Assisting Navigation in Homogenous Fog

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Abstract: An important cause of road accidents is the reduced visibility due to the presence of fog or haze. For this reason, there is a fundamental need for Advanced Driving Assistance Systems (ADAS) based on efficient real time algorithms able to detect the presence of fog, estimate the fog's density, determine the visibility distance and inform the driver about the maximum speed that the vehicle should be traveling. Our solution is an improvement over existing methods of detecting fog due to the temporal integration of the horizon line and inflection point in the image. Our method performs in real time; approximately 50 frames per second. It is based on a single in-vehicle camera and is able to detect day time fog in real time in a wide range of scenarios, including urban scenarios.

1 INTRODUCTION

During the last decade a special attention was given to advanced driving assistance systems. Nowadays vehicles are equipped with active safety systems, in order to reduce the number of traffic accidents. Thus an important aspect, for avoiding accidents and reducing the risk of accident, while driving, is the ability of an advanced driving assistance system to anticipate such risks and to notify the driver of the hazardous situations. The National Highway Traffic Safety Administration (NHTSA) states that the top six most common causes of automobile crashes are: distracted drivers, speeding, aggressive driving, drunk driving, driver fatigue and weather phenomena. In the case of driver inattention 80% of accidents happen due to 3 seconds of distraction. Even though there is a significant improvement in road infrastructure the number of accidents caused by extreme weather conditions is higher every year. Among these conditions fog is considered to be the most dangerous one because the visibility distance decreases exponentially as fog density increases. When the weather is affected by fog, drivers tend to overestimate the visibility distances and drive with excessive speed (Hautiere et al., 2006). For this reason we developed a system for assisting the driver in foggy situations. Our system is capable of detecting the presence of fog in images, measuring the visibility distance in such situations and informing the driver about the maximum speed that they should travel on the given road segment. An important improvement of our method consists in the fact that the horizon line and the inflection point are detected frame-by-frame and then time filtered, resulting in a very stable and reliable solution for fog detection. Our solution performs in real time (approximately 50 frames per second). It can be ported easily on a modern smartphone or tablet, making it an inexpensive and very accessible ADAS solution. In addition the detection results could be transmitted to a regional traffic information system that gathers and distributes weather information in real time.

2 RELATED WORK

Fog detection systems were studied in the past years with the aim of detecting the presence of fog and removing the fog effects from images. Pomerleau (Pomerleau, 1997) estimates visibility in fog conditions by means of contrast attenuation at road markings in front of the vehicle. This approach requires the presence and detection of road markings. Another approach consists in the combination of an in-vehicle camera and radar (Mori et al., 2006). Based on Koschmieder's law they classify the fog density according to a visibility feature of a preceding vehicle.

In (Bronte et al., 2009) a method for fog detection based on the computation of the vanishing

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point is presented. 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. Object detection on foggy images is presented in (Dong et al., 2011). The method uses a fixed camera and performs object detection based on the subtraction of the observed dense map and a background depth map. The drawback of this method is that it cannot be used in real traffic scenes, where the background scenario is continuously changing.

In (Pavlic et al., 2012) an approach based on image descriptors and classification is used in order to detect fog conditions. The image descriptors used are Gabor Filters at different frequencies, scales and orientations. The visibility distance estimation in fog conditions is presented in (Hautiere et al., 2006). Their algorithm is based on Koschmieder's law and is able to detect the visibility distance in day time traffic scenarios. In order to assess if fog is present in images they use a region growing procedure for detecting the inflection point in the image. Knowing the position of the inflection point and the horizon line position (that is computed offline) they are able to compute the visibility distance in the image.

Because accidents that happen during fog conditions result in a high number of casualties, there is a growing concern in providing assistance to the drivers. One such approach was implemented by the California Department of Transportation (Berman et al., 2009). They have developed a fog detection and warning system based on an array of sensors able to detect fog. These sensors are deployed every half mile on both direction of a freeway. In addition this system is able to provide drivers with information about the fog density and the maximum speed that they should travel. The information is displayed on Changeable Message Signs. Although it is a very expensive system the fact that the drivers are informed about the weather conditions and speed limits reduced drastically the number of accidents on this highway. Our intention is to develop a more cost effective approach to the problem of fog detection and to inform the driver about the maximum speed on the given road segment.

