



DENOISING FRAMEWORK USING SWITCHIG BILATERAL FILTER

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Abstract: To remove the noise in image, denoising filters are used. This noise removal process consists of two steps i.e. detection followed by filtering. Detection and filtering of noise is based on various noise detection algorithm and decision rules. Hence it provides high peak to noise ratio (PSNR) by efficiently removing the impulse/Gaussian mixed noise from image. In Proposed system, it uses switching bilateral filter for detect and remove impulse/Gaussian mixed noise from image. This method detects the noise and set the no. of iteration value automatically. The noise filtering is done by switching bilateral filter. Hence the merits are it needs less time complexity, high PSNR value, avoids the image degradation which is caused by too many no. of iteration and it's suitable for colour as well as gray scale image.

Index Terms: Noise detection, Image Noise, SQMV, Switching Bilateral Filter.

I. Introduction

In this project the image denoising process is effectively done by switching bilateral filter. This filter is used to identify the different types of noises in digital image processing. A bilateral filter is an edge-preserving and noise reducing smoothing filter. The intensity value at each pixel in an image is replaced by a weighted average of intensity values from nearby pixels. This weight is based on a Gaussian distribution. Crucially the weights depend not only on Euclidean distance but also on the radiometric differences (differences in the range, e.g. color intensity or Z distance). This preserves sharp edges by systematically looping through each pixel and adjusting weights to the adjacent pixels accordingly. We propose the sorted quadrant median vector (SQMV) scheme, which includes important features such as edge or texture information. This information is utilized to allocate a reference median from SQMV, which is in turn compared with a current pixel to classify it as impulse noise, Gaussian noise, or noise-free. The SBF removes both Gaussian and impulse noise without adding another weighting function. The range filter inside the bilateral filter switches between the Gaussian and impulse modes depending upon the noise classification result. Simulation results show that our noise detector has a high noise detection rate as well as a high classification rate for salt-and-pepper, uniform impulse noise and mixed impulse noise. Unlike most other impulse noise filters, the proposed SBF achieves high peak signal-to-noise ratio and great image quality by efficiently removing both types of mixed noise, salt-and-pepper with uniform noise and salt-and-pepper with Gaussian noise. In addition, the computational complexity of SBF is significantly less than that of other mixed noise filters.

II. Methodology

Switching Bilateral Filter with a Texture and Noise Detector for Universal Noise Removal Most often perform image processing operation is noise removal, while the enhancement of images. There are many noise and edge detectors with specific algorithm are available for removing noise. Detection are based upon robust Estimators and followed by filtering. Impulse detection and classification rate, shows a good performance in identifying noise even in mixed noise models. The switching scheme, noise detector to identify noisy pixels and differentiate the noisy pixels from noise free pixels.

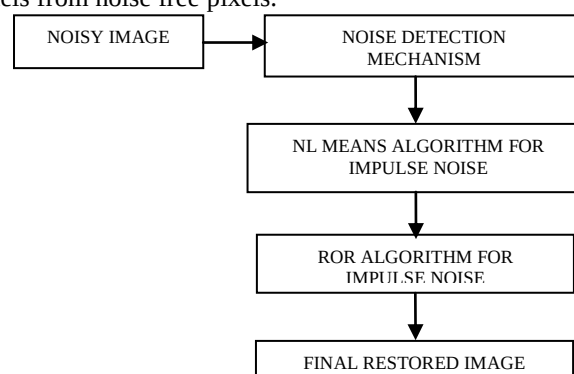


Figure 1: Block Diagram of Noise Removal

In this paper we propose universal noise removal filter and SQMV. This filter is used to remove mixed noise, salt and pepper with uniform noise and salt and pepper with Gaussian noise. Sorted quadrant median vector is used to recognize edge and texture. Difference between the current pixel and reference medians are calculated for detect noise. Detection of noise is completed in two stages. The reference median is choosing for noise detection in an image. If differences are large, the pixel is considered as noisy pixel. Alternatively, when the differences are small, the pixel is considered as noise free pixel. Non proper reference median would guide to incorrect detection. So we have to find proper reference median. In Proper reference median can be selected depend upon edge and texture information.

The noise detector in addition decides whether a current pixel should be filtered through an SBF or whether it should bypass the SBF. Switching bilateral filter is divided into two kinds, one is SBF and another one is SBF. In B1, B2 denote switching control signal created by the noise detector. The restored image has the original pixels if noise detector and edge and texture detector identify the pixels as noise free. If the pixel is detect impulse noise, and then the pixel is processed by the SBF. If the pixel is does not recognized as an impulse noise, although the current pixel and the reference median differences is still larger than a threshold, after that pixel is identified as Gaussian noise and is filtered by SBF.

III. Image Noise

Image noise is random (not present in the object imaged) variation of brightness or color information in images, and is usually an aspect of electronic noise. It can be produced by the sensor and circuitry of a scanner or digital camera. Image noise can also originate in film grain and in the unavoidable shot noise of an ideal photon detector. Image noise is an undesirable by-product of image capture that adds spurious and extraneous information.

