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Fog Detection through Image Processing Methods

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Abstract

This paper presents a fog detection algorithm, highlighting the significance of continued exploration in fog identification through image processing techniques. The advancement and application of this algorithm can significantly benefit various domains, including road safety, environmental monitoring, navigation, security, surveillance, and improving existing systems' performance. The evaluation performed on test images have shown an accuracy of 72%, a precision of 94%, a recall of 57% and an F1 score of 0.71. The proposed algorithm clearly outperformed some existing fog detection methods.

Keywords: image processing, computer vision, fog detection, fog density, visibility

1 Introduction

High image quality can be important in some computer vision methods, specific image restoration like denoising (see [1], [2] and [3]) or inpainting (see [4]) being helpful. Defogging is another image enhancement technique, whose first step is fog detection. Within the intricate landscape of transportation, adverse weather conditions such as fog, rain or snow pose formidable challenges, significantly impacting safety and efficiency. This article addresses these challenges, focusing specifically on the development of a fog detection algorithm grounded in the domain of image processing.

The unpredictability and severity of reduced visibility have long been a pressing concern for drivers, autonomous vehicles and traffic control systems. These natural phenomena not only obscure the visual landscape but also necessitate critical adjustments in speed and navigation. The degradation of contrast and color quality under foggy conditions further increases the risks associated with road transportation, emphasizing the need for a robust solution.

In response to these challenges, this article unveils a comprehensive algorithm designed to detect the adverse effects of fog. Leveraging image processing methods, this approach aims to identify the presence of fog in visual data and subsequently apply corrective measures. The implications of this work extend across various transportation sectors, offering potential enhancements in safety and operational efficacy. From its potential applications in autonomous vehicles to its integration within traffic control systems, this fog detection algorithm represents an advancement toward ensuring safer, more efficient travel in adverse weather conditions

The rest of this paper is organised as follows: Section 2 reviews the related work in fog detection, Section 3 presents the proposed fog detection algorithm, Section 4 discusses the experimental results, whereas Section 5 concludes the paper and establishes some further work directions.

2 Related work

This section concentrates on reviewing and analysing the diverse array of image processing techniques employed in fog detection systems. These methods aim to discern, quantify, and mitigate the impact of fog on visual data, thereby enhancing visibility and safety in various transportation domains. By examining the nuances and efficacy of these image processing approaches, this review aims to provide a comprehensive understanding and potential directions for advancing fog detection algorithms within the domain of image processing. A review of the solutions related to visibility enhancement and fog detection has been presented in [5].

The effects of a foggy environment on light are described by Dumont in [6]. In fog, visible light (with wavelengths from 380 up to 780 nanometers) passing through an aerosol containing a high quantity of water particles becomes dispersed. Along its path, the light beam from headlights is attenuated due to the dual phenomenon of absorption and diffusion, which characterize the fog based on an extinction coefficient K [m^{-1}] (the sum of the diffusion and absorption coefficients). However, in reality, the absorption is negligible, so diffusion remains predominant, causing light to deviate from its initial direction.

Koschmieder's law [7], formulated in 1924, defines how light diminishes through fog as distance or fog particle concentration increases. This law establishes an exponential relationship between light transmission and distance travelled within foggy conditions, where visibility decreases exponentially with increasing fog density or the distance through the fog. It highlights the attenuation of light due to scattering and absorption by fog particles, which is crucial knowledge for designing image processing algorithms aimed at detecting and quantifying fog in visual data.

Initially, the proposed algorithms used multiple images to gather the necessary information, thus forming an image unaffected by fog. The major drawback of this implementation is its dependency on weather conditions and limitations posed on using these systems in real-time scenarios. Polarization-based methods as described by Schechner and Narasimhan in [8] utilize two or more images captured with varying polarization degrees.

Pagani et al. presented an innovative work in [9], with a focus on leveraging neural networks for the automatic detection of fog in surveillance camera images. The study explored the application of advanced machine learning techniques to enhance fog detection capabilities, aiming to address challenges associated with adverse weather conditions in surveillance systems. Their work significantly contributed to the field by demonstrating the potential of neural networks in effectively identifying foggy conditions, thereby enhancing the reliability and efficiency of surveillance systems in varying weather environments.

