Image based fog detection and visibility estimation for driving assistance systems

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Image Based Fog Detection and Visibility Estimation for Driving Assistance Systems

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***Abstract* — An advanced driving assistance system (ADAS) must also take into account the weather conditions. One of the most dangerous weather conditions for driving scenarios is the presence of fog. So an important task for a driving assistance system is to detect the presence of fog, estimate the fog's density and determine the visibility distance of the driver. Our method is based on a single in-vehicle camera and is actually an improvement over existing fog detection solutions, in terms of speed and accuracy. We are able to detect day time fog in a wide range of scenarios, including urban scenarios. After detecting the presence of fog in the image and based on the fog's density we are able to compute the visibility distance and inform the driver about the environment's weather conditions.**

Keywords— fog detection, image processing, advanced driving assistance systems.

I. INTRODUCTION

Recently there is a growing interest in developing and deploying advanced driving assistance systems. In order to reduce the number of accidents, vehicles are equipped with advanced active safety systems. An important aspect for avoiding accidents and reducing the risk of accident is the ability of advanced driving assistance systems to anticipate risks while the care is moving and to inform the driver of the hazardous situations. According to the National Highway Traffic Safety Administration (NHTSA), the top six most common causes of automobile crashes are: distracted drivers, driver fatigue, drunk driving, speeding, aggressive driving and the last one weather. For distracted drivers 80% of the accidents happen due to 3 seconds of inattention. In spite of improvements in road infrastructure, the numbers of accidents caused primarily by adverse weather conditions are higher every year. Fog is the most dangerous weather phenomenon for driving, since in this case the visibility distance decreases exponentially. Whereas highways account for only 2.8% of all road accidents occurring under good weather conditions, this figure doubles in fog. When the weather is "plagued" with fog, drivers tend to overestimate the visibility distances and drive with excessive speed [5]. In this paper we present a system capable of detecting fog from a single image and inform the driver about the fog density and the visibility distance in the given traffic environment.

Most advanced driving assistance systems proposed in the literature are dependent on expensive hardware, which is usually difficult to deploy on older vehicles. The fog detection algorithm we propose is implemented on a regular computer and can be deployed on a modern smartphone or tablet, making it inexpensive and easy to use by any drivers.

This paper is structured as follows: section 2 presents an overview of the state of the art in this field, section 3 describes the effects of fog on images, next our method is described and the last two sections present our experimental results and conclusions.

II. RELATED WORK

In the United States, The California Department of Transportation (Caltrans) [11] has developed a fog detection and warning system based on an array of sensors able to detect fog. The system is able to inform the drivers on Highway 99 about the visibility conditions, fog density and maximum speed that they should travel. The fog detection sensors are deployed every half mile on both directions of the freeway and the necessary information for the drivers is displayed on Changeable Message Signs. Although it is a very expensive system the fact that the drivers are informed of the weather conditions and speed limits reduced drastically the number of accidents on this highway.

Fog detection based on image processing has been studied in the past year with the aim of removing the fog effects from images. Because an image is degraded due to atmospheric conditions Narasimhan and Nayar [1] propose a method for restoring the contrast of the original image. They build an atmospheric point spread function and are able to characterize the weather conditions based on this function. Pomerleau [2] estimates visibility by means of contrast attenuation at road markings in front of the vehicle.

Most approaches presented in literature rely on the Koschmieder's law. In [8] the authors combine an in-vehicle camera and radar in order to classify the fog density according to a visibility feature of a preceding vehicle. Fog detection systems based on stereo-vision are presented in [4], [6] and [7]. By using the "v-disparity" method, the authors are able to build a depth map of the vehicle environment and to perform obstacle detection. Based on this map and using Koschmieder's model they are able to estimate the visibility distance. Bronte [12] developed a method for fog detection based on the computation of the vanishing point. The road lines are taken as reference lines in order to compute the vanishing point. After the vanishing point is found a segmentation of the road and sky is performed. This method is able to classify fog based on its density. An approach based on Gabor Filters, at different frequencies, scales and orientations, and classification for detecting the fog conditions is presented in [17].

