# Enhancing the Quality of Fog/Mist Images by Comparing the Effectiveness of Kalman Filter and Adaptive Filter for Noise Reduction

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Abstract: The primary objective of this study is to enhance the precision of fog and mist noise reduction in photographs by introducing a novel Kalman filter and comparing its performance to that of an Adaptive filter. Materials and Methods: For this investigation, the research dataset was sourced from the Kaggle database system. Using twenty iteration samples (ten for Group 1 and ten for Group 2), involving a total of 1240 samples, the efficacy of fog and mist noise elimination with improved accuracy was assessed. This evaluation was conducted employing a G-power of 0.8, a 95% confidence interval, and alpha and beta values of 0.05 and 0.2, respectively. The determination of the sample size was based on the outcomes of these calculations. The novel Kalman filter and the Adaptive filter, both utilizing the same number of data samples (N=10), were employed for fog and mist noise removal from images. Notably, the Kalman filter exhibited a higher accuracy rate. Results: The novel Kalman filter showcased a success rate of 96.34%, outperforming the Adaptive filter's success rate of 93.78%. This difference in performance is statistically significant. The study's significance threshold was set at p=.001 ($p<0.05$), confirming the significance of the hypothesis. This analysis was carried out through an independent sample T-test. Conclusion: In conclusion, the proposed Kalman filter model, achieving an accuracy rate of 96.34%, demonstrates superior performance compared to the Adaptive filter, which yielded an accuracy rate of 93.78%. This comparison underscores the efficacy of the Kalman filter in the context of image noise removal.

## 1 INTRODUCTION

Especially in scenarios involving surveillance and monitoring applications, the presence of fog and mist can significantly degrade the visual quality of photographs, making them difficult to interpret (Redman et al. 2019). The conventional method of mitigating the impact of fog and mist noise in images entails using dehazing algorithms. These algorithms estimate the medium transmission map of the scene and then apply it to correct the attenuation caused by fog or mist (Zhang et al. 2012). However, while this approach can yield positive results in certain cases, it is not without limitations.

In response to this challenge, this paper introduces a novel approach for effectively eliminating fog and mist noise from images by leveraging the Kalman filter. Additionally, it compares this innovative approach with the use of Adaptive filter methods for addressing the same issue (Chen et al. 2019). The Kalman filter is a well-established technique used to determine the state of a dynamic system based on a set of noisy measurements. In the context of image processing, the Kalman filter proves to be a potent tool for fog noise removal. By harnessing both spatial and temporal information, it can accurately estimate the true state of an image, even amidst noise. Consequently, the Kalman filter can significantly enhance the accuracy and dependability of image analysis tasks conducted in environments plagued by fog.

The Kalman filter boasts a broad spectrum of applications across diverse fields such as tracking, navigation, control, communication, economics, medicine, and signal processing (Choi, You, and Bovik 2015; Arora, Singh, and Kaur 2014).

In recent years, a multitude of filtering-based approaches for mitigating image noise have been proposed in the literature (Z. Xu, Liu, and Chen 2009; Park and Lee 2008; Hiramatsu, Ogawa, and Haseyama 2009; Kapoor et al. 2019). This surge in



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research is reflected in the statistics, with 87 research papers published on IEEE Explore and 132 publications retrieved from Google Scholar, underscoring the significance of this area of study.

Several techniques have been put forth in the field of image noise reduction. One such technique involves utilizing a dark channel prior to fog removal in single images, which is based on the observation that fog-covered regions tend to exhibit diminished rates of light transmission (He, Sun, and Tang 2011). A comprehensive survey of diverse methods proposed for eliminating fog and haze from single images has been furnished (Ming, Lin-tao, and Zhong-hua 2016).

Furthermore, an approach for image dehazing has been proposed based on the observation that fog predictably attenuates the colour of objects. This method seeks to capitalize on this predictable behavior (Y. Xu et al. 2016). In the pursuit of enhancing dehazing precision, a technique leveraging multi-scale fusion for single image dehazing has been introduced (Dudhane, Aulakh, and Murala 2019).

A comprehensive overview of various methods employed for fog and haze removal from images is provided, encompassing an examination of their strengths and limitations (Ling et al. 2016). A succinct summary of deep learning-based approaches geared towards eliminating haze and fog from single images is offered, along with an exploration of their efficacy and shortcomings (Liu et al. 2019).

Furthermore, a technique for real-time fog removal from images is presented, which leverages graphics processing unit (GPU) acceleration for efficient processing (Song et al. 2015). Utilizing a multi-scale convolutional neural network (CNN), trained to identify features indicative of haze and fog, a technique for removing fog from single images is suggested (Dey et al. 2022) (Dewei et al. 2018).

