Dark Channel Based Visibility Measuring from Daytime Scene Videos

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Abstract

Visibility is one of the most important factors of meteorological observation. Low visibility caused by fog often has a great impact on human production and daily life. Therefore, visibility measurements and warnings are given as early as possible to avoid accidents. This paper proposes a new visibility measuring method based on dark channel characteristics of digital images in natural scenes. It uses the means of dark channel values obtained from foggy images and high visibility reference images as inputs of a deep fully connected neural network, and then the trained model is applied to estimate visibility. Experiments conducted on a dataset contained two foggy scenes. The results demonstrate the effectiveness of our proposed method for daytime visibility measurement. At the same time, this paper proposes and designs an automatic detection system based on our algorithm. It implements the real time visibility measuring through edge computing.

Keywords: Meteorological visibility, Dark channel prior, Transmission factor, Edge computing

1 Introduction

In outdoor scenes, bad weather such as heavy fog or haze exerts significant influence on daily production activities, military operations, environmental monitoring, and life. Specifically, low visibility caused by seasonal heavy fog is one of the most common local phenomena and disastrous weather occurrences in coastal areas. Therefore, atmospheric visibility is an important factor in meteorological observation.

To facilitate monitoring and research, visibility is internationally rated along the spectrum by range, as can be seen in Table 1, which presents the international visibility code [1]. When the visibility rating is lower than level 5, i.e., the visibility < 1,000m, it would begin to severely affect land, sea, and air transportation. Such as on the highway, dramatical changes of visibility are challenging for drivers, who need to be informed to prevent traffic accidents in time. For that reason, real-time visibility monitoring and analysis as well as an early warning of low visibility are very important on foggy days [2].

Table 1. International visibility code with meteorological range

Scale	Description	Limit of visibility
1	Dense fog	< 50 m
2	Thick fog	50 m - 200 m
3	Moderate fog	200 m - 500 m
4	Light fog	500 m - 1000 m
5	Thin fog	1 km - 2 km
6	Haze	2 km - 4 km
7	Light haze	4 km - 10 km
8	Clear	10 km - 20 km
9	Very clear	20 km - 50 km
10	Exceptionally clear	>50 km
11	Pure air	277 km

In general, methods of visibility measurement can be divided into visual estimation and instrumental measurement. For the latter, transmission visibility meters and scattering visibility meters are the most widely used today. Although instrumental observation enables automatic estimation of visibility, the instruments are extremely costly and unsuitable for large-scale deployment or application. Along with the development of computer vision and artificial intelligence technology, research on visibility measurement with optical cameras have been initiated [3-6]. These methods work by acquiring the digital images of the scenes to be tested and measuring the actual visibility through image and video analyses. However, few proposed methods discuss the problem of transferring the trained evaluation model to a new visibility detection scene; and few papers focus on designing an automatic detection system for the proposed algorithm. However, these issues deserve further research.

Our work also focused on visibility measurement by using the conventional optical camera. In the field of image restoration, research of fog removal provided some new ways for measurement of visibility. A dark channel prior proposed by He was used to estimate the thickness of the haze and to recover a high quality haze-free image [7], as shown in Figure 1.

In our work, we leveraged this prior to meteorological visibility measurement. That is, the proposed method extrapolated the theory of dark channel prior applicable to digital image defogging to the field of atmospheric visibility measurement, which, combined with a reference image of the scene and a fully-connected neural network, was utilized to train an estimation model with scene transfer capabilities. Experimental results indicated the effectiveness of our

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proposed method for visibility measuring in two difference detection scenes.

Figure 1. Fog removal results by using Dark channel prior Top: input foggy images. Bottom: restored fog-free images [7].

Based on the proposed algorithm, the design thinking of edge computing was adopted herein. We deployed the trained model on the terminal device for edge sensing, and then the visibility data was achieved and sent back to server. Therefore, an automatic daytime visibility measurement system eventually was established.

The main contributions of our work are summarized as follows: (1) dark channel prior was introduced to obtain the features of the foggy scene, and a visibility evaluation model with scene transferability was constructed to measure the real-world visibility; (2) we established an automatic visibility measurement system, which integrated the functions of data acquisition, visibility evaluation, and data presentation; (3) we also introduced a new foggy scenes dataset, which consists of four subsets recorded from two different real scenes.

