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Estimation of the Visibility Distance by Stereovision: a Generic Approach

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Abstract

An atmospheric visibility measurement system capable of quantifying the most common operating range of onboard exteroceptive sensors is a key parameter in the creation of driving assistance systems. This information is then utilized to adapt sensor operations and processing or to alert the driver that the onboard assistance system is momentarily inoperative. Moreover, a system capable of either detecting the presence of fog or estimating visibility distances constitutes in itself a driving aid. In this paper, we present a technique to estimate the mobilized visibility distance through use of onboard CCD cameras. This distance represents the distance to the most distant object on the road surface having a contrast above 5 %. This definition is very close to the definition of the meteorological visibility distance proposed by the International Commission on Illumination (CIE). Our method combines the computations of a depth map of the vehicle environment using stereovision and of local contrasts above 5 %. In this paper, both methods are described separately. Then, their combination is detailed. Our method is operative in every kind of meteorological conditions and is evaluated thanks to video sequences under sunny weather and foggy weather.

1 Introduction

Perception sensors (cameras, laser, radar) are being introduced into certain vehicles. These sensors have been designed to operate within a wide range of situations and conditions (weather, luminosity, etc.) with a prescribed set of variation thresholds. Effectively detecting when a given operating threshold has been surpassed constitutes a key parameter in the creation of driving assistance systems that meet required reliability levels. With this context in mind, an atmospheric visibility measurement system may be capable of quantifying the most common operating range of onboard exteroceptive sensors. This information is then utilized to adapt sensor operations and processings, to automate tasks such as turning on the fog lamps or to alert the driver that the onboard assistance system is momentarily inoperative. Moreover, a system capable of either detecting the presence of fog or estimating visibility distances constitutes in itself a driving aid. During foggy weather, humans actually tend to overestimate visibility distances [10], which can lead to excessive driving speeds. In this paper, we present a generic method to estimate the visibility distance.

2 Mobilized and Mobilizable Visibility Distances

For the CIE [1], the meteorological visibility distance is the greatest distance at which a black object of a suitable dimension can be seen in the sky on the horizon. On the Fig. 1, we represent a simplified road. We can see from the Fig. 1a that the most distant visible object is the extremity of the last road marking. It could be the roadside, a shadow... However, the extremity location depends on the vehicle position. We call this distance to the most distant visible object, which depends on the road scene, the mobilized visibility distance V_{mob}. This distance has to be compared to the mobilizable visibility distance V_{max}. This is the maximum distance at which a potential object on the road surface would be visible.

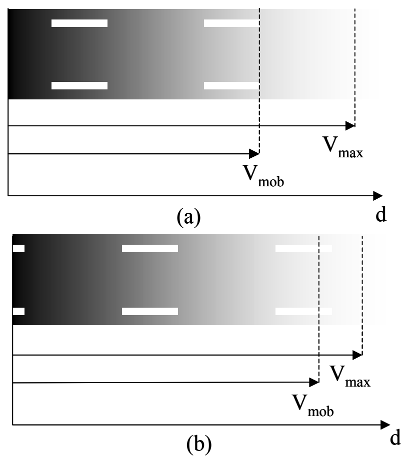

Figure 1: examples of mobilized and mobilizable visibility distances.

Consequently, we have:

$$V_{\max} \geq V_{\text{mob}} \tag{1}$$

Under few assuptions, the mobilizable visibility distance is very close to the meteorological visibility distance. In [2][3], we succeed to instantiate Koschmieder's model [9] and then to estimate the meteorological visibility distance. This method, when its operation assumptions are met, leads to obtain good results under daytime foggy weather.

In order to cover more meteorological situations than solely day fog weather, we propose in this paper to estimate the mobilized visibility distance. In this aim, we estimate the distance to the most distant object on the road surface having a contrast above 5 %. Thus, this method is very close to the definition of the CIE.

This paper is broken up into three parts. The first one presents a method to compute a depth map of the vehicle environment (section 3). The second part presents a method to extract picture elements whose contrast is above 5 % (section 4). Finally, thanks to the combination of both previous techniques, the mobilized visibility distance can be obtained (section 5).

3 Computation of a Depth Map of the Environment by Stereovision

In this section, we present our stereoscopic sensor. Then, we present our technique to compute a depth map of the environment using the "v-disparity" approach. The different stages of computation of this depth map are detailed.