The study of Liu et al. [10], delved into driving obstacle detection technology specifically designed for foggy weather conditions. The research proposed the utilization of GCANet (Generative Contextual Attention Network) along with feature fusion training methodologies. This approach aimed to improve obstacle detection in challenging foggy environments, addressing safety concerns in driving scenarios affected by reduced visibility due to fog. Their work contributes to advancing obstacle detection systems by integrating innovative neural network architectures and feature fusion techniques to enhance performance and safety in foggy weather conditions.

Guo et al. introduced in [11] a novel haze image classification technique using the AlexNet network transfer model. Their study aimed to tackle the classification of haze images by leveraging transfer learning using the AlexNet neural network architecture. This approach sought to improve the classification accuracy of hazy images, addressing challenges related to haze distortion and visibility issues. By applying transfer learning techniques, the authors explored the adaptation of a pre-trained AlexNet model to effectively classify haze images, offering potential advancements in image classification methodologies in the context of varying atmospheric conditions. Their work contributes to enhancing image classification accuracy, particularly in scenarios affected by haze or atmospheric distortions.

Focusing on image processing techniques, the last decade has seen the development of computer vision methods to detect fog in images using various features such as color, texture, and contrast. However, these methods often face accuracy limitations due to variations in illumination and weather conditions. One initial approach to detect fog presence in an image, utilized in the algorithm to be presented in Section 3, involves analysing the brightness level within an image's environment. This process entails evaluating the overall luminance level within the scene depicted in the image, as described in [12] and [13]. In [14], Bronte et al. discuss the application of the Sobel operator for fog detection. The Sobel operator is used for edge or gradient detection in images. By evaluating the intensity gradient in various directions within an image, it highlights areas with abrupt changes in intensity, which can be useful in identifying regions affected by fog. As described by Bronte et al., foggy images have lower contrast and are blurrier than clear images. This means that, in foggy images, information in the higher frequencies is lower.

The algorithm described in this work is an amalgamation that draws from the distinctive, yet complementary methodologies discussed earlier. It intricately intertwines the concepts and practices derived from the evaluation of overall scene luminance, as presented in [12] and [13], with the fundamental principles intrinsic to edge and gradient detection techniques employed through the Sobel operator explained by Bronte et al. in [14].

By blending these different methods together, the goal of our proposed algorithm is to overcome the weakness of using only one method. The objective is to create a fog detection system that is detailed and flexible, not just solving the problems of each method alone, but also able to work well in various weather and lighting situations, while also being lightweight and easy to expand on.

3 Fog detection algorithm

The images obtained through analog or digital cameras can create the illusion of fog presence due to various reasons, including camera settings and influence from light sources. For instance, prolonged exposure might accumulate more noisy pixels, resulting in a blurry image. Additionally, ISO sensitivity can impact the noise level, leading to reduced quality. Exposure time also plays a significant role in creating the illusion of fog, as object or camera movements can cause a blurred effect. Moreover, the light sources within the scene can significantly impact the images. Strong light can reflect off objects in front of the camera, creating the appearance of fog, while intense shadows from strong light can further enhance this effect. Similarly, weak light can equally influence the image, resulting in a dark and blurry picture that might be mistaken for a fog effect.

The presented method for fog detection is designed to consider these influences, aiming to offer precise detection of the fog effect in the input image. A workflow of this method can be observed in Fig. 1, providing a detailed breakdown of each step necessary to determine if an input image is genuinely affected by fog.

