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Study of Different Method Used for Single Image Defogging

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Abstract- As we know that Fog is caused by high concentration of very fine water droplets in the air. When light hits these droplets it scattered and this results in the dense white background, called the atmospheric veil. For further use of foggy image for another application at that time for removal is necessary for better result. In this paper we are discussing about color and contrast enhancement and visibility enhancement, For color and contrast enhancement two algorithms are proposed Multi scale Retinex (MSR) and Contrast limited adaptive histogram equalization (CLAHE) and for visibility enhancement five visibility enhancement algorithms are now presented: enhancement assuming a planar scene assumption (PA), enhancement with free-space segmentation (FSS), enhancement with the no-black-pixel constraint (NBPC) and enhancement with the dark channel prior (DCP), Combining the No-Black-Pixel Constraint and the Planar Assumption (NBPC +PA) A comparative study with several state-of-the-art algorithms is presented which produces better quality results, in particular case of a foggy input image.

Keywords:- Single Image Defogging, Color and Contrast Enhancement, Visibility Enhancement, MSR, FSS, CLAHE.

I. INTRODUCTION

A cause of vehicle accidents is reduced visibility due to bad weather conditions such as fog. This suggests that an algorithm able to improve visibility and contrast in foggy images will be useful for various cameras based Advanced Driver Assistance Systems (ADAS).

In [2], it is shown for several type of detection algorithms, that a visibility enhancement preprocess allows to improve detection performance I presence of fog. This is due to a better respect after pre-processing of the assumption that objects to be detected have aminimal contrast which is setto be uniform over the whole image. Two kinds of ADAS can be considered. The first possibility is to display the image from a frontal camera after visibility enhancement. We call this kind of ADAS a Fog Vision Enhancement System (FVES).

The second possibility is to combine visibility enhancement pre-processing with detection of stopped cars/moving cars/pedestrians/two wheeled vehicles, to deliver adequate warning. An example is a warning when the distance to the previous moving vehicleis too short with respect to the driver's speed.

For ADAS based on the use of a single camera in the vehicle the contrast enhancement algorithm must be able torobustly process each image in a sequence in real time. The key problem is that, from a single foggy image, contrast enhancement is an ill-posed problem. Indeed, due to the physics of fog, visibility restoration requires to estimate both thescene luminance without fog and the scene depth-map. This implies estimating two unknown parameters per pixel froma single image. The first approach proposed to tackle the visibility restoration problem from a single image is described in [3].

The main idea is to provide interactively an approximate depth-map of the scene geometry allowing deducing an approximate luminance map without fog. The drawback of this approach for camera based ADAS is clear: it is not easy to provide the approximate depth-map of the scene geometry from the point of view of the driver all along itsroad path.

In [4], this idea of approximate depth-map was refined by proposing several simple parametric geometric models dedicated to roadscenes seen in front of a vehicle.

For each type of model, the parameters are fit on each view by maximizing the scene depths globally without producing black pixels in the enhanced image. The limit of this approach is the lack of flexibility of the proposed geometric models.

During the same period of time, another approach was proposed in [5] based on the use of color images with pixels having a hue different from gray. A difficulty with this approach, for the applications we focus on, is that a large part of the image corresponds to the road which is gray andwhite. Moreover, in many intelligent vehicle applications, only gray-level images are processed.

More recently and for the first time in [1], [6], [7], three visibility enhancement algorithms were proposed working from a single gray-level or color image without using any other extra source of information. These three algorithms rely on a local spatial regularization to solve the problem. Being local, these algorithms can cope with homogeneous and heterogeneous fog. A fast variant of [7] was very recently proposed in [8].

The disadvantage of these three visibility enhancement methods, and of the other variants or improve algorithms more recently proposed, is that they are not dedicated to road images and thus the road part of the image which is gray may be over-enhanced. This is due to the ambiguity between light colored objects and the presence of fog, and leads to the apparition of unwelcome structures in the enhanced image.

Recently, a visibility enhancement algorithm [2] dedicated to road images was proposed which was also able to enhance contrast for objects out of the road plane.

This algorithm makes good use of the planar road assumption but relies on a homogeneous fog assumption. In this work, we formulate the restoration problem as the inference of the atmospheric veil from to three constraints. The first constraint relies on photometrical properties of the foggy scene. The second constraint, named the no-black-pixel constraint, was not used in [6], [7] and [1].