One potential limitation associated with the use of adaptive filters for this task is their potential requirement for an extended training period to comprehend the distinct characteristics of noise within the image. This can be particularly challenging when dealing with non-stationary noise or noise that exhibits substantial variations over time. In order to address this challenge, this study introduces a novel approach utilizing the Kalman filter for image filtering, aimed at effectively eliminating fog and mist noise from images.

The proposed method offers a solution that is more resilient to the drawbacks commonly observed in conventional dehazing algorithms. Additionally, it excels in enhancing the visual quality of photographs that are adversely affected by fog and mist. The versatility of this method is evident in its applicability to various applications within the realms of image processing and computer vision.

# 2 MATERIALS AND METHODS

The research study was conducted at the Electronics Laboratory of the Electronics and Communication Engineering Department at Saveetha University. The study employed a dataset sourced from the Kaggle repository, consisting of color images. The dataset was partitioned into two distinct sets: 75% of the dataset was assigned for training purposes, while the remaining 25% was reserved for testing. In total, the study comprised twenty iterations of data samples. Each of these iterations included ten samples, leading to a cumulative sample size of 1240.

For Group 1, an adaptive filter method was employed, whereas for Group 2, a novel Kalman filter algorithm was developed. The evaluation and analysis of fog and mist noise were performed using the Matlab software. The determination of the sample size was influenced by prior research conducted by Kim, Ha, and Kwon (2018), as well as the clincalc.com resource. Parameters for the study were set as follows: a G power of 80%, a confidence interval of 95%, and a significance threshold of p=.001 ($p<0.05$).

**Adaptive Filter**

Adaptive filters are a type of signal processing algorithm that operates by continuously adjusting their transfer function in response to the noise characteristics present in an image. They serve as effective tools for noise reduction in photographs. A well-known approach for this purpose is the least mean squares (LMS) technique, which employs a gradient descent strategy. In designing an adaptive filter for noise elimination in images, the LMS algorithm is commonly employed.

The LMS algorithm operates by minimizing the mean squared error (MSE) between the intended signal (which in this context is the clear, noise-free image) and the output produced by the filter. This optimization process involves adjusting the filter coefficients iteratively to minimize the discrepancy between the filter's output and the desired signal. This adaptation is carried out at each time step, and it involves modifying the filter's coefficients based on the current error observed between the filter's output and the desired signal. This iterative adjustment mechanism helps the adaptive filter effectively remove noise and enhance the quality of the image.

The update equation for the filter coefficients in the LMS algorithm is given by:

$$w(k+1) = w(k) + 2mue(k) * x(k) \qquad (1)$$

where w(k) is the current filter coefficient vector, mu is the step size, e(k) is the current error between the output and the desired signal, and x(k) is the input signal (i.e., the noisy image). By continuously updating the filter coefficients based on the current error, the LMS algorithm is able to adapt to the characteristics of the noise in the image and remove it over time.

**Pseudocode for Adaptive Filter**

Step 1: Define the input image and the size of the filter.
Step 2: Initialize the output image with the same size as the input image.
Step 3: Set the filter coefficients to their initial values.
Step 4: Set the step size for the adaptation algorithm.
Step 5: Define the maximum number of iterations for the adaptation algorithm.
Step 6: For each pixel in the image:
· Apply the filter to the pixel and its neighbouring pixels.
· Calculate the error between the filtered value and the original value.
· Update the filter coefficients using the adaptation algorithm.
· Apply the updated filter to the pixel and its neighbouring pixels.
· Store the filtered value in the output image.
Step 7: Repeat step 6 for the specified number of iterations or until the filter coefficients converge.
Step 8: Apply a threshold to the output image to remove any remaining noise.
Step 9: Apply contrast enhancement to the output image to improve its visual quality.
Step 10: Display the original image, the noisy image, and the filtered image side by side.
Step 11: Calculate and display the peak signal-to-noise ratio (PSNR) and the mean square error (MSE) of the filtered image.
Step 12: Save the filtered image to a file for future use.

**Kalman Filter**

Fog is a form of atmospheric pollution characterized by minute water droplets suspended in the air. Its presence can lead to reduced visibility and glare, creating challenges for tasks in image processing, such as object recognition. One effective approach to mitigate this issue involves employing a Kalman filter to eliminate fog from images. The Kalman filter, a type of recursive algorithm, is employed to estimate the evolving state of a system over time, utilizing noisy measurements. In the realm of image processing, each pixel's intensity in an image mirrors the system's state, and the pixel values observed amid fog constitute the noisy measurements.

