SUGISAKA MASANORI

Journal of Advances in Artificial Life Robotics
Vol. 4(1); June (2023), pp. 55–58
ON LINE ISSN 2435-8061; ISSN-L 2435-8061
https://alife-robotics.org/jallr.html

Research Article

Haze Predication Based on Image Quality Score

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ARTICLE INFO

Article History

Received 06 August 2022
Accepted 08 September 2023

Keywords

Haze
Image quality assessment (IQA)
Image quality score
Haze prediction

ABSTRACT

Haze is a prevalent term within the field of image processing, encompassing both naturally occurring phenomena and aerosols generated by human activities. It gives rise to light scattering and absorption, leading to reduced image visibility. This diminished clarity poses challenges for various photographic and computer vision applications, including object recognition and localization. Consequently, there is a growing need for a method to estimate haze density accurately. In this research paper, we introduce a novel model called the "haziness degree evaluator." This model enables the prediction of haze density from a single image, eliminating the necessity for a reference haze-free image. The proposed model quantifies haze density through the optimization of an objective function that encompasses haze-related features derived from correlation and computational analysis.

1. Introduction

Haze is a well-known atmospheric occurrence characterized by the presence of dust, smoke, and various dry particulates that obscure the clarity of the sky. Haze particles, in certain cases, can have adverse effects on the cardiovascular and respiratory systems, particularly in individuals already dealing with chronic heart or lung conditions such as asthma, Chronic Obstructive Pulmonary Disease (COPD), or heart failure. Health effects or symptoms following exposure to haze may manifest with a delay of one to three days [1]. The density of haze, often referred to as "see-through quality," is conventionally assessed using a narrow-angle scattering test. In this test, light is diffused within a limited angle range with high concentration to gauge the degree of clarity through the subject under examination. This method, widely adopted across industries, employs specialized apparatus like ASTM E430, ASTM D4039, and ISO 13803, resembling microscopes, to quantify haze density [2]. Outdoor photographs are frequently marred by haze, an atmospheric phenomenon generated by minute airborne particles that both absorb and scatter light in various directions. Haze has a detrimental impact on image visibility, particularly evident in the loss of contrast for distant objects within the image [3]. In the realm of computer vision applications, dehazing techniques are employed to enhance the visibility of outdoor images by mitigating the undesirable effects resulting from light scattering and absorption due to atmospheric particles. Dehazing is indispensable for an array of human activities and numerous algorithms, including object recognition, object tracking, remote sensing, and sometimes computational photography. In scenarios characterized by poor visibility, such applications necessitate dehazed images to achieve optimal performance. Consequently, research endeavors have focused on haze removal to enhance the quality of degraded images [3]. Furthermore, the assessment of image quality serves as a pivotal gauge for determining the extent of degradation and

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improvement. Image Quality Assessment (IQA) is a well-established domain within the field of image processing, categorized into two primary methods: subjective and objective. The subjective method seeks to capture human perception of image quality, simulating the perceptual processes of the human visual system to estimate it. The outcomes of this method are translated into Mean Opinion Scores (MOS), which are subsequently employed to formulate the objective method, namely, the proposed IQA metric [4], [5].

2. Methodology

This paper introduces a model known as the "haziness degree evaluator," designed to predict haze density from a single image without the need for a corresponding haze-free reference image. The proposed model quantifies haze density through the optimization of an objective function that incorporates relevant haze-related features derived from correlation and computational analysis. To validate the model's accuracy, the Mean Opinion Score (MOS) was initially obtained from twenty human subjects for hazy images [4]. These MOS values were subsequently compared to various Image Quality Assessment (IQA) metrics, including Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) [7], Naturalness Image Quality Evaluator (NIQE) [8], Structural Similarity Index (SSIM) [9], Feature Similarity (FSIM) [10], and Gradient Magnitude Similarity Deviation (GMSD) [11]. Next, Gaussian features were extracted from the hazy images, and in conjunction with the validated MOS values, they were input into a Support Vector Machine (SVM) Regression (SVR) model. The purpose was to train the machine to establish a mapping between these features and the MOS values, ultimately yielding an optimized model. This optimized model was then employed to predict the quality scores for test hazy images, which, in turn, were used to predict haze density within the images.