2 Related Works

In the field of meteorological visibility instrumental measurement, the main idea of a camera visibility meter is using computer vision technology to work out the visibility of the scene from the image or video. At present, there are two ways to achieve the purpose of visibility measurement.

The first is to obtain visibility only using the traditional surveillance camera. Extracting edge information from the camera scene as the detection features is the most common approach [3-4]. Research in [3] focused on using techniques based on the Sobel gradient magnitude to achieve atmospheric visibility estimation; meanwhile, the authors gave a discussion of the application in roadside visibility meters. We are also interested in emerging applications; but a practically implemented design scheme was proposed. The approach using the edge information and a threshold technique to achieve visibility estimation was introduced in the study [4]. However, edge extracting based technology in these researches usually addressed the visibility detection issues for certain specific scene, but no scene transferring measurements were attempted. In addition, research in [4] also developed a new diffusion model according to the dual differential luminance (DLL) theory. For this theory, Lv et al. analyzed the errors in visibility measurement using the DLL based algorithm [8]. Different from single image evaluating approaches, a variational framework was proposed for visibility estimation and took the extinction coefficients as a time-varying function [5]. But it relied on searching vanish points in road traffic surveillance video; therefore, the application of this approach had been limited. The transfer was discussed in [6, 9]. Nevertheless, instead of visibility measurement scenes transferring, these methods divided foggy images into several subdomains, and only transfered a trained VGG-16 model to extract subdomains features.

Secondly, approaches combed with other assistant instruments were studied. Visible-infrared image captured by a binocular camera was used as input to measure visibility, and a method adopted multimodal deep fusion architecture based on a CNN to learn the robust joint features [10-11]. In [12], a sensor fusion method was proposed and used in foggy expressways. It tracked the vehicle taillights in the camera and measured visibility with a radar. Qin et al. [13] proposed an algorithm called traffic sensibility visibility estimation (TSVE), which combined laser transmission and image processing without reference to the corresponding fog-free images and camera calibration. In [14], another equipment called high dynamic range (HDR) camera was introduced, the authors used it to obtain observation images, and proposed a lighting invariant descriptor by projecting the scene images with lighting normalization, and then the method was suggested for scene visibility classification. However, additional equipment usually is not cost-efficient and would limit to the wide practical application of automatic detection systems, hence the approach proposed in this paper belongs to the first category.

3 Visibility Measurement Based on Dark Channel Prior

3.1 Dark Channel Prior in Visibility Estimation

Dark channel prior is originally a theory applicable to digital image defogging [7]. In general, each pixel in a color digital image is expressed in the intensities of red, green, and blue channels. Based on the statistics of fog-free outdoor images, [7] noticed that in digital images of fog-free scenes, most pixels in the non-sky areas always show a very low value (near zero) in one of the color channels. In other words, the minimum light intensity in the area is very dark. For an image $\boldsymbol{J}$, its dark channel intensity J^{dark} is defined as Equation (1):

$$J^{dark}(x) = \min_{c\in\{r,g,b\}}\left(\min_{y\in\Omega(x)}(\boldsymbol{J}^c(y))\right), \quad \textbf{(1)}$$

where $\boldsymbol{J}^c$ is a color channel of the image $\boldsymbol{J}$ and $\boldsymbol{\Omega}(\boldsymbol{x})$ is a local image block centered at $\boldsymbol{x}$. The experimental statistical result whereby the dark channel intensity approaches zero is defined herein as dark channel prior. Figure 2 depicts the comparison among the images' dark channel calculations, with and without fog.

