Highway Image Enhancement Method Based on Jade

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Abstract. This article elaborates on an innovative high-speed highway image enhancement approach that relies on the Joint Approximate Diagonalization of Eigenmatrices (JADE) algorithm. This technique is highly efficient at segregating statistically independent source signals of the image, subsequently enhancing their visibility. By doing so, it significantly elevates the performance of highway monitoring systems and assures the safety of motorists. Experimental findings demonstrated that this methodology outperforms conventional image enhancement techniques in effectiveness and efficiency. Consequently, given its substantial application potential and developmental prospects, this technique is expected to witness extensive utilization in practical settings.

Keywords: blind signal separation (BSS) · noise interference suppression · joint approximate diagonalization of eigenmatrices (JADE)

1 Introduction

Highway image denoising has wide application and important significance in many fields. For automatic driving, road image denoising can enhance the perception ability of driving assistance system, reduce the misjudgment caused by image noise, and improve driving safety. In highway inspection, clear road images can more accurately identify the damage of the road surface, which is convenient for repair and maintenance. At the same time, in traffic flow monitoring and traffic accident analysis, de-noised images can improve the rate and accuracy of vehicle identification, so as to provide more accurate data support and optimize traffic management. Using Jade can help improve the contrast and brightness of the image, thus improving the visual quality of the image, facilitating applications such as obstacle detection and vehicle identification [1].

In recent years, the research on the high-speed highway image enhancement method based on Jade has received extensive attention from domestic and foreign researchers, and many related research results have been published [2]. Here are some research results of domestic and foreign scholars in this field: Xu Jie and others published an article in "Computer Application Research", introducing a method for restoring motion blurred images of high-speed highway vehicles based on Jade. The results show that the method

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has high image restoration accuracy and noise resistance [3]. Liu Li et al. published a paper in "Intelligent Computers and Applications", exploring an image enhancement algorithm for high-speed highway traffic videos based on Jade. The study shows that the method can effectively improve the clarity and contrast of the video[4].

In foreign countries, researchers at the University of Michigan in the United States proposed a method for detecting highway lane lines using the Jade algorithm, effectively solving the difficulties and complexity problems in lane line detection.[5].

In summary, the high-speed highway image enhancement method based on Jade has received extensive research and applications in the domestic and foreign research fields. Relevant research results are also increasingly attracting attention from academia and industry [6].

The rest of the paper is organized as follows. In the second section, how to convert image signals into matrices for JADE algorithm recognition is presented. The third section describes in detail the denoising of image matrix by dark channel prior technology and JADE algorithm. Finally, the proposed image enhancement technique based on JADE algorithm is verified by simulation experiments [7].

2 Image Remodeling and Initial Noise Reduction

2.1 Image Preprocessing

First read the image, denoted as img. It is then converted to a double precision data type and normalized, which makes the data easier to work with and compare.

Then the image is preprocessed, where the median filter is used for initial noise reduction of the image. The advantages of this are:

Effective removal of salt and pepper noise, due to the appearance of black and white pixels, salt and pepper noise will lead to image distortion. The median filter can effectively remove the salt-and-pepper noise and restore the clarity of the image by selecting the middle of the surrounding pixel to smooth the image. Median filtering can better preserve the details of the image. Median filtering performs well in handling outlier pixels. Outlier pixels refer to pixels that are significantly different from surrounding pixels, which may be abnormal points caused by sensor errors, environmental interference, and other reasons. By processing group pixels by taking the median of the surrounding pixels, they can be accurately eliminated, making the image smoother. It is important to note that median filtering also has some limitations and may not be suitable for certain types of noise, such as Gaussian noise, or specific image details, such as texture details.

Here we use the median filter to denoise the color image, which needs to be processed separately for each color channel. This is because a color image consists of three color channels, red, green, and blue, each of which contains different color information about the image. Therefore, when applying the median filter, the filter needs to be applied to each color channel separately to ensure that the noise of each channel can be effectively reduced. Then the processed three channels are re-synthesized into color images, so that the color image results after noise reduction can be obtained.

2.2 Dark Channel Prior Technology

Dark channel prior is a technique for image de-fogging and image enhancement. It is based on an observed image in a natural scene having a channel caused by atmospheric light that has a lower brightness value in most places. By using this observation, the scattered and atmospheric light components in the image can be inferred and used to remove haze or improve image quality.