The computation process began with the calculation of the Mean Subtracted Contrast Normalized (MSCN) for the hazy images [6]. Two distinct types of Gaussian distribution functions, the Generalized Gaussian Distribution (GGD) and Asymmetric Generalized Gaussian Distribution (AGGD), were incorporated into this study to account for the varied characteristics of the MSCN coefficients [5]. The GGD, characterized by parameters α (representing the distribution's shape) and σ^2 (representing the variance), along with AGGD parameters, were calculated Eqs. (1), (2), (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 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), (5), (6), (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

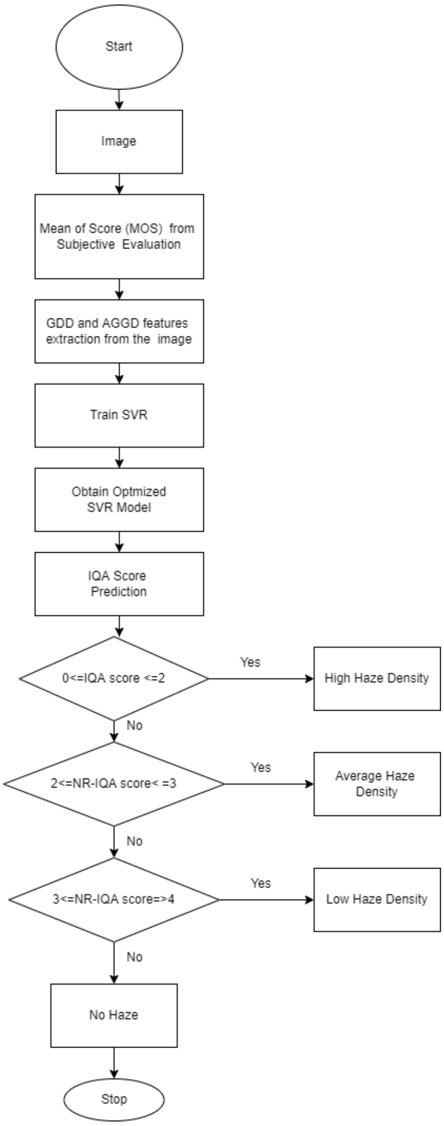

Fig.1.Flowchart of the system

3. Findings

3.1. *Validation of MOS*

The Mean Opinion Score (MOS) values gathered from the assessment of twenty human subjects were subjected to validation using established Image Quality Assessment (IQA) metrics, specifically NIQE, BRISQUE, SSIM, FSIM, and GMSD. The degree of correlation between the MOS and these IQAs was determined through the calculation of Pearson's Linear Correlation Coefficient (PLCC). The resulting PLCC values for the correlation between MOS and IQAs are presented 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

In line with Taylor's findings (Taylor, 1990), a high correlation between two datasets is typically indicated when the correlation coefficient values fall within the range of 0.68 to 1.0 [5]. Given that all the calculated PLCC values surpass the threshold of 0.68, it demonstrates the validity of the MOS values obtained from the subjective evaluation. Consequently, these MOS values can be considered reliable and suitable for training the Support Vector Regression (SVR) model.

3.2. *Performance of the Proposed System*

The effectiveness of the proposed system was assessed by evaluating the Pearson's Linear Correlation Coefficient (PLCC) between the MOS and various IQA metrics, including NIQE, BRISQUE, SSIM, FSIM, GMSD, and the newly proposed IQA metrics, as outlined in Table 2. According to the data presented in Table 2, the newly proposed IQA metric outperformed the other IQA metrics, namely BRISQUE, NIQE, SSIM, GMSD, and FSIM, by achieving the highest PLCC value. This outcome underscores the superiority of the proposed IQA metric in evaluating hazy images, as it closely aligns with 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

The primary focus of this paper is the development of an IQA system tailored for the automated assessment of haze density within images. This system represents an efficient and economical solution compared to traditional methods that involve the use of specialized sensors for haze detection. By sidestepping the requirement for such sensors, this approach not only reduces costs but also simplifies the deployment of the system, making it accessible in various practical scenarios.
Moreover, the distinguishing feature of this IQA system lies in its ability to determine haze density autonomously,

without the necessity of having reference images for comparison. Many existing methods rely on comparing hazy images with their haze-free counterparts to estimate haze density. However, this newly proposed system breaks free from this dependency, making it versatile and suitable for situations where reference images may not be available or practical to use. This attribute enhances the system's applicability and robustness in real-world applications where accurate haze density assessment is crucial.

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