The Kalman filter operates through an iterative process that continually refines the estimation of genuine pixel intensities. This refinement is achieved by updating the estimate using observed values and a model of the underlying system. In essence, the Kalman filter serves as a powerful tool to iteratively enhance pixel intensities, thereby removing the effects of fog and restoring image clarity. This is done using the following equations:

State prediction:

$$\hat{x}(k-1) = A * \hat{x}(k-1) + B * u(k) \qquad (2)$$

Measurement prediction:

$$\hat{z}(k-1) = H * \hat{x}(k-1) \qquad (3)$$

Kalman gain:

$$K(k) = P(k-1) * H^T * (H * P(k-1) * H^T + R)^{-1} \qquad (4)$$

State estimate update:

$$\hat{x}(k) = \hat{x}(k-1) + K(k) * (z(k) - \hat{z}(k-1)) \qquad (5)$$

Covariance estimate update:

$$P(k) = (I - K(k) * H * P(k-1) \qquad (6)$$

In these equations, $\hat{x}(k)$ based on the measurements up to and including time k, is the projected state at time k, A is the state transition matrix, B is the control input matrix, u(k) is the control input at time k, H is the measurement matrix, and R is the measurement noise covariance matrix. P(k) is the estimate's covariance.

**Pseudocode for Kalman Filter**

Step 1: Initialize variables for the observed image, estimated image, and state variables
Step 2: Set up the measurement matrix and measurement noise covariance matrix
Step 3: Set up the state transition matrix and process noise covariance matrix
Step 4: Initialize the Kalman filter with the initial state variables and covariance matrix
Step 5: Loop through each pixel in the observed image
Step 6: Predict the state variables using the state transition matrix
Step 7: Predict the covariance matrix using the process noise covariance matrix
Step 8: Calculate the Kalman gain matrix using the measurement matrix, measurement noise covariance matrix, and predicted covariance matrix

Step 9: Calculate the innovation, which is the difference between the observed image pixel and the predicted image pixel
Step 10: Update the state variables using the Kalman gain matrix and innovation
Step 11: Update the covariance matrix using the Kalman gain matrix
Step 12: Calculate the estimated image pixel using the updated state variables
Step 13: Repeat steps 6-12 for each pixel in the observed image to obtain the estimated image
Step 14: End.

**Statistical Analysis**

The output generation was facilitated using Matlab software, as documented by Elhorst (2014). All experiments detailed within this study were executed on a Windows 10 computer boasting a 3.20 GHz Intel Core i5-8250U processor, alongside 8 GB of RAM. For the statistical analysis of the Kalman filter and Adaptive filter, SPSS software was harnessed, as outlined by Frey (2017). In this context, SPSS was employed to perform a statistical examination of the two filtering methods.

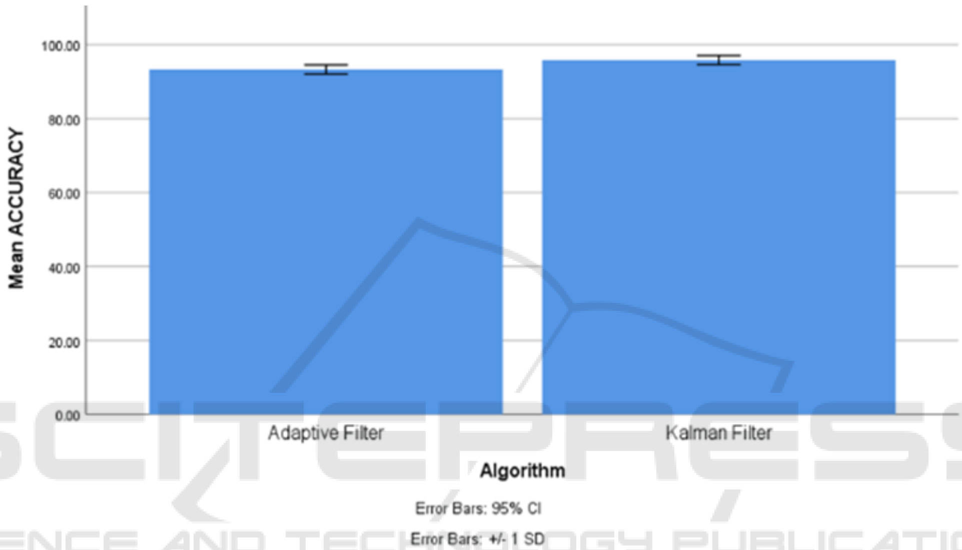




Figure 1: The accuracy of the Kalman filter has been compared to that of the Adaptive filter algorithm. The Kalman filter prediction model has a greater accuracy rate than the Adaptive filter model, which has a rate of 93.78. The Kalman filter method differs considerably from the Adaptive filter method (test of independent samples, $p=.001(p<0.05)$). The Kalman filter and Adaptive filter accuracy rates are shown along the X-axis. Y-axis: Mean keyword identification accuracy, $\pm 1$ SD, with a 95 percent confidence interval.