It can be noticed in a natural scene that, on the one hand, fog-free images with dark channel intensity approaching zero look dark overall. On the other hand, images with fog show significant changes in dark channel intensity under the effect of the fog, appearing as grayish white on the whole image. This phenomenon agrees with the principle of dark channel prior. Therefore, this principle was applied to the digital image

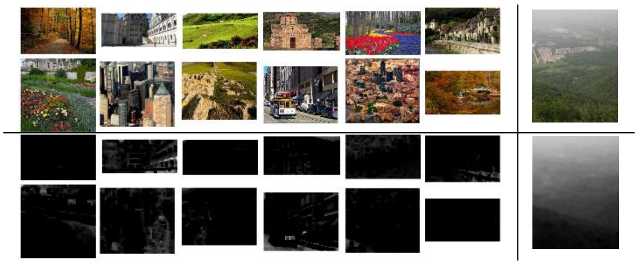


Figure 2. Left: examples of fog-free image (top) and the corresponding dark channels (bottom)
Right: a foggy image (top) and its dark channel (bottom) [7]

fogging model, on which basis the defogging algorithm was proposed in [7], producing satisfactory defogging performance as shown in Figure 1. In the physical sense, the heavier the fog is, the higher the dark channel intensity of the fog image will be. For the problem studied in this paper, the magnitude of atmospheric visibility is a direct result of the fog, which therefore shares a significant relationship with the dark channel intensity of the image. For these reasons, our proposed method measures scene visibility based on an image's dark channel intensity.

3.2 The Principle of Meteorological Visibility Measurement

For meteorological purposes, visibility was first estimated by a human observer. Atmospheric visibility refers to the maximum horizontal distance from which a person with normal vision can identify a target object against the sky background under the weather conditions at that time [15]. It is subject to many factors, among which transparency of atmosphere, apparent contrast, and visual contrast threshold are the three leading impact factors [16]. Thereinto, atmospheric transparency is a direct impact factor of visibility. It refers to the content of impurities in the atmosphere—the more the impurities, the lower the transparency. According to Koschmieder law [17], atmospheric visibility v can be expressed as:

$$v = g(\sigma) = -\frac{\ln \varepsilon}{\sigma}, \tag{2}$$

where σ is atmospheric extinction coefficient and ε is visual contrast threshold. Equation (2) indicates a certain function relationship g between visibility and atmospheric extinction coefficient, while atmospheric visibility can be obtained from atmospheric extinction coefficient. Currently, the widely used atmospheric visibility instrumental measurement devices estimate visibility by working out the atmospheric extinction coefficient.

The atmospheric extinction coefficient was proposed to describe the combined effect of different factors on atmospheric transparency. It is a measure of luminous intensity attenuation caused by absorption and scattering. According to the Bouguer-Lambert law [15], there is a certain functional relationship between the atmospheric extinction coefficient and transmission factor. Transmissivity (transmission factor) t is the ratio of luminous intensity I when the light arrives to the intensity I_0 of light source, which can be expressed as Equation 3:

$$t = \frac{I}{I_0} = e^{-\sigma d}, \tag{3}$$

where d is the distance. Suppose that $\sigma = f(t, d)$ represents the functional relationship between atmospheric extinction coefficient and visibility. By combining Formula 2 and Formula 3, we have:

$$v = g\big(f(t, d)\big) = h(t, d). \tag{4}$$

Let D be the dark channel intensity of image $\boldsymbol{I}$ at the location x. For foggy images, transmissivity t can be obtained from the dark channel intensity D [7]:

$$t(x) = 1 - D = 1 - \min_{c}\left(\min_{y\in\Omega(x)} \frac{I^c(y)}{A^c}\right), \tag{5}$$

where A is atmospheric light that can be obtained by averaging the intensities of $\boldsymbol{I}$ in top 0.1% pixels with the brightest dark channels.

3.3 Measurement of Atmospheric Visibility

Combining the concept of dark channel prior and the detection principle of visibility, a neural network-based detection method for atmospheric visibility is proposed. According to the prior theory, the corresponding dark channels value of the images with different visibilities were analyzed. Through comparison, it could be noticed that the change in dark channel intensity in the scene is related to the thickness of the fog. In general, the thicker the fog is, the brighter the dark channel image of the scene and the higher the average intensity will be, and the converse is also true. The comparison results are as shown in Figure 3.

