Unsymmetrically Trimmed Mean Filter for Noise Removal of Robot Vision in Dark Environments

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Abstract

Robotic vision systems in low-light conditions are prone to overexpose, which will produce noise spots in the image. These spots, primarily salt and pepper noise, interferes with robots' ability to do routine tasks like target tracking and object recognition. In this Paper, Yang et al. present a an unsymmetrically trimmed mean filter (UTMF) to recover salt-and-pepper noise-corrupted dark-captured images and preserve details.
First, the noise points are located using SPN extreme characteristics then statistics of difference is used to determine if the local pixels around a noise point are smooth or saltant. Relevant filtering algorithms are developed for both scenarios

Standard pictures taken in low light with noise ratios ranging from 30% to 70% were tested. The novel technique outperforms state-of-the-art methods in terms of peak signal-to-noise ratio by 0.1 to 1.2 dB and in structural similarity scores .

Introduction

A mobile robot particularly a surveillance robot must function in a dark, when light overexposure is likely to develop in the robot's vision system.
Generated noise points in the video or image will significantly obstruct the robot's ability to do its subsequent tasks. SPN which is defined by a dramatic increase or decrease in the gray value of the contaminated pixel, makes up the majority of the noise points brought on by overexposure. To eliminate the noise points, a suitable denoising technique must be used.

The traditional **median filter** is an order-statistics filter, which sorts all the pixels in the filter window and then take the median as the output. Compared to linear smoothing filter, the median filter can reduce the image blur and the low-density SPN, but pixel is distorted and detail is destroyed.

Adaptive Median Filter: To preserve image details, AMF excels at low noise density, but at high noise density, the window size needs to be increased . Denoising using a 3x3 filter window at high noise density, the median of all pixels in the window will likely be a contaminated pixel 0 or 255.
Repetitive substitutions of such adjacent pixels will produce a trailing effect
Lu et al. set up **12 directions** to detect the edge, but it is susceptible to noise interference. In Sree et al., the second generation wavelet is combined with the improved adaptive median filter, has good effect on high-density-noise image recovery. Dawood et al. use **Weber's law** to identify SPN and propose two methods to deal with noise pixels. Lv et al. use 3 × 3 filter window for mean filtering. if all the pixels in the window are noise pixels, they are not processed.
Neural network filters based on learning principle utilize priori knowledge for performance. Reference images are training samples to train the network. In Deng et al. [9], **Multilayered Pulse Coupled Neural Network (PCNN)** is used to locate the SPN, AMF algorithm deals with the noise pixels.

This paper uses UTMF to remove SPN in the image, new filtering window and neighbor pixel selection for different noise pixel distributions and then two filtering strategies for both smooth and saltant conditions. When removing the noise, Edge and detail loss can be alleviated. The idea of a trimmed filter is to reject the noise pixels in the filtering window.

This UTMF was compared with the mean filter, adaptive median filter, Modified Directional Weighted Filter, Weber's law Noise Identifier and Multilayered Pulse Coupled Neural Network (PCNN).

Proposed method

Range of Regional Change:
- Take 8-neighborhoods of processed pixel g(i,j), I(0 or255) sort remaining pixels in ascending order of gray
- Calculate **dmax**: max gray difference of adjacent pixels, Compare **dmax** to threshold T: If **dmax > T**, the pixel is in a region of dramatic change; otherwise, in a region of smooth variation.

- Processed pixel g(i,j) is an uncorrupted pixel and its value is left unchanged if $0 < g(i,j) < 255$.
  When $g(i,j) = 0$ or 255, the region variation width is determined based on the eight neighborhoods.
- If the region changes smoothly or due to lack of sufficient effective pixels for judging the regional change range, try to select a smaller filter window for **asymmetric trimmed mean filter**

(i) **4-Neighborhoods**: Test the 4-connected region of center point g(i,j) in the window, pixels whose gray values are 0 or 255 are cut off in the filter window. If the number of remaining no of pixels is equal to or greater than 2, average the gray values of their pixels otherwise pass to step ii

$$f(i,j) = \frac{g(i-1,j+1)+g(i+1,j-1)+g(i+1,j+1)}{3}.$$

(ii) **3x3 Window:** Change the window to 8-connected area, cut off the pixels with gray value of 0 or 255, and do average operation on the remaining pixels to get the output f(i,j). If the 8-connected area becomes empty after cutting off the extreme value, turn to step iii