It involves filtering the image. The algorithm described in [1] corresponds to the particular case where two constraints are used with the median filter. To take into account that a large part of the image is a planar road, as introduced first in [2], a third constraint based on the planar road assumption is added.

The new algorithm can thus be seen as the extension of the local visibility enhancement algorithm [1] combined with the road-specific enhancement algorithm [9].

The proposed algorithm is suitable for FVES since it is able to process gray-level as well as color images and runs close to real time.

To compare the proposed algorithm to previously presented algorithms, we propose an evaluation scheme and we build up a set of synthetic and camera images with and without homogeneous and heterogeneous fog. The algorithms are applied on foggy images and results are compared with the images without fog. For FVES in which the image after visibility enhancement is displayed to the driver, we also propose an accident scenario and a model of the probability of fatal injury as a functionof the setting of the visibility enhancement algorithm.

II. EFFECTS OF FOG

Let an object of intrinsic luminance L0 (u, v), its apparent luminance L (u, v) in presence of a fog of extinction coefficient k is modeled by Koschmieder's law [11]

$$\boldsymbol{L(u,v) = L\,(u,v)e^{-kd(u,v)} + Ls\left(1 - e^{-kd(u,v)}\right)}\text{.. } \mathbf{(1)}$$

Where; d(u, v) is the distance of the object at pixel (u, v) and Isis the luminance of the sky.

As described by (1), fog has two effects: first an exponential decay e^(-kd(u,v)) of the intrinsic luminance L0 (u, v), and second the addition of the luminance of the atmospheric veil Is (1-e^(-kd (u,v))) which is an increasing function of the object distance d (u, v).

We assume that the camera response is linear, and thus image intensity I is substituted to luminance L.

III. COLOR AND CONTRAST ENHANCEMENT

The Multiscale Retinex (MSR) and Contrast limited adaptive histogram equalization (CLAHE) algorithms. These two algorithms are not based on Koschmieder's law (1) and thus are only able to remove a fog of constant thickness on an image. They are not visibility enhancement algorithms.

However, we found it interesting to include these two algorithms in our comparison in order to verify that visibility enhancement algorithms achieve better results.

1. Multiscale Retinex (MSR)

The multiscale retinex (MSR) is a non-linear image enhancement algorithm proposed by [10]. The overall impact is to brighten up areas of poor contrast/brightness but not at the expense of saturating areas of good contrast/brightness. The MSR output is simply the weighted sum of the outputs of several single scale retinex (SSR) at different scales.

Each color component being processed independently, the basic form of the SSR for on input image I (u,v) is:

$$\mathbf{Rk(u,v)=logI\ (u,v)-log[Fk\ (u,v)*I(u,v)]} \quad \ldots \quad (2)$$

Where; Rk (u,v) is the SSR output, Fkrepresents the kth surround function, and) is the convolution operator.

The surround functions, Fk are given as normalized Gaussians,

$$\boldsymbol{F\ (u,v) = ke^{-(u^2+v^2)/\sigma^2}} \qquad \cdot (3)$$

Whereσk is the scale controlling the extent of the surround and Ikis for unit normalization. Finally the MSR output is:

$$\boldsymbol{R(u,v)}=\sum_{k=1}^{k=K} \boldsymbol{WkRk\ (u,v)}, \qquad .. \quad (4)$$

Where; Wk is the weight associated to Fk. The number of scales used for the MSR is, of course, application dependent. We have tested different sets of parameters, and we did not find a better parameterization than the one proposed by [10]

2. Contrast-Limited Adaptive Histogram Equalization (CLAHE):

Contrast-limited adaptive histogram equalization (CLAHE) locally enhances the image contrast. As proposed in [12], CLAHE operates on 8 # 8 regions in the image, called tiles, rather than the entire image.

Each tile's contrast is enhanced, so that the histogram of the output region approximately matches a flat histogram.

The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The enhanced contrast, especially in homogeneous areas, is limited to avoid amplifying noise or unwelcome structures, such as object textures, that might be present in the image.

IV. ENHANCEMENT BASED ON KOSCHMIEDER'S LAW

Four visibility enhancement algorithms are now presented: enhancement assuming a planar scene assumption (PA), enhancement with free-space segmentation (FSS), enhancement with the no-black-pixel constraint (NBPC) and enhancement with the dark channel prior (DCP). The advantages and limits of these algorithms are discussed. A new algorithm, named NBPC+PA, which combines the advantages of PA and NBPC algorithms, is proposed. The results obtained by the five algorithms are presented in Fig. 1 on three images.