Figure 3. Images with different visibilities (left) and their corresponding dark channel images (right), visibility from top to bottom: 283 m, 1747 m, and 5511 m

Because of the correlation between dark channels and visibility, a neural network is introduced here to learn the mapping relationship between dark channels and visibility. Meanwhile, considering the correlation between transmission factor $\boldsymbol{t}$ and distance $\boldsymbol{d}$, which is decided by the actual layout of objects in the scene, a high-visibility dark channel image $\boldsymbol{I_R}$ and its corresponding ground truth visibility $\boldsymbol{v_R}$ therefore were input to the neural network to endow the trained model with considerable transfer capabilities. It promoted applicability to various scenes.

Figure 4 illustrates the flowchart of the process. The image $\boldsymbol{I_E}$ to be estimated is an image with fog and the reference image $\boldsymbol{I_R}$ is one with a higher definition in the same scene, usually with visibility higher than 2,000 m. By comparing the dark channel obtained from the image to be estimated with that of the reference image, the relative impact of fog on the scene can be revealed. Subsequently, a visibility detection model with certain scene transfer capabilities can then be established by analyzing the relationship between both images. Each of the references and to-be-tested images will go through three steps: image preprocessing, dark channel extraction, and averaging.

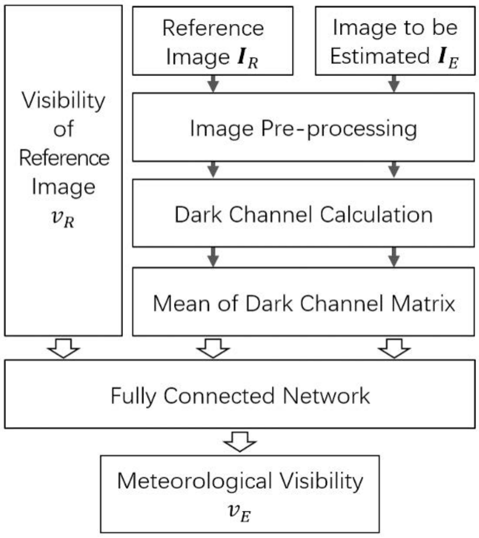


Figure 4. The flowchart of the proposed meteorological visibility measurement method

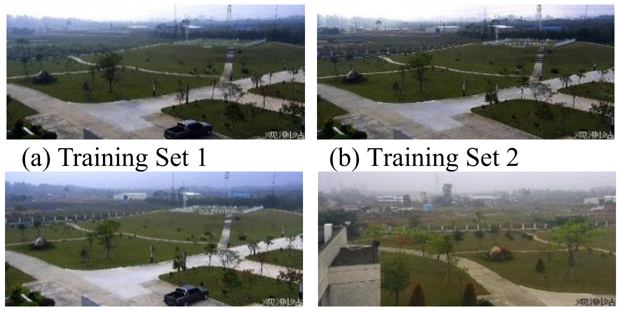
As mentioned in Section 3.1, in a natural fog-free scene, there is always one out of three color channels in an image with an intensity approaching zero. As per the definition of dark channel prior, as well as to avoid errors from slight changes in video scenes, a sliding window (radius: 3, sliding step: 1) was adopted here to acquire the dark channel intensities of an area, the minimum of which was then taken as the dark channel intensity for this area. Since the overall dark channel intensity of the scene is to a certain extent related to the thickness of the fog, the average of them was taken as the feature value of the scene to represent the general magnitude of the overall caculated intensity.

After feature extraction, we need to regress the feature data to the meteorological visibility. Then, a fully connected neural network was adopted. It provided our method with ability to map the output average dark channel intensity to visibility value via a non-linear transformation. It consists of three hidden layers with the Relu activation function: the first layer has 32 neurons, the second 8, and the third 4. The neural network features an Adam optimizer with 0.01 constant learning rate, and mean square error (MSE) taken as loss function.

4 Experimental Results

4.1 Dataset

The experimental footage consists of 4 clips recorded in real scene, including clips dated Oct. 23, 2016, Nov. 14, 2016, Nov. 15, 2016, and Mar. 9, 2019, which, had its scenes with visibility higher than 2 km removed. In the end, a total of 3,734 images were included for this study. Slight changes were observed in the scene captured on Nov. 14 and 15, 2016, compared to that on Oct. 23 of the same year, mostly on the objects, leaving the shooting angle and direction unchanged nonetheless. The captured scene changed significantly on Mar. 9, 2019. This time it changed the shooting angle, direction, and objects. Sample images captured on these 4 days are shown in Figure 5.