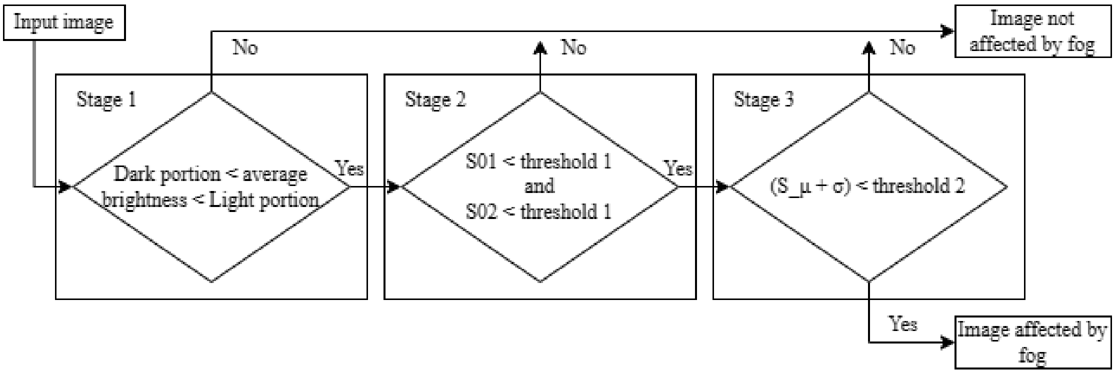

Figure 1. The workflow of the fog detection algorithm

Before applying the algorithm to the image, some specific preprocessing steps are essential for ensuring accurate detection. One of these steps involves converting the color image into a grayscale image, facilitating better detection of pixel intensity differences. In color images, colors can influence the visual perception of fog, potentially leading to inaccurate detection. Additionally, this conversion reduces the information load required for processing, potentially improving performance. Another preprocessing step involves calculating the image histogram. The histogram aids in assessing the distribution of pixels based on their intensity. In foggy images, a majority of pixels are expected to have a low intensity. Analysing the histogram provides insights into the brightness level of the image, crucial information influencing the decisions of the algorithm.

The first stage of the algorithm involves analysing the average brightness of the input image. As the average brightness of images produced in foggy conditions varies within certain limits, this analysis proves useful in determining whether an image is affected by fog. Typically, the average brightness of fog-affected images falls within a grayscale level ranging between 100 and 160, with histogram variations usually between 30 and 220. Based on this analysis, a condition is derived requiring the input image to possess an average brightness within a predefined range. Further analysis of the image's brightness reveals that the image histogram can be utilized to determine the distribution of grayscale levels from dark to light as seen below.

The second stage involves applying the Sobel operator to the input image, aiming to extract distinctive features of objects and structures present in the image, even in foggy conditions. This operator is commonly used in object recognition and scene analysis applications. In fog detection, this step is crucial to highlight edges and outlines of objects or structures visible despite foggy conditions. The detection algorithm utilizes the edge gradient changes from the Sobel image to analyse differences between fog-affected and unaffected images. During this process, grayscale levels of edge pixels typically range between 250 and 255 on the histogram distribution. Analysing the probability density function, an increase in the average number of pixels with grayscale levels between 250 and 255 indicates the image is not affected by fog, whereas a decrease in this number suggests the opposite. Therefore, when the number of pixels within this range surpasses a certain threshold, the image is considered unaffected by fog. Conversely, when the number falls below the threshold, it indicates the image is affected by fog. Due to varying image size, normalization is necessary to ensure accurate comparison. The normalization applied by the Sobel algorithm ensures that the number of pixels contributing to detecting fog in an image is not influenced by its size. For instance, a larger image may have a higher number of fog-affected pixels, but this absolute value may be comparable to a smaller image with fewer fog-affected pixels. Normalization compares the proportions of fog-affected pixels in each image, resulting in a more objective and precise comparison. Additionally, normalization can help reduce uneven brightness effects or contrast differences that may appear in different images, potentially leading to false positives.

The third and final stage of the fog detection algorithm in an image involves analysing the standard deviation and mean of the pixels obtained from the Sobel-processed image in the previous stage. These measures provide significant information about the intensity of edges in the image, which can be utilized to evaluate the presence or absence of fog. In foggy environments, images often exhibit reduced visibility, with details hard to discern, resulting in a blurry and unclear appearance. From an image processing standpoint, a fog-affected image appears smoother and more uniform, with minimal variation in pixel intensity. Conversely, a clear image is characterized by numerous details, intricate textures, and significant pixel intensity variations. Thus, determining if the image is affected by fog involves using the information acquired from the previous stage to calculate the pixel mean and standard deviation of the Sobel-processed image. Using the Sobel operator yields a pixel mean as per the equation:

$$S_{\mu} = \frac{\sum_{i=1}^{n*m} S_i}{n*m} \quad (1)$$

where S_{μ} represents the Sobel image's mean, S_i denotes each pixel of the Sobel image, and $n * m$ denotes the image size.