Image restoration approaches were intensively studied in the literature. Hautiere et al. [3], [9] developed a method for contrast restoration by using an onboard camera and the flat world hypothesis. These methods are real time and require only the presence of road and sky. By performing contrast restoration under the flat world assumption the free space in front of the moving vehicle can be estimated [13].

Some methods for restoring the contrast of fog degraded images are presented in [10], [14], [15] and [16]. Tan [10] proposes a single image haze removal technique by maximizing the local contrast of the restored image. He's algorithm cannot perform in real time (5 to 7 minutes on a single image) but it is able to restore both color and gray scale images. In [14] He et al. use the dark channel prior on a color image in order to detect haze and restore the contrast of the original image. The dark channel prior states "that in most of the non-sky patches, at least one color channel has very low intensity at some pixels". A haze image model is computed based on the dark channel of the image and the haze is removed form images by using this model. In [15] Tarel et al. introduce new methods for contrast restoration based on their algorithm for fog detection: planar assumption (PA), free space segmentation (FSS), no-black pixel constrains (NBPC) and NBPC combined with PA. A comparison of these methods is thoroughly presented in [16] and [18] on both real world images and synthetically generated images.

III. The Effects of fog on vision

A. *Koschmieder's Law*

In 1924, Koschmieder [20] studied the attenuation of luminance through the atmosphere and proposed a relationship between the attenuation of an object's luminance L at distance d and the luminance L_0 close to the object:

$$L = L_0 e^{-kd} + L_\infty (1 - e^{-kd}) \tag{1}$$

L_∞ is the atmospheric luminance and k is the extinction coefficient. This equation states that the luminance of an object seen through fog is attenuated with an exponential factor e^{-kd}; the atmospheric veil obtained from daylight scattered by fog between the object and the observer is expressed by $L_\infty(1 - e^{-kd})$. By re-writing this equation and dividing by L_∞ we obtain the following:

$$C = \left(\frac{L_0 - L_\infty}{L_\infty}\right) e^{-kd} = C_0 e^{-kd} \tag{2}$$

This equation is called Duntley's attenuation law [3] and it states that an object having the contrast C_0 with the background is perceived at distance d with contrast C. Duntley's law is applicable only in daylight uniform illumination conditions. By using this law one can derive the meteorological visibility distance ("the greatest distance at which a black object, having contrast (C_0=1), of a suitable dimension can be seen in the sky on the horizon"). In order for an object to be barely visible the International Commission on Illumination has adopted a threshold for the contrast, i.e. 5%. By solving equation (2) we are able to derive a formula for the visibility distance:

$$d_{vis} = -\frac{1}{k}\log(0.05) \simeq \frac{3}{k} \tag{3}$$

For image processing applications, in order to model the mapping from scene luminance to image intensity the response function of a digital camera is applied to the Koschmieder's equation. Thus, the intensity perceived in the image is the result of a function (f) applied to the sum of the air light (A) and the direct transmission (T):

$$\begin{aligned} I &= f(L) = f(T + A) = f\left(L_0 e^{-kd}\right) + f\left(L_\infty\left(1 - e^{-kd}\right)\right) \\ I &= f(L_0) e^{-kd} + f(L_\infty)\left(1 - e^{-kd}\right) \\ I &= Re^{-kd} + A_\infty\left(1 - e^{-kd}\right) \end{aligned} \tag{4}$$

A_∞ is the sky intensity and R is the intrinsic pixel intensity.

B. *Flat World Assumption*

In single camera systems the flat world hypothesis is used in order to approximate the distance to each line in the image. This hypothesis is relevant only in the case of road scenes, where a large part of the image is formed by the road surface, which can be assumed to be planar.

