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Performance of Haze Removal Filter for Hazy and Noisy Images

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Abstracts- Haze and noise performance detection (HNPD) filter is proposed for impulse noise and haze removal in images. In this approach, the noisy pixels are detected in single phase, based on a set of irreplaceable connection criteria. Simulation results show that the HNPD filter outperforms others at medium to high noise rates and suppresses impulse noise and haze effectively while preserving image details, even thin edges.

Keywords—Haze, Noisy image, Single phase, Haze removal filter.

I. Introduction

Digital images are often affected by impulse and salt pepper noise during their acquisition or transmission processes [1]. Median filtering is an efficient nonlinear technique widely used for impulse and salt pepper noise removal. However, it tends to remove desirable details and produces haziness and spots in restored images. To remove impulse noise as well as to preserve fine details, various filters are proposed with noise detector schemes, such as the tri-state median (TSM) filter [1]. Haze and noise are different to remove from images and have different techniques to solve these problems. We want to give a common technique to remove haze and noise. They show good performance at low noise rates, but still fail to suppress impulse noise effectively and preserve image details, particularly at noise rates greater than 30%. In this Letter, we propose a single phase noise detection technique to detect a random valued impulse noise, which is distributed uniformly in the dynamic range of (0, 255) [2-3]. At first median filtering [4] is applied. In this paper proposed approach is based on sufficient akin neighbour criteria, a pixel that has at least a certain number of similar pixels among its neighbours in the filtering window is considered to be an original pixel. A significant feature of the offered method is that its performance remains relatively constant over a wide range of noise rates and it is able to effectively suppress impulse noise [5] in heavily corrupted images. HNPD is a combination of these two median filtering and guided filtering. The remaining part of this paper as follows II section covers the haze and noise removal, III section covers the performance parameters, IV part includes the simulation results and final V section covers the conclusion remark and future work.

II. Haze and Noise Removal

In this process, we try to restore each noisy pixel X_{ij} that was flagged as 1 in image f, by replacing it with the mean value of its good neighbouring pixels X_{ij} in the filtering window W as:

$$X_{ij} = \{ X_{i-s,j-t} | -1 \leq s,t \leq 1, (s,t) \neq (0,0)\} \quad (1)$$

$$X_{ij,rest} = (1 - f_{ij}) * X_{ij} + f_{ij} * mean(X_{ij}) \quad (2)$$

Where $f_{ij} = \{0,1\}$.The pixels that are previously detected as noise in the neighbour set X_{ij} are excluded, and the mean in (2) is calculated based on the remaining. After this we apply the guided filter method [7] and get the result as shown in the fig.1.

III. Performance Parameters

Modelling the pdf parametrically involves the data driven optimal estimation of the parameters associated with the potential functions V_c. The model parameters must be estimated for each data set as part of the image processing algorithm. In our algorithms, the noise variance σ^2 in (3) and the parameter **a** in the coefficient MRF pdf in (4) are unknown. Thus, we need to estimate these parameters in our algorithms. Because we assume that the noise in the fusion model is a Gaussian noise, it is straightforward to estimate the noise variance by the maximum likelihood (ML) criterion. It is given by

$$\sigma^2 = \quad argmaxP(Y|H,X,\sigma^2)$$

$$= \frac{1}{MN}\sum_i (Y_i\_ \ H_iX)^T (Y_i\_ \ H_iX). \quad (3)$$

The direct ML estimation of the parameters associated with the pdf of H is known to be a difficult problem [12]. The ML estimate of **a** is

$$\hat{a} = arg\ \max_a (H,a) \ = \ \arg\min_a V_c(H,a) - ln Z_H \quad (4)$$

The potential function $Vc\ (H,a)$ can be simply computed. However, the normalization term Z_{H} involves a summation over all possible configurations of **H**, which is practically impossible due to the large computation time. Note that, for two source images with size 300 * 300, **H** has a total of 490000 possible configurations. An alternative method for approximation to ML estimation is maximum pseudo likelihood (MPL) estimation, which was proposed by Besag [9]. The MPL estimation method is a suboptimal method, which is given by

$$\hat{a} \ = arg\ \max_a \prod_s P(H(s),a)$$

$$= arg\ \min_a \sum_s V_c(H(s),a) - lnZ_{H(s)}. \quad (5)$$

The differences among the fused results are usually difficult to be measured only based on observation, particularly when the fused images are multiband. Objective and quantitative analysis can benefit to a comprehensive evaluation. Various image quality indices have been developed for the purpose of image fusion [10]. Some of these indices validate the spatial resolution, while others focus on the spectral properties of the obtained fused result. In this paper, we employ three such indices.

