}_{\mathrm{mob}} \leq \mathrm{V}_{\mathrm{max}} \approx \mathrm{~V}_{\mathrm{met}} \tag{5}
\end{equation*}
$$

Finally, (5) means that the maximum visibility distance of a white object located on a black road surface is the same one as that of a black object observed against its background sky.

### 2.3 Computation Methods

### 2.3.1 Fog Detection and Estimation of Meteorological Visibility Distance

By adopting the assumption of a flat road, which makes it possible to associate a distance d with each line v of a digital image, the distance d is expressed as follows:

$$
d=\left\{\begin{array}{c}
\frac{\lambda}{v-v_{h}} \text { if } v>v_{h}  \tag{6}\\
\infty \text { if } v \leq v_{h}
\end{array}\right.
$$

where $\mathrm{v}_{\mathrm{h}}$ is the vertical position of the horizon in the image plane and $\lambda$ depends on intrinsic and extrinsic parameters of the camera. If a change of variable based on (6) is carried out, the derivative of (1) with respect to v can be taken twice so as to obtain:
$\frac{d^{2} L}{d v^{2}}=k \lambda \frac{L_{0}-L_{f}}{\left(v-v_{h}\right)^{3}} e^{-\frac{k \lambda}{v-v_{h}}}\left(\frac{k \lambda}{v-v_{h}}-2\right)$
$\frac{d^{2} L}{d v^{2}}$ has two zeros, only one of which is useful: $k=\frac{v_{i}-v_{h}}{\lambda}$, where $v_{i}$ denotes the position of the inflection point. Hence, assuming that the camera response is linear, parameter k of Koschmieder's law is obtained once $\mathrm{v}_{\mathrm{i}}$ is known. Finally, by virtue of (3), $\mathrm{V}_{\text {met }}$ is deduced:

$$
\begin{equation*}
V_{m e t}=\frac{3 \lambda}{2\left(v_{i}-v_{h}\right)} \tag{8}
\end{equation*}
$$

To implement this method, the median intensity is measured on each line of a vertical band in the image. As this band should only take into account a homogeneous area and the sky, a region is identified within the image which displays minimal line-to-line gradient variation
when crossed from bottom to top using a region growing algorithm (Fig.1a). A vertical band is then selected in the segmented area. Thus, the vertical variation of the intensity in the image is obtained and allows to deduce $\mathrm{V}_{\text {met }}$ using (8). An example of meteorological visibility distance computation is given on Fig.1b. This method was patented (Lavenant, 2002). Details can be found in (Hautière, 2006a).


Fig.1: (a) detection of the road and the sky by region growing; (b) the horizontal white line represents the estimation of the visibility distance. The small white triangle on the image top left indicates that the system is operative. Conversely, a small black triangle indicates that the system is temporarily inoperative. The black vertical lines represent the limits of the vertical band analyzed ( $\mathrm{V}_{\mathrm{met}} \approx 60 \mathrm{~m}$ ).

### 2.3.2 Estimation of Mobilized Visibility Distance

The previous method leads to good results in daytime foggy weather. In order to extend the range of covered meteorological situations, a different approach was developed which consists in estimating $\mathrm{V}_{\text {mob }}$. In this aim, two tasks must be achieved and combined:

1. Detection of local contrasts above $5 \%$
2. Computation of the 3D structure of the road scene.

To detect local contrasts above $5 \%$, it was decided to estimate Weber's contrast (Cornsweet, 1970) in order to remain consistent with the formulation of contrast used by the CIE (1987) in their definition of the meteorological visibility distance. The method we developed uses the algorithm of Köhler (1981) which is quite robust to noise and fits to the selected local formulation of contrast (Fig.2b). This algorithm, which was initially designed to binarise an image, is extremely costly when used on an entire image, and has therefore been optimized with regard to processing time.