IV. SQMV

Switching-based median filters are commonly found to be nonadaptive to noise density variations and prone to misclassifying pixel characteristics at high noise density interference. This reveals the critical need of having a sophisticated switching scheme and an adaptive weighted median filter. In this paper, we propose a novel switching-based median filter with incorporation of fuzzy-set concept, called the noise adaptive soft-switching median (NASM) filter, to achieve much improved filtering performance in terms of effectiveness in removing impulse noise while preserving signal details and robustness in combating noise density variations. The proposed NASM filter consists of two stages. A soft-switching noise-detection scheme is developed to classify each pixel to be uncorrupted pixel, isolated impulse noise, non isolated impulse noise or image object's edge pixel. "No filtering" (or identity filter), standard median (SM) filter or our developed fuzzy weighted median (FWM) filter will then be employed according to the respective characteristic type identified. Experimental results show that our NASM filter impressively outperforms other techniques by achieving fairly close performance to that of ideal-switching median filter across a wide range of noise densities, ranging from 10% to 70%.

V Switching Bilateral Filter

In this section, we propose a new universal noise removal algorithm: the switching bilateral filter (SBF). Let be the current pixel, and let be the pixels in a window surrounding.

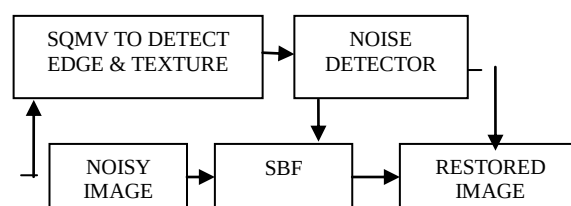


Figure 2: Flow diagram of Switching Bilateral Filter

It is difficult for a bilateral filter to remove impulse noise because the difference between the noisy pixel and its neighbors is huge. This makes the radiometric weighting function too small to change the noisy pixel. The trilateral filter adds a new weighting function which is based upon ROAD statistic to remove the impulse noise. However, the trilateral filter has to be implemented iteratively.

$$w_{s,i} = \exp - (1 - X_i + S_j + t)^2 / 2\sigma^2 r$$

For an image with impulse noise, the trilateral filter processes each pixel individually and it takes too much processing time and creates a blurred result. By replacing with SQMR of the window in a bilateral filter, we can remove impulse noise without adding another weighting function. Additive Gaussian noise is characterized by adding to each image pixel a value with a zero-mean Gaussian distribution, and it affects all pixels of the image. Such noise is usually introduced during image acquisition.

The zero-mean distribution property allows such noise to be removed by average pixel values locally. This relatively new class of denoising methods originates from the NL-means. $U_{i,j}$ will be

$$\sum_{S=-N}^N \sum_{t=-N}^N Wg(S,t) Wsr(S,T)xi + sj + 1$$

Un-like previous denoising methods, which were developed under local regularity assumption, the NL-means exploits the correlation in the entire image. Basically, the NL-means filter estimates a noise-free intensity as a weighted average of all pixel intensities in the image, and the weights are proportional to the similarity between the local neighborhood of the pixel being processed and the local neighborhoods of the surrounding pixels. Therefore, these nonlocal methods are very powerful of pre-serving image details when denoising.

Figure 2 shows denoising algorithm for removing the impulse/Gaussian mixed noise from the image. The detection operation is done by the help of ROR value and for filtering operation ROR is extended to NLM means to remove the Impulse/Gaussian mixed noise.

VI. Result & Analysis

The switching bilateral filter removes the noise from the image very accurately without affecting the quality of the image.

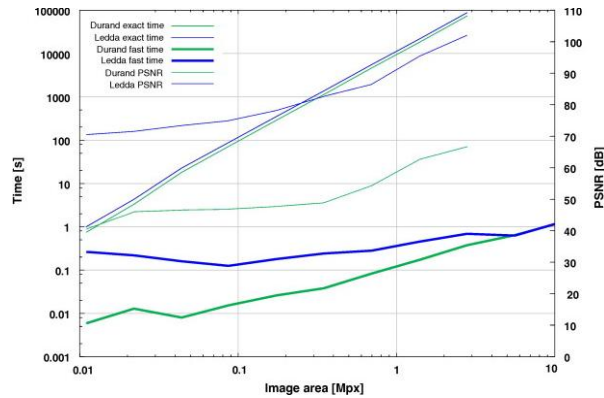


Figure 3: shows the relationship between the PSNR, Time and image area.



Figure 4: Input image

Image	30%	40%	50%
Lena	32.2007	33.2001	34.4035
Bridge	23.0002	24.3411	25.4309
Penguin	27.5032	29.7600	31.7809

Table 1: Time complexity Analysis

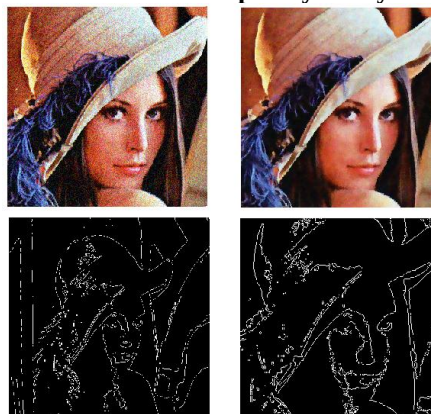


Figure 5: Noisy input image and Denoised Output Image

Figure 5 shows the noisy input content and denoised image with edge detection mechanism.

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