Figure 1 presents a typical camera system on board a vehicle. In the image plane, the (u, v) coordinates identify the position of a pixel, the optical center C is given by (u_0, v_0) and f represents the focal length of the camera. Let $\alpha = \frac{f}{t_p}$ denote the value of the focal length expressed in pixels (t_p=t_{pu}=t_{pv} is the pixel size). H represents the height of the camera relative to the S(X, Y, Z) coordinate system and θ represents the pitch angle (the angle between the optical axis of the camera and the horizontal). From the perspective camera model we know that:

$$\begin{cases} u = u_0 + \alpha \dfrac{x}{z} \\ v = v_0 + \alpha \dfrac{y}{z} \end{cases} \tag{5}$$

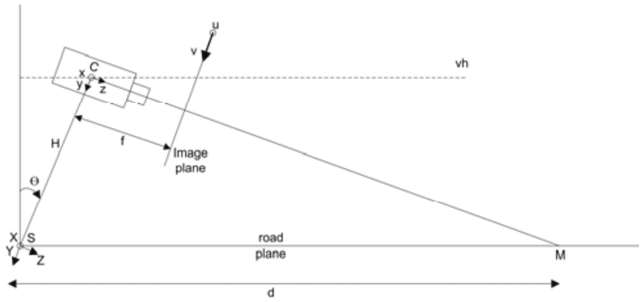

Figure 1 The camera model in the vehicle environment

The horizontal line that passes through the optical center makes an angle θ with the z axis, so it can be expressed as:

$$v_h = v_0 - \alpha \tan\theta \qquad (6)$$

From equation (6) and the expression of v from equation (5) we can deduce that:

$$\frac{v - v_h}{\alpha} = \frac{y}{z} + \tan\theta \qquad (7)$$

By considering the S(X, Y, Z) coordinate system relative to the scene we obtain the following:

$$\frac{v - v_h}{\alpha} = \frac{Y + H}{Z} + \tan\theta \qquad (8)$$

Taking into account that a road point M at distance d from the origin is expressed by:

$$M\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = M\begin{pmatrix} X \\ -d\sin\theta \\ d\cos\theta \end{pmatrix} \qquad (9)$$

We obtain:

$$\frac{v - v_h}{\alpha} = \frac{H}{d\cos\theta} \qquad (10)$$

Finally, the distance d (from the camera) of an image line v can be expressed as:

$$d = \begin{cases} \dfrac{\lambda}{v - v_h} & if\ v > v_h \\ \infty & if\ v \le v_h \end{cases} \qquad (11)$$

Where $\lambda = \frac{\alpha H}{\cos\theta}$ and v_h represents the position of the horizon line in the image. The value of d obtained in equation (11) will be further used, in the rest of the paper, in order to compute the visibility distance in fog conditions.

IV. Fog Detection Algorithm

A. Visibility distance estimation

In order to estimate the extinction coefficient k we must first determine if there exists an inflection point in the image that will provide the basis of our solution. By expressing d as in equation (11) and by performing a change of variable, equation (4) becomes:

$$I = Re^{\frac{-k\lambda}{v - v_h}} + A_\infty(1 - e^{\frac{-k\lambda}{v - v_h}}) \qquad (12)$$

By taking the derivative of equation (12) with respect to v, we obtain the following

$$\frac{dI}{dv} = \frac{k\lambda}{(v - v_h)^2}(R - A_\infty)e^{\frac{-k\lambda}{v - v_h}} \qquad (13)$$

From a qualitative point of view, as fog density increases, objects tend to get obscured more quickly by the luminance emanating from the sky. Moreover, the maximum derivative decreases significantly and deviates more substantially from the horizon line. By computing again the derivative of I with respect to v, we get the following equation:

$$\frac{d^2 I}{dv} = \frac{k\lambda(R - A_\infty)}{(v - v_h)^3}e^{\frac{-k\lambda}{v - v_h}}\left[\frac{k\lambda}{v - v_h} - 2\right] \qquad (14)$$