In fog-affected images, due to airborne particles, the image appears disrupted, and objects seem less defined, making edge highlighting by the Sobel operator more challenging. Comparing the gradient change of a Sobel image for a fog-free and fog-affected image reveals that for the latter, the change appears relatively disordered and diffuse, while for the fog-free image, the change is more evident and well-defined. This difference arises because fog-affected images' disturbances hinder edge detection.

The standard deviation measures the variation or dispersion of data concerning their mean. In image processing, the standard deviation indicates how much the pixel values in the image deviate from the image's mean. A higher standard deviation implies greater variation in pixel values around the mean, suggesting increased contrast. Conversely, a lower standard deviation indicates minimal variation in pixel values concerning the image's mean, suggesting reduced contrast.

$$\mu = \frac{\sum_{i=1}^{n*m} P_i}{n*m} \quad (2)$$

The following equation can be used to calculate the mean μ, where P_i represents a pixel of the original image, and $n * m$ denotes the image size. Using the mean μ, the subsequent equation can be employed to obtain the standard deviation.

4 Experimental results

This section thoroughly examines the performance of the proposed fog detection algorithm, showcasing its effectiveness in identifying fog in images. It presents and analyses results obtained from applying the algorithm to a diverse dataset of 462 images, capturing various scenarios of fog density and lighting conditions. These experiments evaluate the algorithm's accuracy across different settings. The computing system used for these evaluations comprises an Intel Core i5 processor (1.5 GHz, 16 GB RAM, and Intel Iris Xe Graphics). The hardware significantly influences the algorithm's processing speed and capacity. Results are system-specific, with potential variations in performance on other systems. A snapshot of these findings is outlined in Table 1, displaying selected images from the dataset and the algorithm's outcomes based on Sobel image mean, standard deviation, and average brightness levels.

Table 1. Experimental results for the fog detection algorithm

NAME	MEAN	DEVIATION	BRIGHTNESS	DETECTION
0001-0.jpg	60	85.6	126	CORRECT
0001-1.jpg	35	54.3	107.7	CORRECT
0001-2.jpg	38	59.8	123.9	WRONG
0002-0.jpg	32	47.8	108.9	CORRECT
0002-1.jpg	16	19.2	112.6	CORRECT
0002-2.jpg	17	19.4	114.5	CORRECT
0002-3.jpg	17	16.1	135.8	CORRECT
0002-4.jpg	14	13.7	120.8	CORRECT
0007-0.jpg	49	77.8	112.3	CORRECT
0007-1.jpg	31	58.5	109.4	CORRECT
0007-2.jpg	28	49.8	120.4	WRONG
0007-3.jpg	20	41	136.6	WRONG
0007-4.jpg	14	30.6	134.1	CORRECT
0011-0.jpg	46	76.2	152.5	CORRECT
0011-1.jpg	29	54.9	149.8	CORRECT
0011-2.jpg	15	31.4	141.6	WRONG
0011-3.jpg	8	13.8	142.7	CORRECT
0011-4.jpg	8	10.7	145.9	CORRECT
0012-0.jpg	89	116.3	137.2	CORRECT
0012-1.jpg	35	51.6	126.5	CORRECT

There are several evaluation metrics used to measure the accuracy of fog detection algorithms in images. Among the most critical metrics are the following: accuracy, precision, recall and F1 score. The accuracy determines the ratio of correct classifications to the total classifications made by the algorithm. For the presented algorithm in this work, the accuracy for the dataset used is approximately 72%. The precision reflects the proportion of correctly identified clear images among all images classified as clear. After applying the algorithm to the dataset, the precision is approximately 94%. The recall quantifies the algorithm's ability to correctly identify foggy images among all foggy images in the dataset. The algorithm's recall value for the dataset is approximately 57%. The F1 Score combines precision and recall to provide a balanced assessment of fog detection. The calculated F1 score for this algorithm is approximately 0.71, indicating its ability to distinguish between foggy and clear images.