3 MODELING THE EFFECTS OF FOG ON VISION

3.1 Koschmieder's Law

In 1924, Koschmieder (Middleton, 1952) 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 Duntley's attenuation law (Hautiere et al., 2006) that states that an object having the contrast C_0 with the background is perceived at distance d with contrast C:

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

This law can be applied only in day light uniform illumination conditions. From this expression the meteorological visibility distance is derived (d_{vis}): "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%. It results that:

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

When dealing with images, the response function of a camera can be applied to the Koschmieder's equation in order to model the mapping from scene luminance to image intensity. Thus, the intensity perceived in the image is the result of a function (f) applied to equation (1):

$$I = f\left(L\right) = Re^{-kd} + A_\infty \left(1 - e^{-kd}\right) \tag{4}$$

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

3.2 Modelling the Camera in the Vehicle Environment

Figure 1 presents a typical camera system mounted inside a vehicle. The position of a pixel in the image plane is given by its (u, v) coordinates, the position of the optical center C is given by (u0, v0) and f represents the focal length of the camera. Nowadays cameras usually have square pixels, so the horizontal pixel size tpu is equal to the vertical pixel size tpv, ($t_{pu} = t_{pv} = t_p$) thus we can introduce a new constant denoted by $\alpha = f/t_p$ in order to express the value of the focal length in pixels. The camera is mounted at height H relative to the S(X, Y, Z) coordinate system and θ represents the pitch angle.

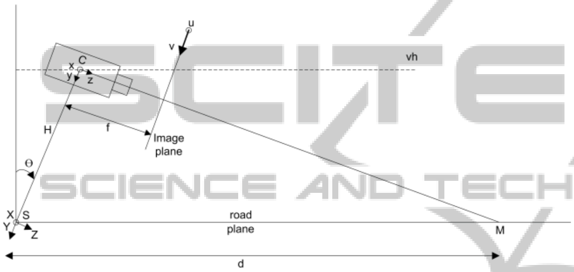

Figure 1: The camera model in the vehicle environment.

From Figure 1 one can observe that the horizontal line passing through the optical center makes an angle θ with the z axis. Therefore it can be expressed as:

$$v_h = v_0 - \alpha \tan\theta \tag{5}$$

In the case of a single camera, the flat world hypothesis can be used to estimate the distance to each line in the image (Negru and Nedevschi, 2013). This hypothesis is used in the case of road scene images, since a large part of an image is formed by the road surface, which can be assumed to be planar. So, the distance d of an image line v, can be expressed by the following equation:

$$d = \begin{cases} \dfrac{\lambda}{v - v_h} & if\ v > v_h \\ \infty & if\ v \leq v_h \end{cases} \tag{6}$$

Where $\lambda = \frac{\alpha H}{\cos\theta}$ and v_h represents the horizon line in the image. The value of d from equation (6) will be used in order to assess the visibility distance in fog conditions.

4 METHOD DESCRIPTION

4.1 Estimation of the Visibility Distance

In order to estimate the visibility distance we must first examine the mathematical properties of the Koschmieder's law, presented in the previous section. For estimating the extinction coefficient k we must investigate the existence of an inflection point in the image that will provide the basis for our solution. By expressing d as in equation (6) and by performing a change of variable, equation (4) becomes:

$$I = Re^{\frac{-k\lambda}{v-v_h}} + A_\infty(1 - e^{\frac{-k\lambda}{v-v_h}}) \tag{7}$$

If we take the derivative of I with respect to v, taking into account that the camera response is a linear function, one obtains:

$$\frac{dI}{dv} = \frac{k\lambda}{\left(v - v_h\right)^2}(R - A_\infty)e^{\frac{-k\lambda}{v-v_h}} \tag{8}$$

We know that objects tend to get obscured more quickly when fog density increases. Moreover, the maximum derivative decreases significantly and deviates more substantially from the horizon line. So the inflection point in the image can be found where the derivative has a maximum value. By computing again the derivative of I with respect to v, we get the following equation:

$$\frac{d^2 I}{dv} = \frac{k\lambda(R - A_\infty)}{\left(v - v_h\right)^3} e^{\frac{-k\lambda}{v-v_h}} \left[\frac{k\lambda}{v - v_h} - 2\right] \tag{9}$$

Equation $\frac{d^2 I}{dv} = 0$ has two possible solutions. We search for a positive solution of k, so k=0 is not acceptable. Thus the solution obtained is:

$$k = \frac{2(v_i - v_h)}{\lambda} = \frac{2}{d_i} \tag{10}$$

v_i represents the position of the inflection point in the image and d_i represents its distance to the camera.