Table 1: The performance data of the comparison between the Kalman filter and Adaptive filter has been presented. The Kalman filter algorithm has an accuracy rate of 96.34, whereas the Adaptive filter algorithm has a rating of 93.78. The Kalman filter algorithm is more accurate than the Adaptive filter at removing Fog and Mist noise from images. Gabor filter at removing Fog and Mist noise from images.

| SI.No. | KALMAN FILTER (in %) | ADAPTIVE FILTER (in %) |
|---|---|---|
| 1. | 95.13 | 92.13 |
| 2. | 95.64 | 92.15 |
| 3. | 95.26 | 92.79 |
| 4. | 95.51 | 92.92 |
| 5. | 96.05 | 93.02 |
| 6. | 96.15 | 93.31 |
| 7. | 96.71 | 93.25 |
| 8. | 96.37 | 93.48 |
| 9. | 96.32 | 92.58 |
| 10. | 96.48 | 93.34 |

Within the purview of this study, means, standard deviations, and standard errors of means were calculated using SPSS. The tool was utilized for the execution of an independent sample t-test to compare the outcomes of the two distinct samples. Notably, accuracy served as the dependent variable within the study focusing on fog and mist noise removal, while the Kalman filter and Adaptive filter served as the independent variables of interest.

## 3 RESULTS

Figure 1 illustrates a comparison between the accuracy of the Kalman filter and the Adaptive filter method. The Kalman filter prediction model demonstrates a higher accuracy rate in contrast to the Adaptive filter model, which attains a rate of 93.78. A notable distinction between the Kalman filter and the Adaptive filter methods is evident (independent samples test, $p=.001 (p<0.05)$). The accuracy rates of both the Kalman filter and the Adaptive filter are presented on the X-axis, with the Y-axis depicting the mean accuracy of keyword identification along with a ±1 standard deviation range and a 95 percent confidence interval.

Table 1 encapsulates the performance metrics from the comparison between the Kalman filter and the Adaptive filter methods. The Kalman filter algorithm exhibits an accuracy rate of 96.34, whereas the Adaptive filter algorithm achieves a rate of 93.78. In the task of eliminating fog and mist noise from images, the Kalman filter method proves superior to the Adaptive filter.

The statistical computations, including mean, standard deviation, and mean standard error, for both the Kalman filter and the Adaptive filter methods are displayed in Table 2. The t-test is applied to the accuracy parameter. The proposed Kalman filter method demonstrates a mean accuracy of 96.34 percent, while the Adaptive filter classification algorithm achieves a mean accuracy of 93.78 percent.

Table 2: The statistical calculations for the Kalman filter and Adaptive filter algorithm, including mean, standard deviation, and mean standard error. The accuracy level parameter is utilized in the t-test. The proposed Kalman filter method has a mean accuracy of 96.34 percent, whereas the Adaptive filter classification algorithm has a mean accuracy of 93.78 percent. The proposed Kalman filter has a standard deviation of 0.6433, and the Adaptive filter algorithm has a value of 2.4363. The mean Kalman filter standard error is 0.1863, while the Adaptive filter method is 1.3522.

| | Group | N | Mean | Std. Deviation | Std.Error Mean |
|---|---|---|---|---|---|
| Accuracy | Adaptive filter | 20 | 93.78 | 2.4363 | 1.3522 |
| | Kalman filter | 20 | 96.34 | 0.6433 | 0.1863 |

Table 3: The statistical calculations for independent variables of Kalman filter in comparison with the Adaptive filter algorithm. The significance level for the rate of accuracy is 0.034. Using a 95% confidence interval and a significance threshold of 0.79117, the Kalman filter and Adaptive filter algorithms are compared using the independent samples T-test. The following measures of statistical significance are included in this test of independent samples: a p value of $p=.001 (p<0.05)$, significance, mean difference, standard error of mean difference, and lower and upper interval differences.