To compute the 3D structure of the scene, stereovision was used which allows distance information to be recovered by triangulation. An effective stereovision technique was used (Labayrade, 2003). This technique uses a two-pass algorithm. It provides high-quality depth/disparity maps on the road surface and detects objects above the road surface (Fig.2a). Then, as a consequence of the structure of this disparity map, if this is scanned from top to bottom, the objects encountered on the surface of the road are nearer and nearer the equipped vehicle.
The method consists therefore in scanning the disparity map from top to bottom, starting at the horizon line and computing the contrast for each pixel of known disparity. Once the process finds a pixel with a contrast higher than $5 \%$, computation ends. On the basis of the disparity of this pixel, it is possible to obtain the mobilized visibility distance. An example of mobilized visibility distance computation is given on Fig.2c. This method was patented in (Hautière, 2004). Details can be found in (Hautière, 2006b).


Fig.2: (a) disparity map obtained using a two- passe algorithm based on the "v-disparity" approach under dense foggy weather before night-fall; (b) computation of local contrasts above 5\% on the whole image; (c) final result. The most distant window with a contrast above $5 \%$, in which a point of disparity is known, is painted white. The disparity point is represented with a black cross inside the white window ( $\mathrm{V}_{\mathrm{mob}} \approx 30 \mathrm{~m}$ ).

Currently, the method is being extended to the use of a single camera. Knowing precisely the relative motion of the vehicle between two instants, the road plane in successive images is aligned, like in (Stein, 2000). By perspective projection, the objects belonging to the road surface are correctly aligned, whereas the vertical objects are deformed. This allows estimating the mobilized visibility distance. A prototyping of the method shows some promising results (Boussard, 2006).

### 2.4 Experimental Validation based on a Dedicated Site

### 2.4.1 Setting up of a Dedicated Site

So far, both methods were only qualitatively evaluated, through a subjective analysis of the mean and standard deviation of measures in the cases of different rides assuming constant adverse visibility conditions. Quantitative assessment has not been endeavoured yet, due to the lack of a reference visibility sensor. To fill this gap, a test track in Versailles (France) was equipped with five large specific targets, located between 65 m and 200 m from the cameras onboard the stationed vehicle. An additional mobile target is used at a closer range when the fog is very dense. The idea is to take pictures of these targets in adverse weather conditions and to estimate the meteorological visibility distance based on the attenuation of their contrast. This static measurement, which uses reference targets, can then be compared on the same images to the results of our onboard dynamic techniques, which require no reference.

The targets are designed for maximum intrinsic contrast as illustrated in Fig.3b. Also, to take only the effects of the atmosphere into account, the different targets have the same apparent size in the image. A picture of the validation site in sunny weather conditions is given on Fig.3a.

(b)

Fig.3: (a) Actual picture of the validation site dedicated to visibility measurement, taken in sunny weather conditions. (b) Graphic design of the reference targets.