If we are able to compute the position of the inflection point and of the horizon line we can compute the extinction coefficient from Koschmieder's law. 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. From equations (3) and (10) we can estimate the visibility distance in the image:

$$d_{vis} = \frac{3\lambda}{2(v_i - v_h)} \quad (11)$$

Using this visibility distance and taking into account the braking distances at various speeds, we can infer the fog density and the maximum safe driving speed of the vehicle should.

4.2 Algorithm Overview

The architecture of our framework is presented in Figure 2. The main contributions of our work are in the blue highlighted areas. Our method uses grey scale images as input and is able to provide information about the presence of fog in the image and to estimate the maximum speed on the given road segment. First we apply a Canny-Deriche edge detector on the input image. Then we estimate the horizon line and the inflection point in order to assess whether fog is present in the image. If fog is present in the image, then we perform visibility estimation and speed warning recommendation.

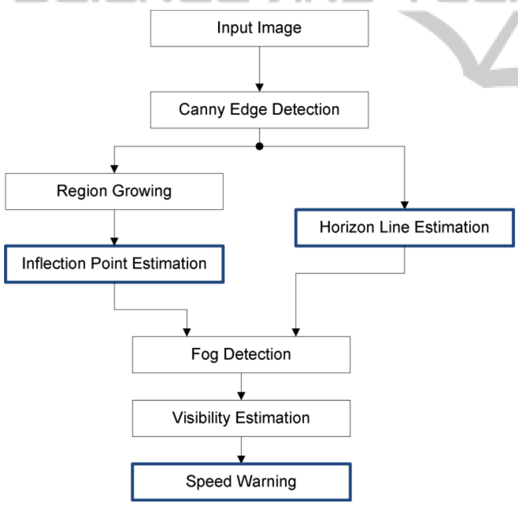

Figure 2: System Architecture.

4.2.1 Horizon Line Estimation

Several methods can be employed for computing the horizon line in the image. The first one relies on using a simple calibration procedure to compute the pitch angle of the camera (Hautiere et al., 2006). An alternative, our choice, is to estimate the horizon line based on the image features. This will ensure a better result for the horizon line estimation in different traffic situations.

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 (Bronte et al., 2009) 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 (Se, 2000). The main steps for the detection of the vanishing point are:

1. Select a set of relevant lines in the half lower part of the image (road area). The Hough accumulator was built from the edge points 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.

2. A RANdom SAmple Consensus (RANSAC) 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 having the largest consensus set is selected.

3. 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 applying the horizon line detection process. The bottom image presents only the detected Hough lines that form the consensus set and their intersection points in green colour.

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 in a temporal scheme 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. This temporal integration makes the horizon line detection algorithm more stable.

4.2.2 Region Growing

The region growing process follows the guidelines presented in (Hautiere et al., 2006). The objective is to find a region within the image that displays minimal row to row gradient variation.

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

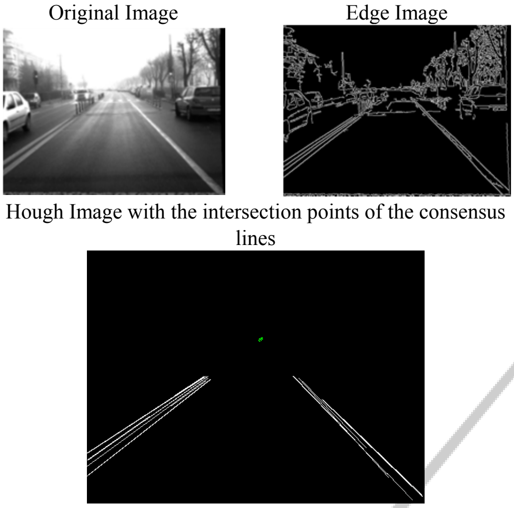

Figure 3: Horizon Line estimation algorithm based on Random Sample Consensus.

not belong to the region, it is not an edge point and presents a similarity with the seed and the pixel located below.