3.1 Modeling of the stereo sensor

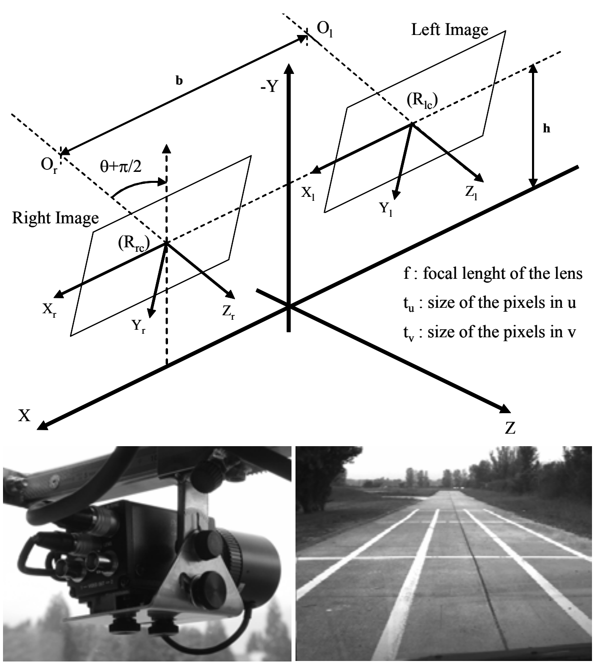

Figure 2: (a) the stereo sensor and the coordinate systems used. (b) Cameras currently in use in the prototype cars of the LIVIC. (c) Calibration site on the test track at Versailles.

The two image planes of the stereo sensor are supposed to belong merely to the same plane and are at the same height above the road (see Fig. 2a). This camera geometry means that the epipolar lines are parallel.

3.2 The image of a plane in the "v-disparity" image

In this study, we segment the environment into planes which are horizontal, vertical or oblique with respect to the plane of the stereoscopic sensor. In a cross-section of the scene in the optical axis of the camera, the projection of any of these planes is a straight line. In the rest of this paper, we will build and use a specific image representation, in which the detection of straight lines will be equivalent to the detection of planes in the scene. Indeed, we will represent the v coordinate of a pixel towards the disparity Δ and detect straight lines and curves in this 2D image. The mathematical details are given in [8].

3.3 "V-disparity" image construction and 3D surface extraction

To compute a disparity map I_Δ, the primitives used are horizontal local maxima of the gradient. The matching process is based on normalized correlation around the local maxima. It is quite simple and fast. Once I_Δ has been computed, the "v-disparity" image $I_{v\Delta}$ is built by accumulating the pixels of same disparity in I_Δ along the **v** axis. Then straight lines are detected in $I_{v\Delta}$ thanks to a hough transform. This leads to extract global surfaces, which correspond either to the road surface, or to obstacles. Details of this method are given in [8]. The accuracy of the method is presented in [6].

3.4 Disparity map improvement

In order to quickly compute the "v-disparity" image, a sparse and rough disparity map has been built. This disparity map may contain numerous false matches, which prevents us to use it as a depth map of the environment. Thanks to the global surfaces extracted from the "v-disparity" image, false matches can be removed. In this aim, we check whether a pixel of the disparity map belongs to any global surface extracted using the same matching process. If it is the case, the disparity value is mapped to the pixel.

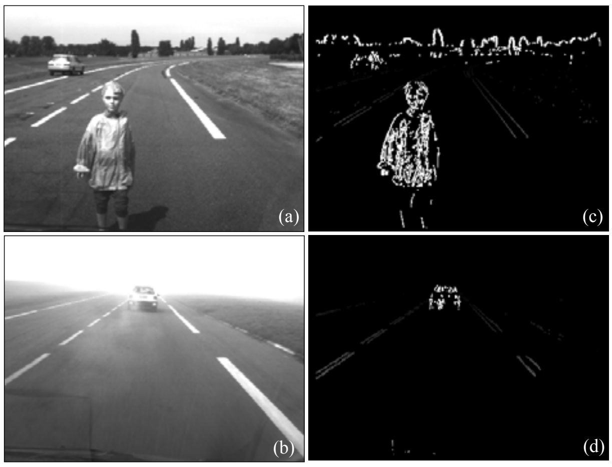

Figure 3: images captured in the vehicle (a) under sunny weather, (b) under foggy weather. Examples of disparity map of the vehicle environment (c) under sunny weather, (d) under foggy weather. White points are considered as obstacles points. The gray level of other points is proportional to their disparity.