### 2.4.2 Using the targets

Let consider the black part of two targets located at distances $\mathrm{d}_{1}$ and $\mathrm{d}_{2}$ from the camera. Let assume that their intrinsic luminance is negligible $\left(\mathrm{L}_{B}(0)=0\right)$. In daytime fog their apparent luminances are given by Koschmieder's Law (1). Taking the ratio $r=\frac{L_{B}\left(d_{1}\right)}{L_{B}\left(d_{2}\right)}$ of these values allows us to deduce the value of the extinction coefficient k in different ways:
$\mathrm{k}=\left\{\begin{array}{c}-\frac{1}{\mathrm{~d}_{1}} \log (\mathrm{r}-1){\text { if } \mathrm{d}_{2}=2 \mathrm{~d}_{1}}^{-\frac{1}{\mathrm{~d}_{1}} \log \left(\frac{\sqrt{4 \mathrm{r}-3}-1}{2}\right) \text { if } \mathrm{d}_{2}=3 \mathrm{~d}_{1}} \\ -\frac{1}{\mathrm{~d}_{1}} \log \left(\frac{(\mathrm{r}-1)(\sqrt{\mathrm{r}+3}-\sqrt{\mathrm{r}-1})^{2}}{4}\right) \text { if } \mathrm{d}_{2}=\frac{3}{2} \mathrm{~d}_{1}\end{array}\right.$
An alternative technique consists in using the white and the black parts of the targets, with their apparent luminances $\mathrm{L}_{\mathrm{w}}(\mathrm{d})$ and $\mathrm{L}_{\mathrm{B}}(\mathrm{d})$ also given by Koschmieder's Law (1). Again taking the ratio of these values, the value of extinction coefficient k is deduced:
$\mathrm{k}=-\frac{1}{\mathrm{~d}_{2}-\mathrm{d}_{1}} \log \left(\frac{\mathrm{~L}_{\mathrm{W}}\left(\mathrm{d}_{2}\right)-\mathrm{L}_{\mathrm{B}}\left(\mathrm{d}_{2}\right)}{\mathrm{L}_{\mathrm{w}}\left(\mathrm{d}_{1}\right)-\mathrm{L}_{\mathrm{B}}\left(\mathrm{d}_{1}\right)}\right)$
An estimation of the variance of $k$ is associated with each formula (9) or (10). Assuming that the measurements are not correlated, they can be optimally averaged using the variances to obtain a reliable estimation $\hat{V}_{\text {met }}$ of the meteorological visibility with (3).


Fig.4: Images grabbed on the validation site under various weather conditions and with occlusions of the road: (a) haze ( $\hat{\mathrm{V}}_{\mathrm{met}} \approx 2000 \mathrm{~m}$ ); (b) snow fall ( $\hat{\mathrm{V}}_{\mathrm{met}} \approx 1000 \mathrm{~m}$ ); (c) dense fog +obstacles ( $\hat{\mathrm{V}}_{\mathrm{met}} \approx 120 \mathrm{~m}$ ).

### 2.4.3 Construction of a Reference Data Set

Some images of the validation site have been grabbed under various weather conditions: sun, light rain, haze, snow fall, fog, etc. $\hat{\mathrm{V}}_{\text {met }}$ is estimated from each image. However, taking into account the fact that the resolution of the used cameras is poor beyond 250 m , the methods are compared only if $\hat{\mathrm{V}}_{\text {met }}$ is smaller than this distance. Consequently, only foggy conditions are considered. The database holds approximately 60 pictures of the validation site under foggy conditions. On some pictures, a car (light on/off) and a pedestrian are set on the road at various distances of the equipped vehicle in order to test the robustness of the methods. Some samples of the processed images are given in Fig.4. $\hat{\mathrm{V}}_{\text {met }}$ is computed as well as its variance for each image. The visible targets are selected interactively.

### 2.4.4 Results

On Fig.5a, $\mathrm{V}_{\text {met }}$ is plotted versus $\hat{V}_{\text {met }}$. The correlation line between both measurements is good (about 95\%). On Fig.5b, $\mathrm{V}_{\text {mob }}$ is plotted versus $\hat{\mathrm{V}}_{\text {met }}$. The correlation line between both measurements is as good as for Fig.5a (about 96\%). The accuracy of in-vehicle methods is approximately $10 \%$. The results are satisfactory, taking into account the fact that it is not possible to control the weather conditions and the fog homogeneity.


Fig.5: Points: (a) meteorological visibility distance $\mathrm{V}_{\text {met }}$, (b) mobilized visibility distance $\mathrm{V}_{\text {mob }}$, versus the reference visibility distance $\hat{\mathrm{V}}_{\text {met }}$ obtained thanks to the reference targets. Line: correlation line of the points, whose equation is shown on the graph.