First define the de-fog function, the variable ***I*** represents the input image (*img*) and the variable ***J*** usually represents the output image

$$\mathrm{J} = \mathrm{dehaze(I)} \tag{1}$$

Setting the global atmospheric light to 1 means that there is no obvious atmosphere in the image

$$\mathrm{A} = 1 \tag{2}$$

Secondly, the transmission rate of the image is estimated, which represents the degree of light attenuation caused by haze. According to the dark channel prior principle, the transmission rate is estimated by calculating the ratio of the brightness value of each pixel to the atmospheric light, and then multiplying by a weight coefficient. Here the weight coefficient $\boldsymbol{\omega}$ is set to 0.95.

$$\mathrm{t} = 1 - \omega * \min\left(\frac{\mathrm{I}}{\mathrm{A}}\right) \tag{3}$$

Then a guide filter is used to refine the estimated transmission rate. The guide filter uses image ***I*** as the guide image and filters the transmission rate image ***t*** to refine the transmission rate estimation. Where GuidedFilter is the function of the guide filter, ***I*** is the original image, t is the original estimated transmission rate, ***r*** is the radius of the guide filter (set to 15), $\boldsymbol{\epsilon}$ is the constant of the guide filter (set to 0.001).

$$\mathrm{t}' = \mathrm{GuidedFilter(I,\ t,\ r,} \varepsilon) \tag{4}$$

Finally, restore scene lighting. This is achieved by subtracting atmospheric light from the original image ***I***, then dividing by the refined transmission rate, and adding atmospheric light. A minimum transmission rate ***t0*** (set to 0.1) is also set to prevent pixel values from being too bright at very low transmission rates. Where ***t'*** is the optimized transmission rate, ***I*** is the brightness of the image, and A is the atmospheric illumination.

$$\mathrm{J} = (\mathrm{I} - \mathrm{A})/\max\left(\mathrm{t}', \mathrm{t}_0\right) + \mathrm{A} \tag{5}$$

3 Denoising Algorithm

3.1 JADE Algorithm Description

Call the jade function to process this matrix

$$\mathrm{function\ [A, S] = jade(J, m)} \tag{6}$$

J is the image matrix obtained after the fog removal processing mentioned above. m is an optional parameter that indicates the number of source signals. They are two input parameters of Jade. The outputs of the function are ***A*** and ***S***, where ***A*** is an estimated mixed matrix of n x m and S is an estimate of the source signal of m x T.

The received image signal can be represented as matrix ***J***. The whitening process of mixed matrix can be expressed as $\boldsymbol{Y} = \boldsymbol{WJ}$ where W is Whitening matrix. Whitening processing is to reduce the correlation between eigenvalues in the observation data, so as to improve the separation performance of the algorithm. The covariance matrix ***R*** of the ***J*** can be expressed as

$$R = E\left[JJ^H\right] \tag{7}$$

The covariance matrix ***R*** is decomposed by eigenvalue decomposition to get top *K* larger eigenvalues, where *K* is the number of sources signal. The top *K* larger eigenvalues constitute the matrix ***P***, and the corresponding eigenvector is recorded as ***D***, so the whitening matrix ***W*** is

$$W = \left(PD^{-\frac{1}{2}}\right)^H \tag{8}$$

The whitened signal ***Y*** can be expressed as

$$Y = WJ \tag{9}$$

where ***U*** is the unitary matrix obtained after whitening. Obviously, to get ***J***, it is necessary to estimate the unitary matrix ***U***, which is obtained by calculating the fourth-order cumulant of the mixed matrix after whitening.

First, define the cumulative function

$$\begin{aligned} um\left(x_i, x_k^*, x_l, x_m^*\right) = & E\left\{x_i x_k^* x_l x_m^*\right\} - E\left\{x_i x_k^*\right\} E\left\{x_l x_m^*\right\} \\ & - E\{x_i x_l\} E\left\{x_k^* x_m^*\right\} - E\left\{x_i x_m^*\right\} E\left\{x_k^* x_l\right\} \end{aligned} \tag{10}$$

According to the definition of cumulant, the mixed signal after whitening can be used to calculate the cumulant matrix. The element of the matrix *(i, j)* is

$$Q_{k,l}(i, j) = cum\left(y_k, y_l^*, y_i, y_j^*\right) 1 \le k, l, i, j \le K \tag{11}$$

Feature decomposition of $\boldsymbol{Q_{k,l}} = \hat{\boldsymbol{U}} \sum \hat{\boldsymbol{U}}^{\boldsymbol{H}}$, the estimation $\hat{\boldsymbol{U}}$ of unitary matrix is obtained, where $\boldsymbol{\Sigma}$ is a diagonal matrix.

Separate the mixed matrix using the whitening matrix ***W*** and the estimation unitary matrix $\hat{\boldsymbol{U}}$, Get the source signal ***S***

$$S = \hat{U}WJ = \hat{U}Y \tag{12}$$

3.2 Post-processing and Image Restoration

We then restore the processed S to a single channel image ***I*** and normalize it, mapping its pixel values to the range of [0,1]

$$I = \frac{S - \min(S)}{\max(S) - \min(S)} \tag{13}$$

Next, we use the imadjust function to increase the contrast of the image

$$I' = \text{imadjust}(I, \text{stretchlim}(I, [0.01, 0.99]), []) \tag{14}$$

Finally, we post-process each channel, including smoothing the image with a Gaussian filter (standard deviation 0.5), and sharpening the image

