Development of Image Quality Assessment (IQA) For Haze Prediction

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Abstract

Haze is a term that is widely used in image processing to refer to natural and human activity-emitted aerosols. It causes light scattering and absorption, which reduce the visibility of captured images. This reduction hinders the proper operation of many photographic and computer vision applications, such as object recognition/localization. Therefore, an approach for haze density estimation is highly demanded. This paper proposes a model that is known as the haziness degree evaluator to predict haze density from a single image without reference to a corresponding haze-free image. The proposed model quantifies haze density by optimizing an objective function comprising haze-relevant features that result from correlation and computation analysis.

Keywords: Haze, Image Quality Assessment (IQA), Hazy Images, Haze Density

1. Introduction

Haze is traditionally an atmospheric phenomenon in which dust, smoke, and other dry particulates obscure the clarity of the sky. Haze particles can sometimes affect the heart and lungs, especially in people who already have chronic heart or lung disease e.g., asthma, Chronic Obstructive Pulmonary Disease (COPD), or heart failure. There may be up to one to three days of time between exposure to haze and health effects or symptoms[1]. Haze density (or usually referred to as see through quality) is measured with a narrow angle scattering test in which light is diffused in a small range with high concentration. This test measures the clarity with which finer details can be seen through the object being tested. This is the method currently used by most of the industry to measure haze, the main apparatus used are ASTM E430, ASTM D4039, ISO 13803 these are shaped like microscope and can identify the haze density[2]. Most of the times photos taken outdoors are often degraded by haze, an atmospheric phenomenon produced by small floating particles which absorbs and scatter light from its multiple direction. Haze influences the visibility of the picture as it generates loss of contrast of the distant object in the image[3]. In computer vision applications, dehazing is applied to enhance the visibility of outdoor images by reducing the undesirable effects due to scattering and absorption caused by atmospheric particles. Dehazing is needed for human activities and in many algorithms like objects recognition, objects tracking, remote sensing and sometimes in computational photography. In bad visibility environments, such applications require dehazed images for a proper performance[3]. Therefore, studies have been conducted to remove haze and then improve the quality of degraded images[3]. In addition, a quality scale is an important indicator of the degrees of degradation and improvement. Image Quality Assessment (IQA) is well known in the scope of image processing. The IQA is classified into two methods, namely, subjective and objective methods[4]. The subjective method is used to obtain human's perception on the image quality[5]. This method simulates the perception technique of a people, a visual system to estimate it. Then, their perception is converted in the form of Mean Opinion Score (MOS) which were used to model the objective method which is the proposed IQA metric.

2. Methods

This paper proposed a model that is known as the haziness degree evaluator to predict haze density from a single image without reference to a corresponding haze-free image. The proposed model quantifies haze density by optimizing an objective function comprising haze-relevant features that result from correlation and computation analysis. First the mean of score (MOS)[4] was obtained for the hazy images from twenty (20) human subjects, then the MOS values will be validated by comparing them IQA metrics such as Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE)[7], Naturalness Image Quality Evaluator (NIQE)[8], Structural Similarity Index (SSIM)[9], Feature Similarity (FSIM)[10], Gradient Magnitude Similarity Deviation (GMSD)[11]. Next, gaussian features were extracted from the hazy images. Then, these features together with the validated MOS were fed into the Support Vector Machine (SVM) Regression (SVR) model to train the machine to map the features with the MOS where an optimized model will be obtained. The optimized model was then used to predict the quality score of the test hazy images. Then, the quality scores were used to predict the haze density on the images.

Firstly, the Mean Subtracted Contrast Normalized (MSCN) of the hazy images were calculated[6]. Then, two types of Gaussian distribution functions were incorporated in this study to accommodate the diverse characteristics of MSCN coefficient, namely the Generalized Gaussian Distribution (GGD) and Asymmetric Generalized Gaussian Distribution (AGGD)[5]. The GGD, where α represents the shape of the distribution and σ^2 represents the variance and AGGD parameters were calculated using the Eqs. (1) – (3):

$$GGD(x;\alpha,\sigma^2) = \frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)} \exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \tag{1}$$

Where x represents the MSCN and

$$\beta = \sigma\sqrt{\frac{\Gamma\left(\frac{1}{\alpha}\right)}{\Gamma\left(\frac{3}{\alpha}\right)}} \tag{2}$$

$$\Gamma(a) = \int_0^{\infty} t^{a-1}\, e^{-t}\, dt, a > 0 \tag{3}$$

The AGGD, AGGD, namely v, which represents the shape of the distribution, σ_l^2 and σ_r^2 which represent the left and right-scale parameters, respectively, and η which represents the mean of the distribution. using the Eqs. (4) – (7):

$$AGGD(x;v,\sigma_l^2,\sigma_r^2,\eta) = \begin{cases} \frac{v}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\frac{-x}{\beta_l}\right)^{v}\right) & x < 0 \\ \frac{v}{(\beta_l+\beta_r)\Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\frac{x}{\beta_r}\right)^{v}\right) & x \geq 0 \end{cases} \tag{4}$$