$$f(i,j) = \frac{g(i,j-1)+g(i,j+1)+g(i+1,j)}{3}.$$

(iii) **5x5 Window**: When the SPN density is very large, all pixels in the 8-connected areas may have been contaminated, all cut off, the size of the filter window is changed to 5 × 5. At this point the output is the mean of outermost 16 pixels cutting off the value of 0 and 255:

$$f(i,j) = \frac{\mathrm{sum}(N)}{\mathrm{card}(N)},$$

Sum (N) = sum of the elements in the set N
card (N) = number of elements in the set N

$$N = \{g(i,j), 0 < g(i,j) < 255, g(i,j) \in W\},$$

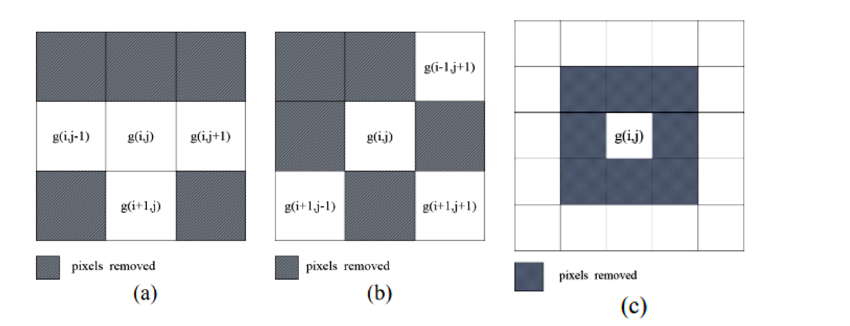
If the 5 × 5 filter window is empty after cutting off the extreme value, turn to step iv

(iv) **Recursive window**: we deal with g(i,j) the pixels in its upper and on its left side have already processed, and we can use these basic noise-free pixels to obtain the output:

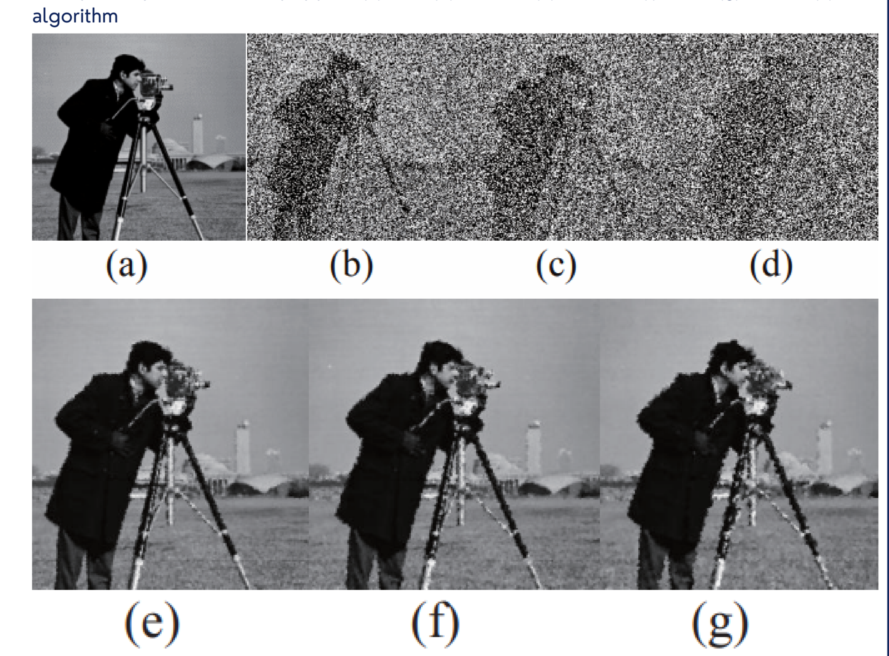
$$f(i,j) = \frac{f(i-1,j-1)+f(i-1,j)+f(i-1,j+1)+f(i,j-1)}{4}.$$

(iv) **Judge window**: if violent variation exist at regional gray value scale, the pixels on both sides of dmax are divided into two categories, the current pixel g(i,j) belongs to the category whose number of pixels is larger and the pixels are averaged as output to avoid blurring