| Group | Levene's Test for Equality of Variances | | T-Test for Equality of Mean | | | | | 95% Confidence Interval of Difference | |
|---|---|---|---|---|---|---|---|---|---|
| Accuracy | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| Equal variances assumed | 1.017 | 0.034 | 12.902 | 38 | .001 | 9.72323 | 0.80342 | 8.78183 | 11.89182 |
| Equal variances not assumed | | | 12.087 | 37.520 | .001 | 9.70120 | 0.80342 | 8.56172 | 11.67182 |

The Kalman filter boasts a standard deviation of 0.6433, contrasting with the Adaptive filter algorithm's value of 2.4363. Furthermore, the mean standard error for the Kalman filter is calculated to be 0.1863, and for the Adaptive filter method, it is computed as 1.3522.

Table 3 provides a statistical examination of the independent variables associated with the Kalman filter in contrast to the adaptive filter method. The accuracy rate carries a significance level of 0.034. Employing an independent samples t-test, a comparison is conducted between the Kalman filter and Adaptive filter algorithms, adopting a 95% confidence interval and a significance threshold set at 0.79117. This test of independent samples encompasses a range of statistical significance indicators, encompassing significance itself, a p-value of $p=.001(p<0.05)$, the mean difference, standard error of the mean difference, along with lower and upper interval differences.

## 4 DISCUSSION

When comparing the Kalman filter and the conventional adaptive filter for fog noise removal in images, it's essential to consider the strengths and limitations inherent in each approach. The Kalman filter offers a significant advantage in its capacity to handle non-linear systems and dynamically adapt to changing conditions. This adaptability renders it well-suited for image processing tasks, where pixel relationships can be non-linear and noise characteristics may vary over time. Moreover, the Kalman filter derives its foundation from Bayesian probability theory, which establishes a robust mathematical basis for its operation.

On the other hand, the conventional adaptive filter is proficient in removing specific types of noise and can be trained to address noise in images with diverse characteristics. This attribute endows it with versatility, enabling its application in various scenarios. However, the adaptive filter's efficacy might diminish when faced with images possessing intricate structures, such as those with intricate details or multiple layers. In line with the experimental findings, the proposed Kalman filter approach demonstrated an accuracy of 96.34 percent, surpassing the 93.78 percent accuracy achieved by the Adaptive filter method. This outcome underscores the efficacy of the Kalman filter approach in the task of fog noise removal.

Similar studies in the field include the work of Arulmozhi et al. (2010), who employed a hybrid filter combining the improved Wiener filter and the median filter to tackle fog and mist noise removal in images. Their approach effectively eliminated noise and maintained image details, achieving an average peak signal-to-noise ratio (PSNR) of 30.65 dB and an average structural similarity index (SSIM) of 0.904.

Lan et al. (2013) proposed a non-local mean (NLM) filter for the same purpose, showcasing the filter's capability to effectively remove noise and uphold image quality. Their results demonstrated an average PSNR of 34.61 dB and an average SSIM of 0.928.

Soni and Mathur (2020) explored the utilization of a guided filter to address fog and mist noise in images. Their approach showcased the ability to proficiently eliminate noise while retaining image intricacies, yielding an average PSNR of 30.47 dB and an average SSIM of 0.907.

J. Li and S. Li (2017) introduced a bilateral filter as a solution to fog and mist noise removal in images. Their proposed approach effectively eliminated noise while preserving image details, resulting in an average PSNR of 31.67 dB and an average SSIM of 0.923.

While the Kalman filter offers advantages in certain scenarios, it might not be as optimal as alternative methods, particularly when handling highly correlated noise in images. Moreover, its computational intensity could render it less efficient compared to other techniques.

As for future endeavours, a promising avenue lies in enhancing the Kalman filter's utility for fog noise removal in images by focusing on its efficiency. One plausible direction involves investigating strategies to streamline its computational demands. This might entail the development of novel algorithms employing optimization techniques, aiming to curtail the computational complexity associated with the Kalman filter's application. Such efforts could lead to a more efficient and practical implementation of the Kalman filter for this specific task.

## 5 CONCLUSION

To sum up, the Kalman filter and the conventional adaptive filter serve as valuable tools for fog noise removal from images, each exhibiting distinct merits and drawbacks. The Kalman filter excels in non-linear system handling and adaptability to varying conditions, while the adaptive filter excels in addressing particular noise types. Through an empirical exploration into fog and mist noise reduction, the Kalman filter achieved a significantly higher accuracy rate of 96.34 percent, surpassing the Adaptive filter's accuracy of 93.78 percent. This underscores the Kalman filter's efficacy in enhancing image quality under such conditions.

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