1. With the Planar Assumption (PA):

In-vehicle applications, the algorithm proposed in [13], [11] is able to detect the presence of fog and to estimate the visibility distance which is directly related to the k in Koschmieder's law (1). This algorithm, also known as the inflection point algorithm, mainly relies on three assumptions: fog is homogeneous; the main part of the image displays the road surface which is assumed to be planar and homogeneous surface. From the estimated fog parameters, the contrast in the road part of the image can be restored as explained in [9].

Using the planar road surface assumption and knowing the approximate camera calibration with respect to the road, it is possible to associate a distance d with each line v of the image:

$$d = \frac{\lambda}{v - vh} \quad if\ v > vh \qquad (5)$$

Where vh is the vertical position of the horizon line in the image and m depends on intrinsic and extrinsic parameters of the camera, see [11] for details. Using the assumption of a road with homogeneous photometric properties (I0 is constant), fog can be detected and the extinction coefficient of the atmosphere k can be estimated using Koschmieder's law (1).

After substitution of d given by (5), (1) becomes:

$$I(v) = I0e^{-k\frac{\lambda}{v-vh}} + Is(1 - e^{-k\frac{\lambda}{v-vh}})\ldots(6)$$

By taking twice the derivative of I with respect to v, the following is obtained:

$$\frac{d^2I}{dv^2}(v) = k\frac{\lambda(I0 - Is)}{(v - vh)^3}e^{-k\frac{\lambda}{v-vh}}\left(\frac{k\lambda}{v - vh} - 2\right) \quad \ldots (7)$$

The equation (d^2I)/(dv^2) = 0 has two solutions. The solution k = 0 is of no interest. The only useful solution is given by k = (2(vi - vh))/**λ**, where vide notes the position of the inflection point of I (v).

The value of Isis obtained as the intensity of the sky. Most of the time, it corresponds to the maximum intensity in the image.

Having estimated the value of k and Is, the pixels on the road plane can be restored as R(u,v) by reversing Koschmieder's law [9]:

$$R(u,v) = I(u,v)e^{-k\frac{\lambda}{v-vh}} + Is(1 - e^{k\frac{\lambda}{v-vh}}) \qquad (8)$$

As in [4], the introduction of a clipping plane in equation (5) allows to apply the reverse of Koschmieder's law in the whole image. More precisely, the used geometrical modelconsists in the road plane (5) in the bottom part of the image,and in a vertical plane in front of the camera in thetop part of the image.

The height of the line which separatesthe road model and the clipping plane is denoted c.

In summary,the geometrical model dc (u,v) of a pixel at position(u,v) is expressed as:

$$dc(u,v) = \begin{cases} \dfrac{\lambda}{v - vh} & if\ v > c \\ \dfrac{\lambda}{c - vh} & if\ v \le c \end{cases} \qquad (9)$$

2. With Free-Space Segmentation (FSS):

To enhance the visibility of the scene, an estimate of the depth d(u, v) of each pixel is needed. In [4], a parameterized 3D model of the road scene was proposed with areduced number of geometric parameters. Even if these models are relevant for most road scenes and even if the parameters of the selected mode are optimized to achieve best enhancement without black pixel in the resulting image, the proposed model is not generic enough to handle all traffic configurations.

In [2], a different scheme is proposed. Once again, the road is assumed to be planar with a clipping plane, see (9). When a geometric model (9) is assumed, the contrast of objects belonging to the road plane is correctly restored, as seen in previous section. Conversely, the contrast of vertical objects of the scene (vehicles, trees,) is incorrectly restored since their depth in the scene is largely overestimated. Consequently, their restored intensity using (8) is negative and thus set to zero in the enhanced image. These are named black pixels. The set of all black pixels gives a segmentation of the image in two regions, one inside the road plane in 3D and the other outside. This allows to deduce the free space region.

At each pixel in the free-space region, the road plane model (5) is correct. It is proposed in [2] to use the geometric model (9) and, for each pixel, to search for the smallest value of c which leads to a positive intensity in the restored image. The obtained values are denoted cmin (u,v). Indeed, when c is close to the vh, the clipping plane is far from the camera and the visibility is only slightly enhanced. The larger the value of c, the closer the clipping plane is to the camera and thus the stronger the enhancement. The enhancement in (8) can be so strong that enhanced intensity becomes negative.

Every cmin (u,v) value can be associated with a distance dmin (u,v) using (9). Then, a rough estimate of the depthmap d(u,v) is obtained as a fixed percentage p ofdepth map dmin (u,v).