4 Computation of Contrasts above 5 %

4.1 Measuring the local contrast with Köhler's binarization technique

Köhler's technique [5] used to binarize images finds the threshold which maximizes the contrast between two parts of the image. Let f be a gray level image. A couple of pixels (x,x_1) is said to be separated by the threshold s if two conditions are met. First, $x_1 \in V_4(x)$. Secondly, the condition (2) is respected:

$$\min(f(x), f(x_1)) \leq s < \max(f(x), f(x_1)) \qquad (2)$$

Let $F(s)$ be the set of all couples (x,x_1) separated by s, such as $x \in V_4(x_1)$. With these definitions, for every value of s belonging to [0,255], $F(s)$ is built. For every couple belonging to $F(s)$, the local contrast $C_{x,x1}(s)$ is computed:

$$C_{x,x_1}(s) = \min\left(\left|s - f(x)\right|, \left|s - f(x_1)\right|\right) \qquad (3)$$

The mean contrast (4) associated to $F(s)$ is then performed:

$$C(s) = \frac{1}{\mathrm{card}(F(s))} \sum_{(x,x_1) \in F(s)} C_{x,x_1}(s) \qquad (4)$$

The best threshold s_0 verifies the following condition:

$$C(s0) = \max_{s \in [0,255]} C(s) \qquad (5)$$

s_0 is the threshold which has the best mean contrast along the associated border $F(s_0)$. Instead of using this method to binarize images, we use it to measure the contrast locally. The evaluated contrast is then equal to $2C(s_0)$ along the associated border $F(s_0)$.

4.2 Adaptation to the logarithmic contrast

The previous method is suitable for different definitions of local contrast. To use another local contrast definition, it is enough to use the desired definition in the place of Eq. (3). In our case, we have chosen to estimate the logarithmic contrast [4] so as to be compatible with the definition of the meteorological visibility distance proposed by the CIE (cf. section 2). So, Eq. (3) becomes:

$$C_{x,x_1}(s) = \min\left(\frac{\left|s - f(x)\right|}{\max(s, f(x))}, \frac{\left|s - f(x_1)\right|}{\max(s, f(x_1))}\right) \qquad (6)$$

4.3 Some good properties of our technique

Our technique, inspired from Köhler, is robust to noise. However, the computational cost of the technique is high. A direct implementation of the technique takes 14s to be performed on a whole image of resolution 380x289 on a Pentium IV 2.4 Ghz. By reducing the thresholds number and precalculating the MIN-MAX images, the computing time is inferior to 1s. By vectorizing the optimized algorithm, the computational cost is then about 350ms on a whole image.

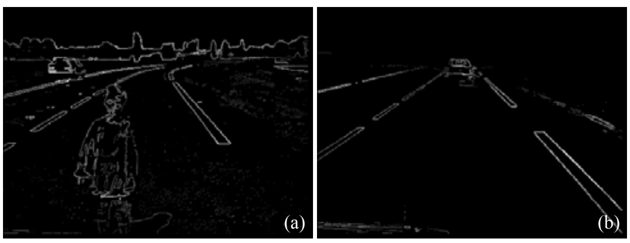

Figure 4: examples of contrasts computation above 5 %, (a) under sunny weather, (b) under foggy weather.

5 Estimation of the Mobilized Distance of Visibility

In section 3, we described the computation of a depth map of the vehicle environment. In section 4, we presented a method to compute the local contrasts above 5 %. To estimate the visibility distance, we have to combine both.

5.3 Direct disparity-contrast combination

The first approach is to replace the computation of the horizontal local maxima of the gradient by the horizontal contrasts above 5 %. So, the visibility distance is the distance of the matched pixel having the smallest disparity. This approach is simple. Its main advantage is to replace the gradient threshold, which is empirically chosen, by the contrast threshold of 5 %. Unfortunately, it is too much time consuming for our real-time application.

5.4 Fast disparity-contrast cooperation

The contrast computation locates precisely the edges, but is quite expensive in term of computing times. Conversely, the gradients computation goes fast but spreads on the edges. Consequently, using the horizontal gradients, the "v-disparity" image is denser and faster to compute. The 3D surface extraction is also faster and more reliable. However, we must ensure that the gradient threshold is small enough, so as to take most picture elements having a contrast above 5 % into account, but large enough so as to not take too much noise into account. The noise measured on the cameras currently in use is gaussian with a standard deviation σ of 1 to 2 gray levels. The gradient threshold to consider is then 3σ, that is to say 6.