Within the experiment, attention was also given to the execution time of the fog detection algorithm. For each processed image, the time interval required for the complete execution of the algorithm was measured. Assessing execution time is crucial to understand the efficiency and performance of the algorithm in handling a large volume of data. This evaluation provides relevant information about the algorithm's speed and effectiveness in practical applications, aiding in identifying potential weaknesses and subsequent optimizations. The execution time can directly impact user experience and the practical applicability of the algorithm in real-time scenarios or applications with strict time requirements.

The experimental results revealed that the algorithm's execution time can vary based on the input image's size and complexity. Images with higher resolution or complex characteristics may require more time to process compared to smaller or simpler images. Fig. 2 represents a valuable resource in understanding the relationship between image resolution and processing time. This information can be useful in taking decisions regarding image selection and the feasibility of the algorithm in different scenarios.

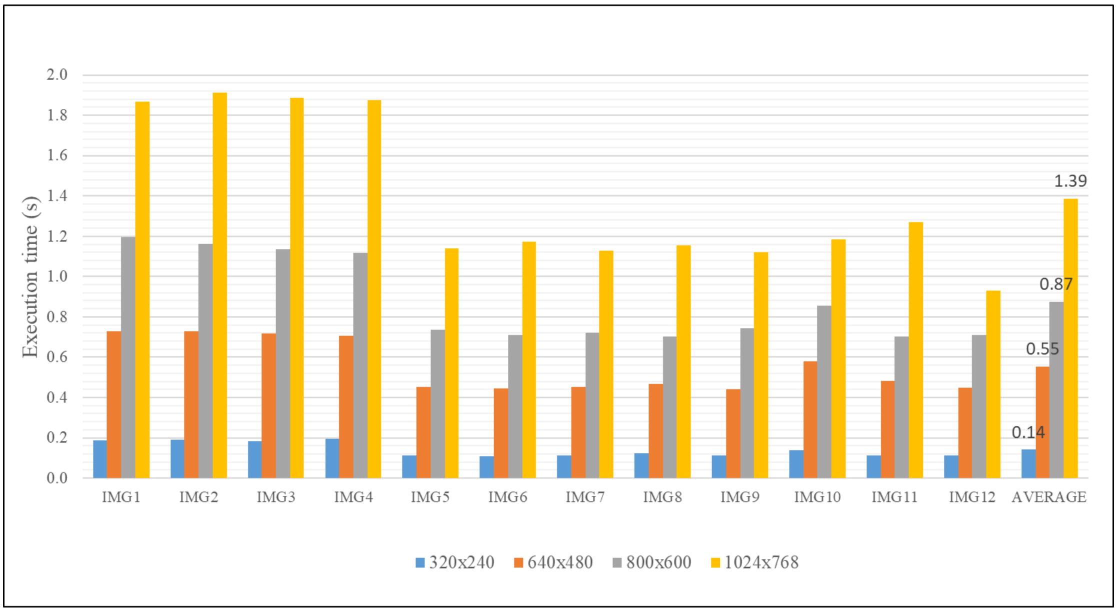

Figure 2. Execution time based on image resolution

Additionally, from the analysis depicted in Fig. 2 it can be inferred that the fog detection algorithm demonstrates significantly faster performance when applied to images with a resolution of 320×240 pixels, yielding consecutive and predictable results. As image resolution increases, execution time significantly extends and becomes less consistent in delivering results. Understanding the execution time associated with each image resolution allows for a quick evaluation of the algorithm's performance based on specific needs. For instance, in real-time applications where processing time is critical, opting for lower-resolution image captures or implementing image resizing techniques may be preferable. Conversely, if maximum accuracy in fog detection is required and processing time is not a major concern, higher-resolution images can be utilized, even though they require more execution time.