1) SNR: The SNR in decibels, is a direct index to compare the fused image to the reference one [11]. For multiband images, it can be calculated band-by-band and also globally averaged

$$SNR\left(Z, \hat{Z}\right) = 10log_{10}\frac{\sum z^2}{\sum (z-\hat{z})^2} \qquad (6)$$

Systems are designed to minimize the MSE and maximize the PSNR.

$$MSE = \sqrt{\frac{\sum_{x=0}^{W-1}\sum_{y=0}^{H-1}\left[f(x,y)-f'(x,y)\right]^2}{WH}} \qquad (7)$$

$$PSNR = 20\log_{10}\frac{255}{MSE} \qquad (8)$$

IV. Simulation Result

To study the performance of our proposed method, we compare it with other method. The peak signal-to-noise ratio defined in [3] is used as an objective measurement of the restored image quality. From Tables 1 it is observed that the proposed HNPD filter is comparable to the best methods at low noise rates, but it clearly outperforms all these methods at medium to high noisy rates, i.e. R _ 30%. Results for the subjective visual qualities are shown in Fig. 1 for 50% noise corrupted Lena image. It is clear that the restored images of the other methods are still seriously corrupted with patches of impulse noise. Clearly, the HNPD filter has the lowest number of the false pixels amongst the others.

Then, the restored images from [R G B] channels are combined to produce the restored colour image. Restoration results shows 20% improvement in PSNR in colour image as shown in Fig. 1. It is noticeable that the HNPD filter still performs very well as illustrated in the table 1.

Table :1

The table shows the comparison parameters between median filtered and the guided filter method

Method	Variance	Mean	SNR	PSNR
Median filter	0.0583	0.4439	6.4129	78.438
Guided filter	0.0202	0.2883	8.2394	89.085

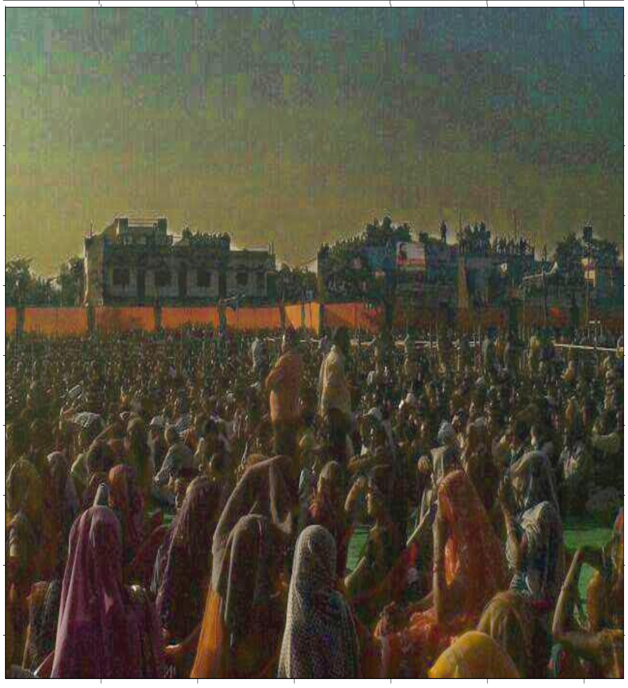

Fig.1 (a) Upper image original hazy and noisy image, (b) Middle image resultant image after median filtering and (c) Lower one resultant image after guided filtering

V. Conclusion

We propose a HNPD filter for detecting random-valued impulse and salt pepper noise in images. The method is based on a normal image feature indicating that each original pixel will have a minimum certain number of similar neighbour pixels within a local window. Extensive simulations show that at medium to high noise rates the proposed approach is superior to others in terms of PSNR and perceptual quality. It also, performs very well for restoring colour images

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