It is possible to draw advantage from the two techniques while decreasing the computing time compared to the only use of horizontal contrasts. The method consists in computing the improved disparity map using the horizontal gradients higher than 6 and to scan it. Because most distant objects on the road surface are on the horizon line, the scanning starts from the horizon line. Within each neighborhood where a point of disparity is known the contrast is computed. The process stops when a contrast above 5 % is met. The visibility distance is then the depth of the picture element with a contrast above 5 %.

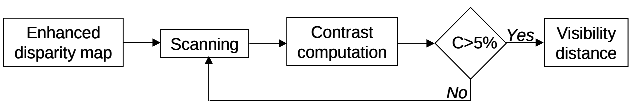

Figure 5: algorithm overview.

6 Results

The whole process for building the depth map of the vehicle environment and computing the mobilized visibility distance by means of our modified Köhler's contrast technique is performed within 60 ms with a current-day PC. The hardware used for the experiments is a Pentium IV 2.4 GHz. Images are grabbed using a Matrox Meteor II graphic card. The focal length is 8.5 mm and image size is 380x289.

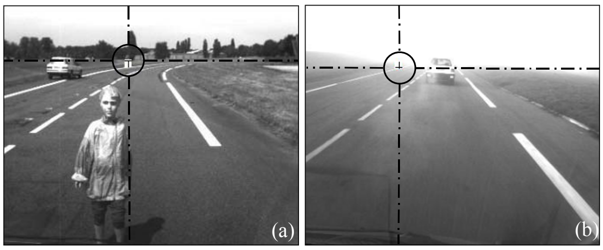

Figure 6: final result. The most distant window having a contrast above 5 %, on which a point of disparity is known, is painted white. The disparity point is represented with a black cross inside the white window. (a) sunny weather (V_{mob}≈260m), (b) foggy weather (V_{mob}≈75m).

On Fig. 3, results of the disparity map computations are presented. On Fig. 3a, the pedestrian, the car and pixels beyond horizon line are considered as obstacles pixels. The depth of the pixels on the road surface is computed. In the same way, on Fig. 3b, the car is considered as an obstacle.

On Fig. 4, results of local contrast computation on the whole images are represented. In fact, as explained in section 5, the contrast will not be computed on the whole image to save computing time. On Fig. 6, the final result is represented.

Finally on Fig. 7, the curves of measured visibility distances are plotted for both video sequences of 1000 images each. Under sunny weather, the maximum resolution of the stereoscopic sensor is reached. Moreover, the visibility distance measurement for a video sequence under dense fog before night-fall is given. Unfortunately, for lack of place, this sequence can not be illustrated.

To conclude, we can say that under foggy weather, the visibility distance measurements are quite stable which let us think that the method is efficient in adverse weather conditions.

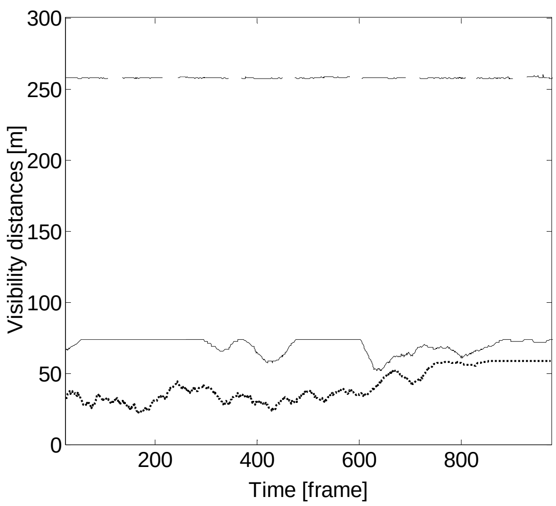

Figure 7: curves of measured mobilized visibility distances (----) under sunny weather, (——) under foggy weather, (….) under dense foggy weather before night-fall.

7 Conclusion

In this paper, we presented a generic method to estimate the mobilized visibility distance, which is the distance to the most distant picture element on the road surface having a contrast above 5 %. This method is close to definition of the meteorological visibility distance. We use the "v-disparity" stereovision approach to build a depth map of the vehicle environment. We combine this map with the computation of local contrasts by means of a technique inspired by R. Köhler. The whole process is real-time performed. This technique, which has been recently patented, has very few assumptions. Consequently, it is operative under lots of meteorological conditions. In order to evaluate the performance of our method, we are currently using specific targets so as to provide a reference measure of the atmospheric diffusion.

Acknowledgments

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