(a) Training Set 1 (b) Training Set 2

(c) Test Set 1 (d) Test Set 2

Figure 5. Screenshots of video clips in proposed dataset

Data of the first two dates, Oct. 23, 2016 and Nov. 14, 2016 were used as the training dataset for the neural network. Data of the last two dates, Nov. 15, 2016, and Mar. 9, 2019, were used as the test datasets, with the former used for the same-scene testing and the latter for migration testing involving a different scene. Details of the dataset are shown in Table 2. Our dataset is released in http://www1.gdou.edu.cn/scxy/foggy/datasetonline.htm.

Table 2. Parameters of experimental dataset

Date	Time	Visibility (m) Min	Visibility (m) Max	Data
2016/10/23	07:00-09:14	135	1998	Training Set 1
2016/11/14/	07:00-09:12	519	1984	Training Set 2
2016/11/15/	07:00-08:11	243	1846	Test Set 1
2019/03/09/	07:30-10:00	233	1875	Test Set 2

4.2 Analysis of Experimental Results

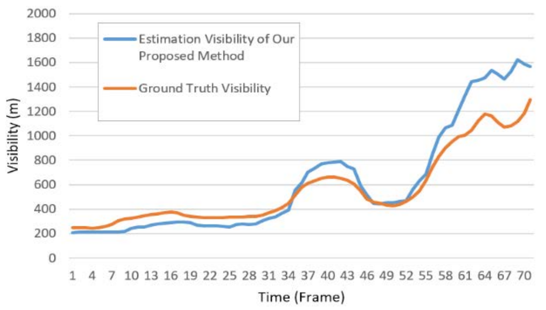
Mean absolute error (MAE) was adopted as the indicator for model evaluation in this study. It was calculated by Equation 6,

$$E_{MAE} = \frac{1}{n}\sum_{i=1}^{n}|v_E - v_R|, \tag{6}$$

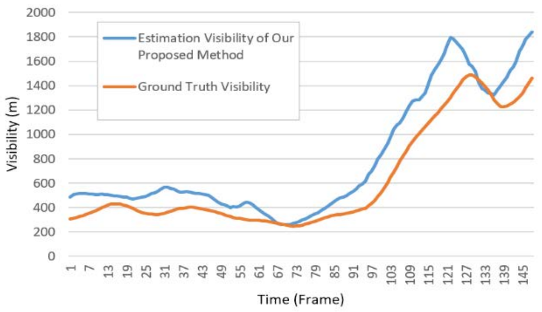
where v_E, v_R, and n are denoted as the estimated visibility, ground truth and the number of samples, respectively. The E_{MAE} refers to the absolute value of the difference between the estimated and ground truth visibilities. Smaller MAE indicates better model performance with the dataset. Meanwhile, the ground truth was collected from the official visibility data released by meteorological department.

According to the experimental data, MAE of the detection model in Test Dataset 1 is 197.38 m, and in Test Dataset 2

180.28 m. Figure 6 shows the comparison between the detected visibility variation curves, which were generated by the detection model with Test Dataset 1 as well as Test Dataset 2, and the respective ground truth visibility variation curves. It can be noticed that the variation trends of detected visibilities agree with the actual counterparts. It demonstrates the effectiveness of our proposed algorithm for visibility evaluating in different scenes.



(a) Test Set 1



(b) Test Set 2

Figure 6. Performance of the proposed method with the dataset

5 Visibility Measuring System Design

To apply the visibility measurement method to actual production, we have implemented a corresponding system called the daytime visibility measuring system. The system consists of image collection, visibility detection, and visibility data visualization. The architecture is as shown in Figure 7.

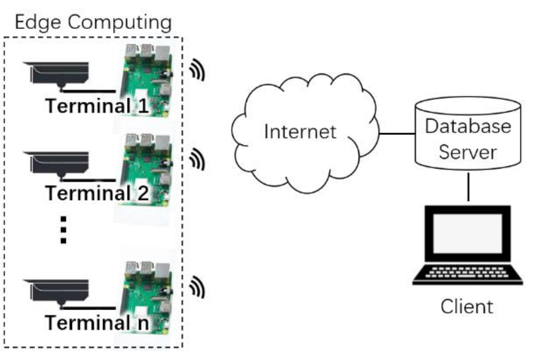


Figure 7. Daytime visibility measuring system architecture

Concepts from edge computing were adopted for the architecture design, as data collection and data processing functions were incorporated into front-end sensing devices. The edge computing system can be divided into the main control module and the camera module, whereas the server system can be divided into the database server module and remote client module.