Where x is the MSCN calculate at four neighborhood pixels and

$$\beta_l = \sigma_l\sqrt{\frac{\Gamma\left(\frac{1}{v}\right)}{\Gamma\left(\frac{3}{v}\right)}} \tag{5}$$

$$\beta_r = \sigma_r\sqrt{\frac{\Gamma\left(\frac{1}{v}\right)}{\Gamma\left(\frac{3}{v}\right)}} \tag{6}$$

$$\eta = (\beta_r - \beta_l)\frac{\Gamma\left(\frac{2}{v}\right)}{\Gamma\left(\frac{1}{v}\right)} \tag{7}$$

The flowchart of the proposed haze prediction system is shown in Fig.1

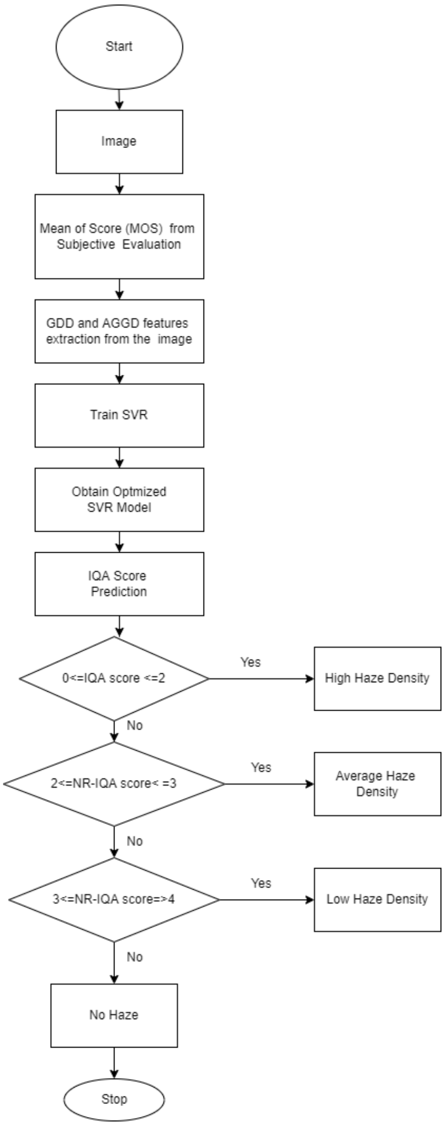

Fig.1.Flowchart of the system

3. Results and Discussion

3.1. *Validation of MOS*

The MOS values obtained from the twenty human subjects were validated by using well-established IQA metrics, namely NIQE, BRISQUE, SSIM, FSIM and GMSD. The correlation between the MOS and these IQAs were calculated using Pearson's Linear Correlation Coefficient (PLCC). The PLCC values between MOS and IQAs are shown in Table 1.

Table 1. PLCC between MOS and NIQE, BRISQUE, SSIM, FSIM and GMSD

FR-IQAs	NIQE	BRISQUE	SSIM	FSIM	GMSD
PLCC	0.819	0.895	0.832	0.788	0.900

According to Taylor R. (Taylor, 1990), two datasets are said to have high correlation if the correlation coefficient values are between 0.68 to 1.0[5]. Since all the PLCC values are more than 0.68, this shows that the MOS values that were obtained from the subjective evaluation is valid and can be used to train SVR.

3.2. *Performance of the Proposed System*

The performance of the proposed system using the PLCC between the MOS, NIQE, BRISQUE, SSIM, FSIM, GMSD and the proposed IQA metrics as shown in Table 2. Based on Table 2, the proposed IQA metric recorded the highest PLCC value compared to the other IQA metrics such as BRISQUE, NIQE, SSIM, GMSD and FSIM. Hence, the proposed IQA metric is the most suitable metric to evaluate hazy images as it is very close to the MOS values.

Table 2. PLCC between MOS and NIQE, BRISQUE, SSIM, FSIM, GMSD and proposed IQA.

IQA	NIQE	BRISQUE	SSIM	FSIM	GMSD	Proposed IQA
PLCC	0.819	0.895	0.832	0.788	0.900	**0.970**

4. Conclusion

In this paper, an IQA has been developed to detect the haze density automatically from an image. The proposed system is beneficial and cost efficient where sensors are not required to detect the haze density. Furthermore, this system is capable to detect the haze density without the need of a reference images.

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