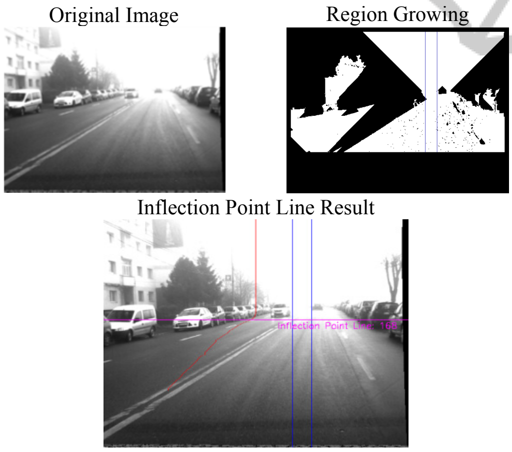

Figure 4: Region Growing and Inflection Point Estimation.

4.2.3 Inflection Point Estimation

In order to compute the inflection point v_i we must first find the maximum band that crosses the region from top to bottom (Hautiere et al., 2006). If we cannot find such a band, then we can assume that there is no fog in the image. Next we compute the median value for each line of this band and we smooth these values such that the obtained function is strictly decreasing. 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. Figure 4 illustrates the results for detecting the inflection point line. The region growing result is displayed in the top right image. The vertical band is presented with blue and the smoothed median values in the inflection point band are displayed with orange in the bottom image. Finally, the inflection point line is displayed in pink. In order to increase the robustness of the inflection point computation, a temporal scheme similar to the one for horizon line detection is employed.

4.2.4 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 d_{vis} from equation (11). If the position of the inflection point line is greater than the vertical position of the horizon line we are able to detect fog in the image. Based on the visibility distance estimation we are able to classify fog into five different categories presented in Table 1.

4.2.5 Speed Warning Recommendation

Many accidents that happen during fog conditions are caused by excessive driving. For this reason a lot of efforts have been made so that advanced driving assistance systems will be able to provide good maximum speeds for driving. A method for determining variable speed limits taking into account the geometry of the road, sight distance, tyre-road friction and vehicle characteristics is presented in (Jimenez et al., 2008). They construct an Intelligent Speed Adaptation (ISA) system based on a very detailed digital map. Although a lot of information is implemented in the ISA, the system is expensive and hard to retrofit on older vehicles. In order to avoid any accidents in fog conditions we consider that a “zero risk” approach would be more cautious (Gallen et al., 2010). Thus we consider the total stopping distance to be equal to the distance travelled during the reaction time and the breaking distance. So, for providing the driver with a good recommendation of safe driving speed we consider that the visibility distance d_{vis} computed by our method is given by the following equation

$$d_{vis} = R_t v_r + \frac{v_r^2}{2gf} \tag{12}$$

The first term of equation (12) represents the

Table 1: Fog Categories.

Visibility distance Min	Visibility distance Max	Fog Category
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

distance travelled during the safety time margin (including the reaction time of the driver), and the second term is the braking distance. This is a generic case formula and does not take into account the mass of the vehicle and the performance of the vehicle's breaking and tire system.

- R_t is a time interval that includes the reaction time of the driver and several seconds before a possible accident may occur. Because we are aiming to obtain a cost effective solution for warning drivers about the speed that they should travel during fog conditions and because we do not take into account the geometry of the road since we do not use an augmented digital map, we have considered this interval to be equal to 5 seconds. This covers the interval of distracted drivers' inattention for most of the dangerous events that might occur during fog conditions.
- g is the gravitational acceleration, 9.8 m/s^2
- f is the friction coefficient. For wet asphalt we use a coefficient equal to 0.35.
- v_r denotes the recommended driving speed.

By solving equation (12) we obtain the following positive solution for v_r:

$$v_r = -gfR_t + \sqrt{g^2 f^2 R_t^2 + 2gfd_{vis}} \qquad (13)$$

Figure 5 represents a plot of the braking distances on wet and dry asphalt according to the speed of traveling. The friction coefficient for dry asphalt was set to 0.7 and for wet asphalt to 0.35 (EnginneringToolbox).