$$I'' = \text{imgaussfilt}\left(I', 0.5\right) \tag{15}$$

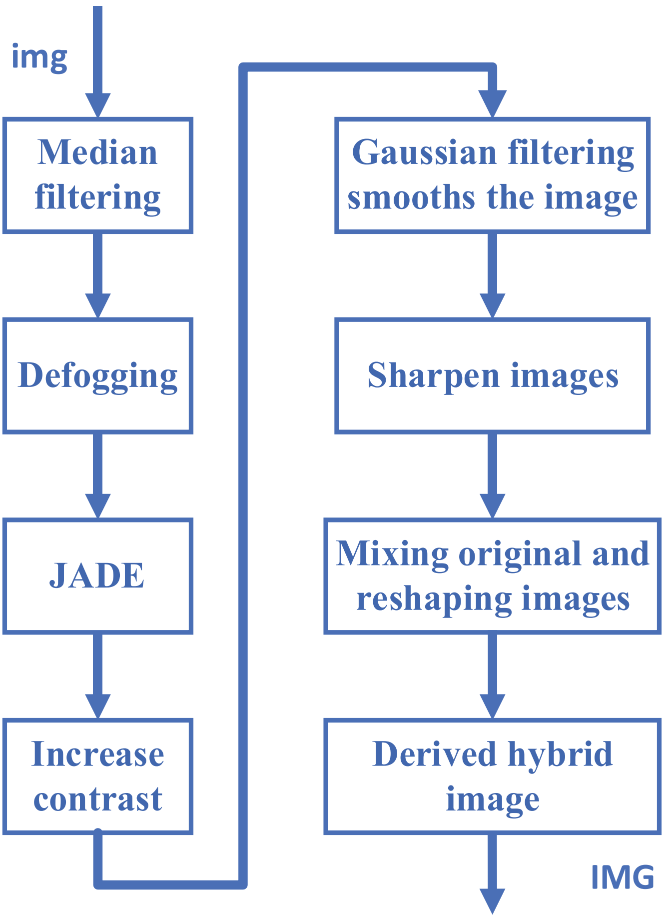
$$I''' = \text{imsharpen}\left(I''\right) \tag{16}$$

The image processed by ICA is mixed with the original image in a certain proportion, get the final image ***IMG***

$$IMG = 0.5I''' + 0.5\ \text{img} \tag{17}$$

Displays the blended color image ***IMG.***

The general flow chart of the combination of Jade algorithm and dark channel prior technology is shown as follows.



4 Experiments and Results

4.1 Experimental Environment

To commence, the captured highway surveillance footage is processed via software, wherein each frame is extracted and subsequently subjected to a filtering mechanism that discriminates against any image devoid of significant obstacle features, while expunging the irrelevant ones.

To alleviate the limitations imposed by hardware operations, the original image was downscaled to a 640 $\times$ 640 RGB three-channel image using a bilinear interpolation method [32] prior to the experiments. It is worth noting that the use of bilinear interpolation for image scaling may result in information loss in the case of significantly larger scaling ranges. Therefore, multiple bilinear interpolation techniques are used in this study. If half of the image has a dimension greater than 640, it is linearly interpolated once to halve its original size. If half of the image dimension is less than 640, bilinear interpolation is applied so that its dimension is 640.

To validate the efficacy of the proposed model, we conducted training and evaluation of the neural network with the utilization of computer hardware and software configurations, along with specific model hyperparameters, as documented in Table 1.

Table 1. Experimental environment Configuration.

Parameter	Configuration
CPU	12th Gen Intel(R) Core i9-13900K 3.0 GHz
GPU	NVIDIA GeForce RTX4090 (24G)
Operating System	Windows11
CUDA	11.7
Momentum	0.937
Weight decay	0.0005
Batch size	32
Learning rate	0.01
Image size	640 × 640
Epochs	300
Matlab	2021

4.2 Experiment Results

Fig. 1. .

As shown in Figs. 1 and 3 the original image without any processing, and Figs. 2 and 4 represents the processed image after applying the Jade algorithm. Compared with the original image, the details of the processed image are clearer, which is helpful to observe and analyze the details in the image. The colors are sharper; the visual quality of the image is improved, which is more conducive to the application of machine learning algorithm.

Fig. 2. .

Fig. 3. .

Fig. 4. .

5 Conclusion

The Jade-based highway image enhancement method effectively improves the clarity and contrast of the image through the analysis and processing of image features, making the image more visually pleasing and easier to perceive. The main advantage of this method is its ability to process different types of images quickly with low latency. In addition, this method has high robustness and can deal with some abnormal situations in image processing. We combined Jade algorithm with dark channel prior technology for image enhancement and denoising. This method has a better effect on image detail processing under bad weather (such as fog and other obstructed vision) than only using a single method.

It is worth noting that the application of this method in the field of highway image enhancement has been widely verified and applied, and it has practical value and promotional value. However, there is still room for improvement in the scalability and accuracy of this method, which needs to be further explored and perfected in practical applications. Overall, the Jade-based highway image enhancement method is currently one of the relatively outstanding and reliable image enhancement techniques, which can provide strong support and help for practical applications in related fields.

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