Equation $\frac{d^2 I}{dv} = 0$ has two possible solutions. The first one k=0 is not acceptable. The second one is:

$$k = \frac{2(v_i - v_h)}{\lambda} = \frac{2}{d_i} \qquad (15)$$

In (15) v_i represents the position of the inflection point in the image and d_i represents its distance to the camera. Once the positions in the image of the inflection point v_i and of the horizontal line v_h are found, the computation of the extinction coefficient k of the Koschmieder's law is straightforward. If v_i is greater than v_h fog will be detected in the image, otherwise we conclude that there is no fog in the scene. Considering equations (3) and (15) we are able to estimate the visibility distance in the image:

$$d_{vis} = \frac{3\lambda}{2(v_i - v_h)} \qquad (16)$$

For estimating the rest of the Koschmieder's law parameters we use I_i and $\frac{dI}{dv}|_{v=v_i}$ which represent the values of the function I and its derivative in $v = v_i$ [16]:

$$R_{road} = I_i - (1 - e^{kd_i})\frac{(v - v_h)}{2e^{-kd_i}}\frac{dI}{dv}|_{v=v_i} \qquad (17)$$

$$A_\infty = I_i + \frac{v_i - v_h}{2}\frac{dI}{dv}|_{v=v_i} \qquad (18)$$

A_∞ is the sky's intensity and R_{road} represents the intensity of the road surface. Only the intensity of the road surface can be correctly estimated by using this method, due to the flat world assumption.

B. Fog Detection Approach

The steps of our fog detection algorithm are presented in Figure 2. We start by applying a Canny-Deriche edge detector on the input image. Then the algorithm performs two main steps: the estimation of the horizon line and the estimation of the inflection point after a region growing procedure. Finally we compute the extinction coefficient and estimate the visibility distance for the given scenario.

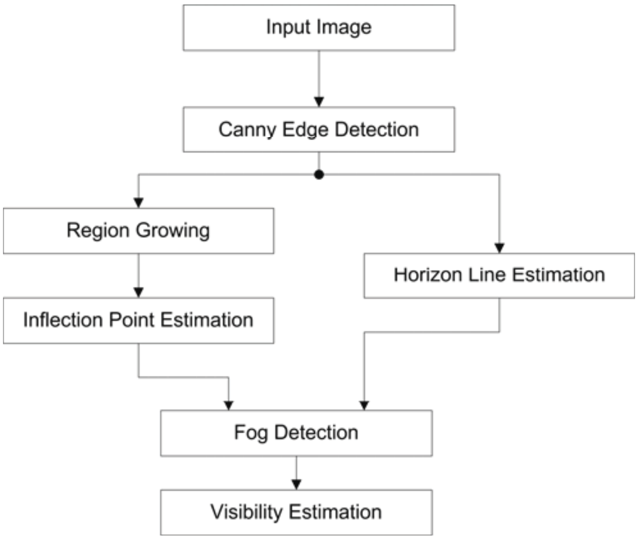

Figure 2 Fog Detection Architecture

a) Horizon Line Estimation

There exist several methods for computing the horizon line. The first one is based on a simple calibration procedure to compute the pitch angle of the camera [16]. An alternative, our choice, is to estimate the horizon line based on the image features. This will eliminate the need to compute the pitch angle offline, but it does require the vehicle to be driven, at least for a small distance.

The horizon line in the image will be detected by finding the vanishing point of the painted quasi-linear and parallel (in 3D) road features such as lane markings. In [12] only the two longest lines are considered for finding the vanishing point. We prefer a more statistical approach that uses more lines and was previously used to find the vanishing point of the 3D parallel lines from pedestrian crossings [21], with the goal of detecting the crossing. First a set of relevant lines is selected in the lower part of the image (mostly road). The Hough accumulator was built from the edge points present in the interest area. The highest m peaks were selected from the accumulator, and those that were having at least n votes were validated as the relevant lines. Then, A RANdom SAmple Consensus (RANSAC – [22]) approach is applied to find the largest subset of relevant lines that pass through the same image point. A number of K (=48 for a success probability p=0.99 and percentage of good lines w=0.3) random samples of two relevant lines are selected. For each sample the intersection P of the two lines is computed and consensus set is determined as the subset of relevant lines that pass through P (within a small circle around P). The sample with the largest consensus set is selected. The intersection points of each distinct pair of lines from the largest consensus set are computed. Finally, the vanishing point is computed as the center of mass of the intersection points. Figure 3 presents the results of the horizon line detection algorithm.