Table 2 presents some maximum recommended speeds according to the fog density and the visibility distance measured by our algorithm. In addition we show the braking distances on wet asphalt. According to our model of computing the recommended speed, the driver has enough time in order to react and to break the vehicle in case of an emergency or hazardous event.

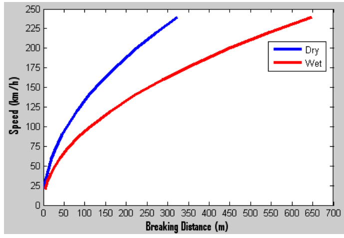

Figure 5: Braking distance on dry and wet asphalt. These values were computed with the following friction coefficients: 0.7 for dry asphalt and 0.35 for wet asphalt.

Table 2: Speed Recommendations under Fog Conditions.

Visibility distance	Maximum Recommended speed m/s	Maximum Recommended speed km/h	Braking distance
20 m	3.61 m/s	13 km/h	1.90 m
50 m	8.09 m/s	29 km/h	9.54 m
100 m	14.15 m/s	51 km/h	29.21 m
150 m	19.22 m/s	69 km/h	53.87 m
200 m	23.66 m/s	85 km/h	81.65 m
300 m	31.34 m/s	113 km/h	143.25 m

5 EXPERIMENTAL RESULTS

In order to assess our method we have synthetically generated images using the GLSCENEINT framework (Bota and Nedevschi, 2006). Then we were able to add fog into these images using Koschmieder's equation, by considering A_∞=255 and varying k from 0.01 to 0.15. Figure 6 presents three scenarios for synthetic images. For k=0.03 (moderate fog in the image) we can observe that in the first two scenarios the results are similar. However, for the third scenario we are not able to compute the inflection point, due to the presence of the vehicles on the road. In the dense fog scenario (k = 0.06) we are able to estimate the inflection point in all three scenarios. For k=0.09 (dense fog situation), we show the results for the second and third scenario.

Figure 7 present the results of our fog detection framework on real traffic images. These images were acquired with a vehicle equipped with JAI-A10-CL cameras during different fog conditions, in the city of Cluj-Napoca. From top to bottom we present different fog situations in accordance to the fog categories presented in Table 1.

Table 3 presents the braking distances and the necessary time for braking in the above four scenarios. We can observe that the recommended speed is accurate enough in order for the driver to reduce the speed of the vehicle or even come to a complete stop so as to avoid any collisions.