Percentage p specifies the strength of the enhancement and is usually set to 95% for this method. The depthmap is used to enhance the contrast on the whole image using the reversed Koschmieder's law.

The algorithm is detailed in [2], [14] and more results are shown in the sixth column of Fig. 1.

3. With No-Black-Pixel Constraint (NBPC):

In [1], an algorithm which relies on a local regularization is proposed. The distance d (u, v) being unknown, the goal of the visibility enhancement in a single image can be set as inferring the intensity of the atmospheric veil. V(u,v)=Is(1-e^(-kd(u,v))).

Most of the time, the intensity of the sky Iscorresponds to the maximum intensity in the image, and thus Is can be set to one without loss of generality, assuming the input image is normalized.

After substitution of V in (1) and with Is=1, Koschmieder's law is rewritten as:

$$I(u,v) = I0(u,v)\big(1 - V(u,v)\big) + V(u,v) \quad .. \quad (10)$$

The foggy image I (u,v) is enhanced as R, the estimate of I0 , simply by the reversing of (10).

$$R(u,v) = \frac{I\,(u,v) - V(u,v)}{1 - V(u,v)} \, (11)$$

The enhancement equation provided by Koschmieder's law is a linear transformation. Interestingly, it gives the exact link between its intercept and its slope.

The atmospheric veil V (u,v) being unknown, let us enumerate the constraints which apply to V (u,v). V (u,v) must be higher or equal to zero and V (u,v) is lower than I (u,v):

$$0 \le \mathbf{V}(\mathbf{u},\mathbf{v}) \le \mathbf{I}(\mathbf{u},\mathbf{v}) \qquad .. \quad (12)$$

These are the photometric constraints as named in [6]. We now introduce a new constraint, not used in [1], which focuses on the reduction of the number of black pixels in the enhanced image R. This constraint is named no-black-pixel constraint and states that the local standard deviation of the enhanced pixels around a given pixel position must be lower than its local average:

$$f\ \mathrm{std}(R) \le \bar{R}\ , \ldots \ldots (13)$$

Wheref is a factor usually set to 1. In case of a Gaussian distribution of the intensities and f = 1, this criterion implies 15.8% of the intensities becoming black. Using f = 2 leads to a stronger criterion where only 2.2% of the intensities become black.

The difficulty with this last constraint is that it is set as a function of the unknown result R. Thanks to the linearity of (11), the no-black-pixel constraint can be turned into a constraint involving V and I only.

For this purpose, we now enforce local spatial regularization by assuming that locally around pixel position (u, v), the scene depth is constant and the fog is homogeneous, i.e., equivalently, the atmospheric veil locally equals V (u, v) at the central position.

Under this assumption we derive using (11) that the local averages I¯and R¯are related by R=(I- V(u,v))/(1 - V(u, v)) and that the standard deviations std(I) and std(R) are related by std(R) = (std (I))/(1 - V(u, v)). We therefore obtain, after substitution of the two previous results in (13), the no-black-pixel constraint rewritten as a function of V (u, v) and I:

$$V\,(u,v) \le \bar{I}\text{-}f\ \mathrm{std}(I) \ldots .(14)$$

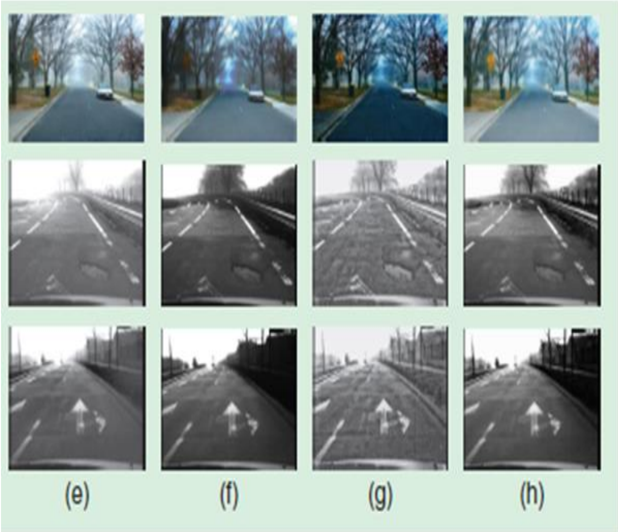

Fig 1. (a) The original image with fog, the images enhanced using algorithms : (b) multistage retinex (MSR), (c) contrast-limited adaptive histogram equalization (CLAHE), (d) planar assumption with clipping (PA), (e) dark channel prior (DCP), (f) free-space segmentation (FFS), (g) no-black pixel constraint (NBPC), and (h) no-black-pixel constraint combined with planar assumption (NBPC+PA).