Comparative analysis of fog detection algorithms plays a pivotal role in understanding their strengths, weaknesses, and overall performance. As the field of fog detection continues to evolve, researchers and practitioners strive to develop robust and precise algorithms capable of efficiently detecting fog in images. Making informed decisions regarding the algorithm to use in a specific application or scenario necessitates a comparative analysis evaluating their performance based on well-defined criteria. Table 2 presents comparative results for the algorithm discussed alongside three other relevant algorithms. The table data reflect the relative performance of the algorithm discussed in this work compared to the three selected algorithms for analysis. These metrics provide insight into the effectiveness and reliability of each algorithm concerning fog detection in images.

Table 2. Metrics for various fog detection algorithms

Algorithm	Accuracy	Precision	Recall	F1 score
Proposed algorithm	72%	94%	57%	0.71
Deep Neural Network [9]	99%	60%	70%	0.65
GCANet	47%	62%	68%	0.64
Alexnet Network Transfer Model	67%	71%	67%	0.64

It is essential to note that these results are specific to the dataset and experimental conditions used in the studies from which they were obtained. The performance of the algorithms may vary depending on different datasets and configuration parameters.

Analyzing Table 2, the algorithm proposed in this paper demonstrates remarkable accuracy – the algorithm's capability to correctly classify images, and higher accuracy values indicate a greater ability to detect fog in images. In comparison with the algorithm proposed by Pagani and colleagues in [9], the proposed algorithm shows moderate accuracy but highlights significantly higher accuracy than the other two algorithms.

However, the experiment reveals that the proposed algorithm achieves high precision values. Precision refers to the correct proportion of positive detections relative to the total images classified as positive and is crucial in evaluating the algorithm's ability to avoid misclassifications. The proposed algorithm exhibits significantly higher precision compared to the other cited algorithms, indicating a superior ability to distinguish correctly between images with and without fog.

On the other hand, the analysis of the algorithm's sensitivity shows comparable results to the other algorithms. Sensitivity, also known as "recall" or the true positive rate, measures the algorithm's ability to detect all positive cases. Similar sensitivity outcomes indicate that the algorithm doesn't present significant advantages or disadvantages regarding the detection of positive fog instances compared to the other selected algorithms for the study.

The F1 score, an aggregated measure that combines precision and sensitivity, provides an overall perspective on the algorithm's performance in detecting positive fog instances. Evaluating the proposed algorithm in terms of F1 score indicates a favorable outcome, demonstrating its ability to achieve an optimal balance between correct fog detection and minimizing misclassifications.

The experimental results obtained in this study highlight the efficacy and performance of the proposed algorithm in fog detection in images. The analysis of evaluation metrics showcases the algorithm's proficiency in producing precise results while minimizing misclassifications. Comparing the algorithm with other existing approaches has demonstrated its consistency and reliability. Thus, the proposed algorithm represents an efficient and promising solution in fog detection in images, with potential applications across various previously discussed domains.

5 Conclusions and further work

In this work, fog detection in images was addressed using an image processing-based algorithm, a justified choice considering its adaptability and automation potential. The domain of image processing, focusing on visual information analysis and manipulation, is relevant due to the fog's impact on image visibility and quality.

Algorithms based on image processing techniques offer flexibility and adaptability, being customizable as per application-specific needs and can be integrated into existing systems, allowing efficient real-time fog detection or handling a large volume of images. The fog detection algorithm employed three conditions, each addressing distinct aspects of detection, resulting in a comprehensive and reliable fog detection system. These conditions analyze ambient luminosity, compute thresholds based on image characteristics, and consider Sobel image mean and standard deviation. Their integration enhances fog detection reliability and efficiency across various scenarios, contributing to a more robust fog detection algorithm. The proposed algorithm presented an accuracy of 72%, a precision of 94%, a recall of 57% and an F1 score of 0.71, clearly outperforming some existing fog detection methods.

Future developments aim to optimize the fog detection algorithm, especially in variable lighting conditions or when dealing with other atmospheric phenomena related to fog. Enhanced fog level estimation methods integrating factors like visibility distance and environmental properties are proposed. Furthermore, a fog removal algorithm utilizing machine learning and neural networks for a better understanding of fog in images could be explored. The adaptation of the algorithm for real-time video fog detection is also considered. These directions intend to achieve more precise and practical outcomes suitable for real-world applications.

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