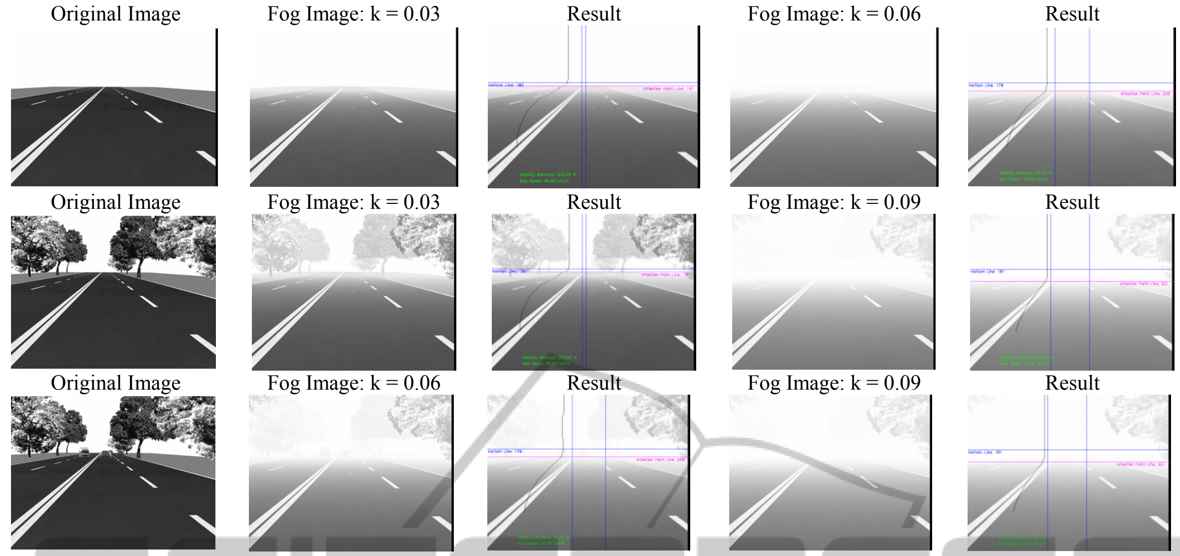

Figure 6: Results obtained on synthetic images. The blue horizontal line represents the horizon line, the pink line represents the inflection point line and the two vertical blue lines delimit the vertical band. The black curve represents the smoothed median values from the vertical band .The visibility distances and the maximum recommended speeds are displayed in green on the resulting images.

Table 3: Braking distance in the presented scenarios.

Fog Scenario	Max Speed	Braking Distance	Braking Time
	km/h	m	s
1. Low Fog	114.95	148.62	4.65
2. Moderate Fog	70.61	56.08	2.86
3. Dense Fog	43.26	21.04	1.75
4.Very Dense Fog	18.88	4.01	0.76

Our algorithm was implemented in C++ and was tested on an i7 based PC running Windows operating system. The synthetic images have a resolution of 688 x 515 pixels and the average processing time is of 21 ms. The real traffic images were obtained with a JAI CV-A10CL camera. Their resolution is 512 x 383 pixels and the average processing time on one image is 18 ms.

6 CONCLUSIONS

In this paper we have presented a framework for detecting fog in images grabbed from a moving vehicle with the goal of assisting the driver with safe speed recommendations and information about the fog density and visibility distance in order to avoid accidents.

Our algorithm is able to detect fog 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. One of our main contributions is the continuous estimation of the horizon line by using the RANSAC method and the temporal integration based on the consensus score. This approach 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). By using the temporal filtering based on the consensus score, we are able to detect the horizon line even in tough scenarios where the lane markings are not visible, during curves, when the vehicle passes over speed bumps or even in situation where the road is not flat. Another important contribution is the temporal integration of the inflection point line. This provides us with the mean of estimating the density of the fog even in the situations where we are not able to detect the vertical band after the region growing process. Thus we are still able to provide the driver with the maximum speed recommendation on the given road segment.

The algorithm used to estimate the maximum speed in fog situations proves to be accurate enough in order for the driver to reduce the driving speed as to avoid any collision with other traffic participants.

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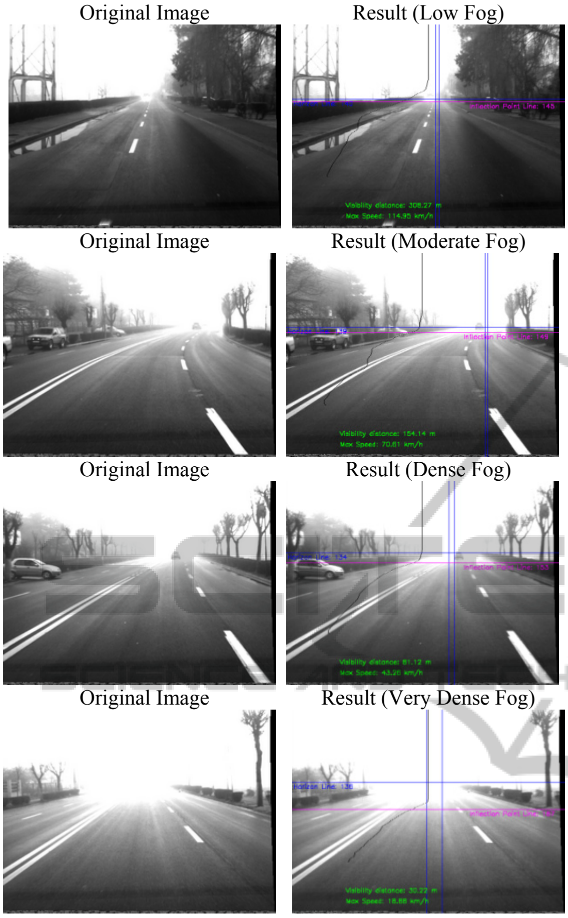

Figure 7: Results obtained on real traffic images. The visibility distance and the maximum recommended speed are written on the resulting images.

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