a. Original Image b. Edge Image

c. Hough Image with the intersection points of the consensus lines

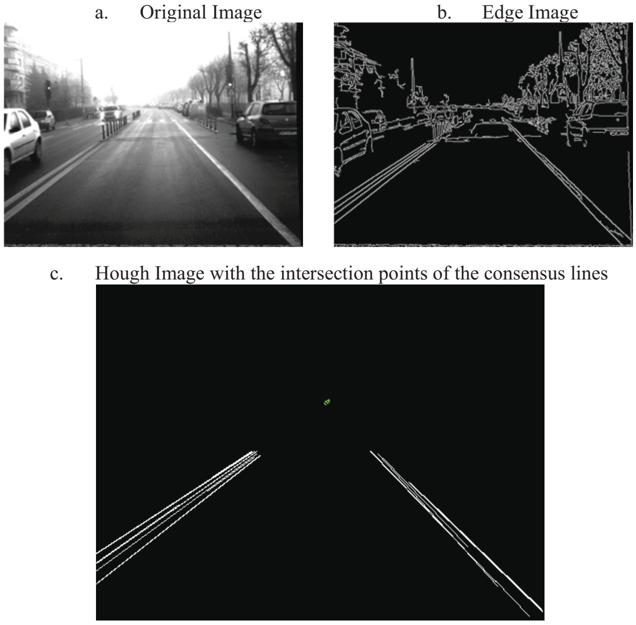

Figure 3 Horizon Line estimation algorithm based on Random Sample Consensus

Using this RANSAC approach for computing the vanishing point provides an additional benefit. The consensus score of the best pair of lines can be used to measure how good the current frame's vanishing point is in comparison to previous frames. A temporal scheme is employed to deal with scenes that lack painted lane markings: the vanishing point with the highest consensus score is selected from the last N frames. N can be chosen large enough to ensure the car has travelled along multiple road segments (hundreds or thousands of frames).

b) Region Growing

The region growing algorithm follows the one described by Hautiere in [5]. Our aim is to find a region in the image that presents minimal row to row gradient variation. We start from a row in the bottom of the image whose pixels belong to the road surface. A pixel from this row is considered to be a seeded pixel only if its intensity is close to the median of the pixels on this row. Starting from a seed point only the three pixels above the current pixel are added to the region if they satisfy the following constraints:

- The pixel does not belong to the region
- The pixel is not an edge point
- The pixel presents a certain similarity with the seed
- The pixel is similar to the one located just below

c) Inflection Point Estimation

In order to compute the inflection point v_i we must first find the maximum band that crosses the region computed in the previous step from top to bottom. If we cannot find such a band, then we conclude that there is no fog in the image. Then we compute the median value for each line of this band and we smooth these values such that the obtained function is strictly decreasing. Next we extract the local maxima of the derivative of this function and compute the values for k, R and A_∞ for these maxima. The point that minimizes the square error between the model and the measured curve is considered to be the global inflection point v_i of the image. A temporal scheme similar to the one for horizon line detection is employed for the estimation of the inflection point.

d) Fog Detection and Visibility Distance Estimation

Once the horizon line v_h and inflection point v_i are computed, we can detect the presence of fog in the image and we can estimate the visibility distance from equation (16). Based on the visibility distance estimation we are able to classify fog into five categories presented in TABLE I.

TABLE I. Fog Categories

Visibility Distance		Fog Category
Min	**Max**	
1000 m	∞ m	No Fog
300 m	1000 m	Low Fog
100 m	300 m	Moderate Fog
50 m	100 m	Dense Fog
0 m	50 m	Very Dense Fog

V. Experimental Results

In order to test our method we have generated synthetic images using the GLSCENEINT framework [19]. Then we added fog into these images using the Koschmieder's equation, by considering A_∞=255 and varying k from 0.01 to 0.15. Figure 4 presents three scenarios for synthetic images. The first scenario is a plain image consisting only in the road surface; the second one includes the road and road-side trees; while the third one also includes some vehicles on the road. The synthetic images have a resolution of 688 x 515 pixels and the average processing time on i7 based PC is of 21 ms.