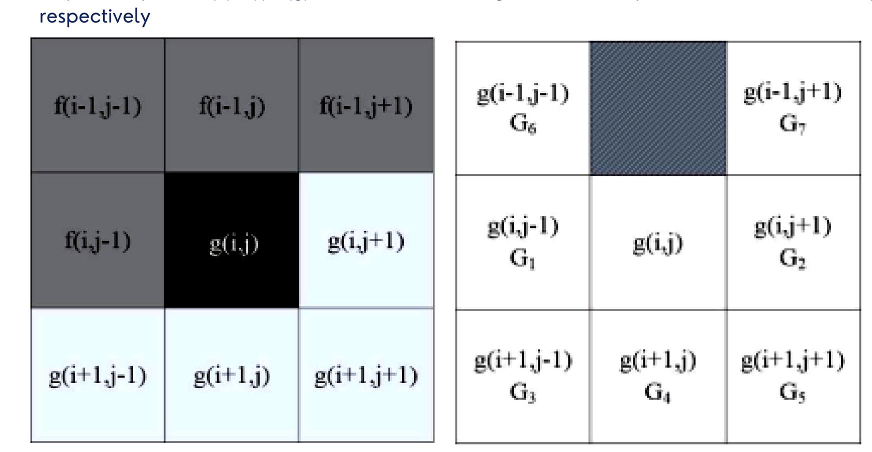
As in figure above, there are 7 valid pixels in the 8 neighborhoods, and their gray values are in ascending order: G1, G2, G3, G4, G5, G6, G7.
Calculate the difference between adjacent gray values **di = Gi+1-Gi, i= 1,2,3,4,5,6**



Comparison with other algorithms with 70% SPN. (a) Original Lena (512 ×512), (b) Image corrupted by 70% salt and pepper, (c) MF, (d) AMFW,(e) MDWF, (f)WLNI,(g)PCNN, (h) our algorithm



(a) Original image (256 ×256), (b), (c), (d) are images corrupted by 60%, 70%, 80% SPN respectively, and (e), (f), (g) are recovered images that correspond to the noise density respectively



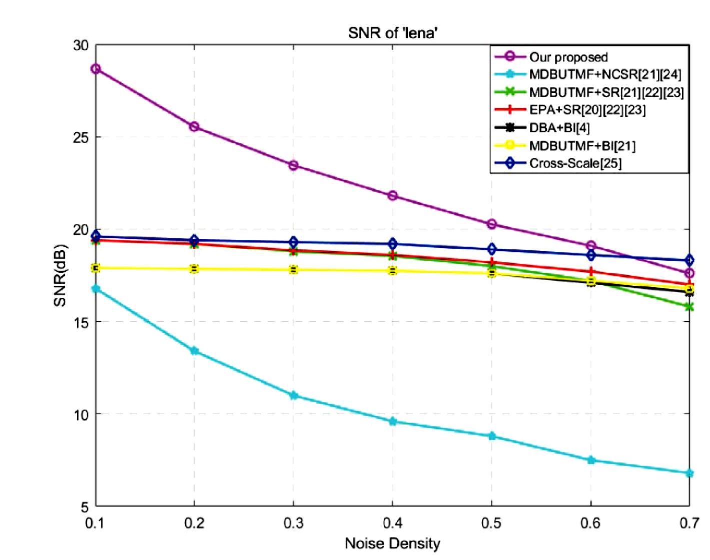
If d5 is maximum and greater than the threshold T, the 7 pixels can be divided into two sets, a = {G1, G2, G3, G4, G5} and b = {G6, G7}. g(i,j) has a larger probability close to the pixel gray values in the set a, and the average gray value of the set a is calculated as the output of g(i,j). When the set a and the set b contain the same number of pixels, take the set whose variance is smaller, that is, who changes in a more stable way, to do the mean operation to get the output.

Tests

At T = 100, the algorithm filtering performance is improved most.
The peak-signal-to-noise ratio (PSNR) and structural similarity scores (SSIM) are used to evaluate the image restoration effectiveness.

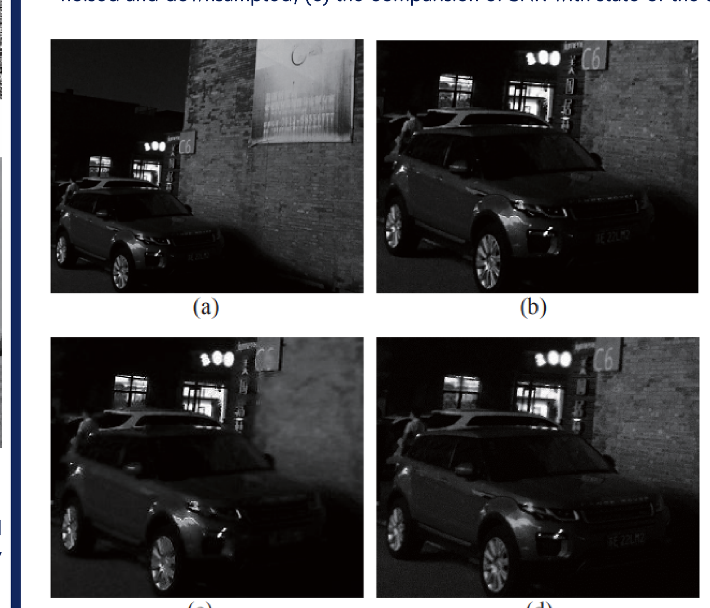
$$\mathrm{PSNR} = 10\log_{10}\frac{255^2 MN}{\sum_{i,j}\left(r_{i,j}-o_{i,j}\right)^2} = 10\log_{10}\frac{255^2}{\mathrm{MSE}},$$