## 3. Applications under Way

### 3.1 Enhancement of the Reliability of Existing Driver Assistances

According to (2), the contrast of images is drastically degraded and varies across the scene under daytime foggy weather. Consequently, advanced driver assistances relying on artificial vision and pattern analysis are no longer able to run properly (Sun, 2006). To mitigate this problem, we proposed to restore the contrast by inverting Koschmieder’s Law to recover the value of the intrinsic luminance $L_{0}$ at each point of the scene, such as:

$$
\begin{equation*}
\mathrm{L}_{0}=\mathrm{Le}^{\mathrm{kd}}+\mathrm{L}_{\mathrm{f}}\left(1-\mathrm{e}^{\mathrm{kd}}\right) \tag{11}
\end{equation*}
$$

Then, according to the strategy used to approximate the depth distribution d of the road scene, different applications can be constructed.

### 3.1.1 Improved Road Departure Prevention

Road departure prevention is usually based on a lane marking detector relying on a single camera mounted behind the windshield of the vehicle. In these conditions, most systems assume a flat road. This assumption can also be used to restore the contrast of the road surface. Thus, using (8) and (11), one obtains:

$$
\left\{\begin{array}{c}
L_{0}=L e^{2 \frac{v_{i}-v_{\mathrm{h}}}{v-v_{\mathrm{h}}}}+L_{f}\left(1-e^{2 \frac{v_{i}-v_{\mathrm{h}}}{v-v_{\mathrm{h}}}}\right)  \tag{12}\\
L_{f}=L_{i}+\frac{v_{i}-v_{h}}{2} \frac{d L}{d v}{ }_{\mid v=v_{i}}
\end{array}\right.
$$

where $L_{i}$ and $\frac{d L}{d v}{ }_{\mid v=v_{i}}$ are respectively the values of the function $L$ and its derivative in $v=v_{i}$. Details of the method are given in (Hautière, 2005). To illustrate the proposal, the lane markings have been extracted in a foggy image with and without contrast restoration using the method described in (Tarel, 2002) by using the same parameters (Fig.6). One can see that the operation range of the lane marking detector is enhanced thanks to the contrast restoration process.


Fig.6: (a) Original foggy image used for lane markings detection using the method described in (Tarel, 2002); (b) image with restored contrast used for lane markings detection using the same parameters as the first image, i.e. a gradient threshold of 10 (blue: pixels likely to be lane markings, green: fitted lane marking, red: level of confidence on the fitting).

### 3.1.2 Obstacles Detection under Adverse Conditions

To detect obstacles under adverse conditions, the 3-D structure of the scene must be taken into account. Two complementary methods are proposed. A first one consists in improving the reliability of stereovision methods relying on sparse matching techniques. It combines the advantages of the "v-disparity" approach (Aubert, 2005) and a quasi-dense matching algorithm. In this aim, the road surface and vertical planes of the scene are first extracted using the sparse "v-disparity" approach. The knowledge of these global surfaces of the scene is then used to guide the quasi-dense matching algorithm (Lhuillier, 2002) and to propagate disparity information on horizontal edges. This algorithm allows the accurate positioning of bounding boxes around road objects in bad contrasted images (Hautière, 2006).
This method can then be used in conjunction with a contrast restoration algorithm to detect obstacles under foggy weather. In this context, the depth distribution in the scene can be roughly modelled in two parts. A first part models the road surface which can be approximated by a plane like in the previous paragraph. A second part models the objects above the road surface. According to classical perspective geometrical representations, the depth of a scene point can be expressed as a function of the euclidian distance in the image plane between the corresponding pixel and the vanishing point ( $\mathrm{u}_{\mathrm{h}}, \mathrm{v}_{\mathrm{h}}$ ) (Narasimhan, 2003). Consequently, the depth $d$ of a pixel with ( $u, v$ ) coordinates can be inferred as:
$d=\min \left(\frac{\lambda}{v-v_{h}}, \frac{\kappa}{\sqrt{\left(u-u_{h}\right)^{2}+\left(v-v_{h}\right)^{2}}}\right)$
where $\kappa>1$ models the relative importance of the flat world against the vertical world. Thus, by adjusting the value of $\kappa$, it is possible to simultaneously restore and detect vertical objects in a poor contrasted scene (Hautière, 2007a). Sample results are given in Fig.7.