Figure 5 presents the fog detection results on real-time images. These images were acquired by a moving vehicle equipped with JAI-A10-CL cameras, during fog conditions in the city of Cluj-Napoca. We present several results in different fog scenarios ranging from low fog scenarios (visibility distance of 319 m) to very dense fog scenarios (visibility distance below 30 m). The resolution of the real time images is of 512 x 383 pixels and the average processing time of our fog detection algorithm is of 12 ms.

VI. Conclusions

This work presents a new framework for fog detection in images grabbed from a moving vehicle. The goal is to provide the driver with the necessary information about the fog's density and the maximum visibility distance on the given road segment. First we estimate the horizon line and the inflection point in the image. Based on these two parameters we are able to infer whether the images are "plagued" with fog, to compute the extinction coefficient (k) and to estimate the visibility distance.

The results are very good on roads that are not very crowded or when the field of view of the ego vehicle's camera is not occluded by other vehicles. In addition, the continuous estimation of the horizon line by using the RANSAC method proves to be very stable and provides accurate results when comparing to the estimation of the horizon line by using only the camera parameters (obtained during the offline calibration). Similarly the inflection point estimation is more stable because of the temporal filtering method used by our algorithm.

Since our method performs in real time, we will focus in the future on the deployment of our algorithm on intelligent mobile devices that run on the Android operating system, thus obtaining a cheap solution for advanced driving assistance.

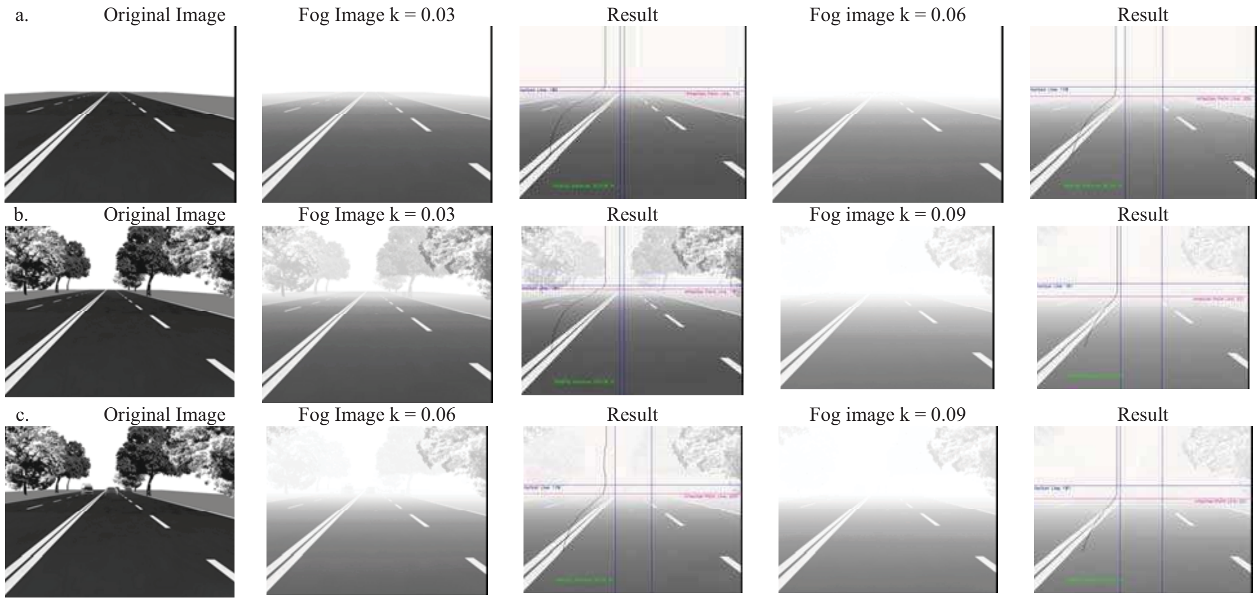

Figure 4. Results obtained on synthetic images. The blue line represents the horizon line, the pink line represents the inflection point line and the two vertical blue lines delimit the vertical band. The black curve represents the smoothed median values from the vertical band .The visibility distance is

Figure 5. Results obtained on real time images. The visibility distance is written on the resulting images.

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