The atmospheric veil V (u,v) is set as a percentage p of the minimum over the two previous upper bounds (12) and (14):

$$V(u\ v) = p\min(I(u,v), \bar{I} - f\ \mathrm{std}(I)). \qquad (15)$$

Percentage p specifies the strength of the enhancement and is usually set to 95% for this method. The enhanced image is obtained by applying (11) using the previous V. V may be threshold to zero in case of negative values. The algorithm derived from the photometric and no-black-pixel constraints turns out to be the one described in [1] where I¯is obtained as the median of the local intensities in a window of size svand the standard deviation as the median of the absolute differences between the intensities and I¯using same window size.

Other edge-preserving filters can be also used, such as the median of median along lines [1] or bilateral filtering. Due to edge smoothing of complex borders, small artifacts are produced in the restored image around complex depth discontinuities such as tree silhouettes. A post-processing with the cross/joint bilateral filter on V using I as a guide can be used to clean these artifacts are proposed in [15].

This enhancement algorithm is presented with a gray level input image but can be extended easily to color images (r(u, v), g(u, v), b(u, v)) by applying the photometric constraint to substitute I in the previous equation by the gray-level image I (u, v) = min(r(u, v), g(u, v), b(u, v)) after adequate white balance. The obtained V gives the amount of white. That must be subtracted to the three color channels. The algorithm is available in MATLAB. One can notice that the contrast on the texture of the road part of the resulting image is over-enhanced. This is due to the fact that the atmospheric veil V (u, v) in the road part of the image is over-estimated. This is a consequence of the locality property of the NBPC algorithm.

4. Dark Channel Prior (DCP):

An algorithm for local visibility enhancement named Dark Channel Prior was proposed in [7]. For gray level images, the DCP algorithm consists first in applying a morphological erosion or opening with a structuring element of size sv, which removes all white objects with a size smaller than sv. Then, the atmospheric veil V (u, v) is set as a percentage p of the opening result. This first step can thus be seen as a particular case of the NBPC algorithm using a morphological operator as filter and with f = 0. In [7], a matting algorithm is used to restore complex borders in V. A faster alternative consists in using iterations of the guided-filter, as proposed in [8]. The cross/joint bilateral filter is another alternative. The implementation used in our experiments is based on the guided filter.

The enhanced image is obtained by applying the inverse of Koschmieder's law (11) using the previous V. Fig. 1 shows the visibility enhancement obtained by the DCP algorithm in the fifth column.

The NBPC algorithm, color images are handled by using I (u, v) = min(r (u, v), g(u, v), b(u, v)) as the input gray-level image.

5. Combining the No-Black-Pixel Constraint and the Planar Assumption (NBPC +PA):

The visibility enhancement with FSS, as explained in section IV-B, performs a segmentation to split the image into three regions: the sky, the objects out of the road plane, and the free-space in the road plane. Various enhancement processes are performed depending on the region. The difficulty with an approach based on segmentation is to manage correctly the transition between regions. On the other hand, the visibility enhancement with NBPC and DCP are local methods which are not dedicated to road images and which are in difficulties in presence of a large uniform gray region such as a road, as underlined in [16]. Indeed, the atmospheric veil in the bottom part of the image is over-estimated.

To combine the advantages of the two approaches, we introduce in the NBPC a third constraint, during the inference of the atmospheric veil V(u, v), which prevents over-estimation in the bottom part of the image by taking into account the reduced distance between the camera and the road.

V. CONCLUSION

The local visibility enhancement algorithm in terms of two constraints on the inference of the atmospheric veil, we introduce a third constraint to take into account the fact that road images contain a large part of planar roadway, assuming a minimum meteorological visibility distance.

The obtained visibility enhancement algorithm performs better than the original algorithm on road images as demonstrated, where a uniform fog is added following Koschmieder's law. We also generated three different types of heterogeneous fog, a situation never considered previously in our domain. The algorithm also demonstrates its ability to improve visibility in such difficult heterogeneous situations. Our results are successfully compared to state-of-the-art algorithms: free space segmentation (FSS) Dark Channel Prior and no-black-pixel constraint (NBPC).

Finally, potential safety benefits of a Fog Vision Enhancement System, based on the proposed visibility enhancement algorithm, are evaluated on a scenario of accident in fog

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