$$\mathrm{SSIM} = \frac{(2\mu_O\mu_R+C_1)(2\sigma_{OR}+C_2)}{(\mu_O^2+\mu_R^2)(\sigma_O^2+\sigma_R^2+C_2)},$$

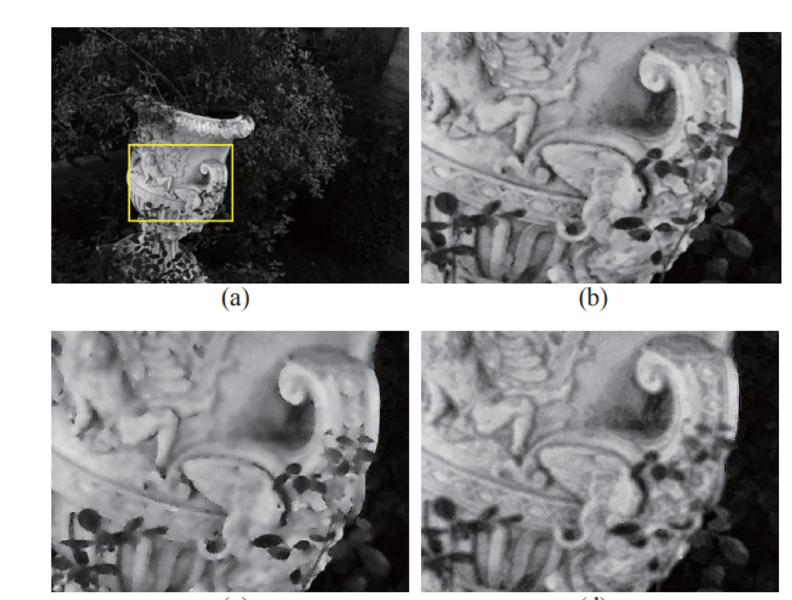


Algorithm		30%	40%	50%	60%	70%
MF	PSNR	20.8540	17.3508	14.3136	11.7130	9.5142
	SSIM	0.6767	0.4356	0.2492	0.1275	0.0688
AMFW[6]	PSNR	28.0659	25.9292	22.8805	19.2857	16.7952
	SSIM	0.9038	0.8421	0.7452	0.6298	0.5018
MDWF[5]	PSNR	28.6581	27.0122	24.6108	23.6576	21.8831
	SSIM	0.9216	0.9088	0.8682	0.7622	0.6536
WLNI[7]	PSNR	29.1879	27.6893	26.3945	24.2837	23.8658
	SSIM	0.9411	0.9206	0.8825	0.7759	0.6849
PCNN[9]	PSNR	29.2582	27.7238	26.4782	25.0704	23.8858
	SSIM	0.9492	0.9267	0.9096	0.8715	0.8334
Our algorithm	PSNR	30.4741	28.3097	27.1925	25.4411	23.9576
	SSIM	0.9578	0.9359	0.9120	0.8765	0.8373

SNR of our method comparing with state-of-the-art methods under different noise densities for the color image 'Lena'. (a) the original 'lena' image, (b) noised and downsampled, (c) the comparision of SNR with state-of-the-art methods



Denoising of dark-captured environment. (a) original image, (b) enlarged local image, (c) denoising by EPA-SR, (d) by our method.



Denoising of dark-captured object. (a) original image, (b) enlarged local image, (c) denoising by EPA-SR, (d) by our method.

Conclusion

This UTMF proposes a statistic of difference method to check if the local area of the noise point is saltant, necessary for edge area of the noise image.
For the saltant area, a filtering algorithm is proposed for adaptive filter window selection and noise point filtering.
The experiments show that the proposed algorithm has a good adaptability and robustness to both the various-density SPN and the images with different gray distributions.

References

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