5.1 The Edge Computing System

The front-end equipment primarily functions as visibility estimation and feeding the results back to the servers for storage, as well as retrieving data from the database server in subsequent processing. Contrary to the conventional direct scene image transmission and centralized server processing, this method can reduce the amount of data for network transmission, relieve data processing workload for the server, and improve system stability. In this proposed system, Raspberry Pi 3B+ was selected as the main control module (4 cores ARM Cortex-A53 CPU, 1.4GHz, 64-bit) of the front-end computing equipment, featuring dual-frequency WLAN, extension slot, and Linux operation system. Raspberry Pi is affordable and small in size, making it suitable for large-scale deployment of visibility detection terminals, on top of being able to fulfill the visibility system design requirements for data acquisition and analysis.

The terminal modules can acquire the scene image data after being connected to the cameras through specialized ports. The system captures images in real-time, as well as carries out preprocessing and extraction of dark channel images every 6 seconds using OpenCV library functions. Then, based on the PyTorch framework, the data are entered into the trained network to obtain the visibility value of the current scene. In the end, via the socket communication module, the detected data are sent to the database server for storage.

5.2 The Database Server

The server-end database stores the visibility data fed back from the front-end equipment. The system database was designed in accordance with the structure in Table 3 and Table 4, allowing it to store visibility data and information from the front-end equipment.

Table 3. The database table for visibility scale

Field Name	Data Type	Description
ID	Int	Primary key.
MAC	String	MAC address of hardware equipment, the unique identifier of equipment.
Visibility	Double	Predicted visibility value, up to two decimal places.
Time	Time	The corresponding time of predicted visibility value.

Table 4. The database table for equipment

Field Name	Data Type	Description
MAC	String	Primary key, MAC address of hardware equipment, the unique identifier of equipment.
IP	String	IP address, address of the equipment.
Name	String	Equipment name, record of the corresponding captured scene.

5.3 The Remote Client

The remote client consists of an equipment management module and a visibility display module. The software interface is as shown in Figure 8.

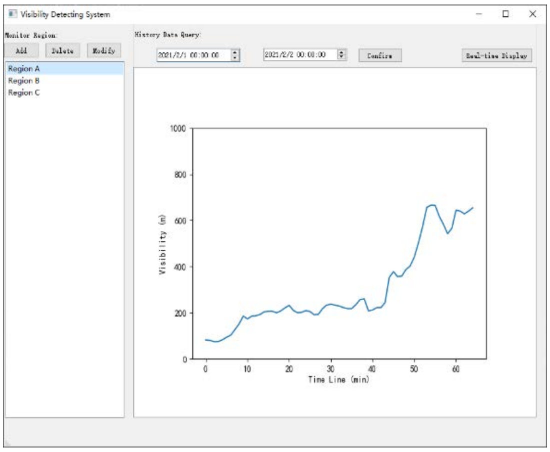


Figure 8. The software interface of the remote client

The equipment management module supports equipment append, equipment information modification, and equipment removal functions. The visibility display module can restore past visibility data or real-time estimation result of the scene in selected region, and give the users a data visualization result.

6 Conclusions and Future Works

Based on the dark channel prior theory and the principle of visibility detection, a method for daytime visibility measurement was proposed with analysis of dark channel images and visibility values in foggy scenes. The proposed method was tested with the dataset featuring two scenes to verify its effectiveness. Following that, an automatic visibility measurement system integrating data acquisition, visibility evaluation, data presentation, etc. was established, facilitating actual applications in visibility detection. Future works and designs will focus on two aspects: first, dividing the scene image into multiple sub-regions, followed by refining the area analyses to improve the accuracy; second, probing deeper into how the variation of illumination affects the results of visibility estimation.

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