Fig.7: (a) original foggy image; (b) image with half restored contrast and a bounding around the detected obstacle; (c) image with contrast full restored.

### 3.2 Development of New Driver Assistances

### 3.2.1 Automation of Fog Lamps

Car manufacturer suppliers are currently developing a new generation of Adaptive Frontlighting Systems (AFS). Soon, the automatic switching as well as the power of light beams will be controlled by a camera (Rebut, 2005). A major application of the methods described in section 2 consists thus at automating the switching and adjusting the power of fog beams according to the fog presence and density.

### 3.2.2 Intelligent Speed Adaptation and Inter-Vehicle Distance Management

Intelligent Speed Adaptation (ISA) is a generic name for advanced systems in which the vehicle knows the speed limit and is capable of using that information to give feedback to the driver or limit maximum speed. Even if the proposed figures may be controversial, according to Carsten (2005), a simple mandatory system, with which it would be impossible for vehicles to exceed the speed limit, would save $20 \%$ of injury accidents and $37 \%$ of fatal accidents in the United Kingdom. A more complex version of the mandatory system, including a capability to respond to current network and weather conditions, would result in a reduction of $36 \%$ in injury accidents and $59 \%$ in fatal accidents.
However, even if there are still some open questions on how mandatory speed limits can be stored in a digital map and directly used by the vehicle, the speed which is adapted with respect to weather conditions is not easy to compute. In this context, the proposed methods could help the vehicle to take the weather conditions into account to compute the adequate speed (Blosseville, 2007).
Then, under foggy weather, people tend to overestimate inter-vehicle distances (Cavallo, 2001). Thus, by establishing a mapping function between the vision of the driver and the vision of the sensor, in particular in terms of dynamic range, resolution and sensitivity, the proposed algorithms can make it possible to generate relevant alarms for the driver in the event of too short headways under foggy weather.
A first step for establishing this mapping function is presented in (Hautière, 2006c). In this paper a parameterless method is proposed, computing the edges in images which are seen by a human eye (Fig.8c) by taking into account the non-linear response of the human visual system to spatial frequencies. Its basic principle is to compare locally the distribution of spatial frequencies of the image with the minimum required by a human eye to be visible (Fig.8b).


Fig.8: (a) original image; (b) visibility map of the different image blocks; (c) "visible" edges.

## 4. Discussion and Future Work

In the previous sections, an approach to deal with adverse visibility conditions in daytime fog was presented: modelling, methods, experimental validation and applications. Admittedly there is still some work ahead to finalize and validate the applications, in a near future we would like to tackle other adverse meteorological or lighting conditions: night-time fog (Fig.10c), rain (Fig.10a), sun at grazing angle (Fig.10b), snow fall, entrance or exit of tunnels, even though existing works on these subjects are quite rare. Consequently, to be able to develop new methods and applications, a lot of work is needed to model, simulate or reproduce these adverse conditions.


Fig.10: (a) rainy weather; (b) sun at grazing angle; (c) night-time fog situation.
However, as mentioned in the introduction, it is one of the keys to obtain a very important level of reliability of the sensor unit inside the vehicles and associated signal processing. Then, new systems for the vehicle using a camera could be developed. It would lead to increase the number of supported functions by the camera (rain sensor, fog sensor, etc.) and thus to reduce the cost of its installation in future vehicles. In this way, the deployment of such onerous systems could be facilitated.

## 5. Conclusion

In this paper, an approach is presented to deal with daytime fog conditions in the future driver assistances using optical sensors. First of all, a daytime fog modelling is recalled and new visibility distances are proposed fitting well with these driving conditions. Then, two methods are described to compute the visibility range. Finally, several applications are derived: enhancement of existing driver assistances, automation of fog beams, intelligent speed alert. In the future, we would like to apply this approach to other adverse conditions like night-time fog, rain, low angled sun, etc. These perspectives fit well with the 7th

Framework Programme of the European Commission, one of the priorities being the robustness of driver assistances regarding the adverse conditions.

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