SEGMENT BASED CONSTRUCTIVE MEDIAN FOR REMOVAL OF IMPULSIVE NOISE

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Abstract

In this paper we proposed an efficient mechanism for removal of impulse noise from the digital images. The proposed filter is Segment based Constructive median (SCM), is integration of a cascaded easy to implement impulse detector and a detail preserving noise filter. In the first phase ,the impulse detector classifies any possible impulsive noise pixels. In the second phase filtering replaces the detected noise pixels. Apart from that the filtering phase employs fuzzy reasoning to deal with uncertainties present in local information. Contrary to many existing filters that only focus on a particular impulse noise model, the SCM filter is capable of filtering different kinds of impulse noise – the random-valued and/or fixed-valued impulse noise models.

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1. INTRODUCTION

Images and videos belong to the most important information carriers in today's world (e.g., traffic observations, surveillance systems, autonomous navigation, etc.. However, the images are likely to be corrupted by noise due to bad acquisition, transmission or recording. Such degradation negatively influences the performance of many image processing techniques and a preprocessing module to filter the images is often required.

With the usage of multimedia material becoming more widespread from day to day, visual information from high quality digital images plays an important role in many daily life applications. Unfortunately, digital images acquired through many consumer electronic products are commonly subjected to the contamination of impulse noise. Some of the probable causes of impulse noise include malfunctioning pixel sensors, faulty memory units, imperfections encountered in channel during transmission, external disturbances in a noisy environment, electromagnetic interferences, and timing errors in analog-to-digital conversion.

With the advancement in image acquisition technologies, density of impulse noise corruption in digital images has fallen significantly over the years. Recently, many methods, for example are the ones mentioned above, only touched on the filtering of heavily corrupted images by a particular impulse noise model. By heavily corrupted we mean the corruption of more than 25% to 95% pixels. Moreover, loss of image details and smoothing of edges are rampant when the image is only contaminated with low noise density. In this paper, we focus on developing a robust filter that caters for any type of impulse noise models. We propose a new recursive filter, called the Segment based Constructive median (SCM), for detail preserving restoration. The SCM filter operates at a wide range of impulse noise densities without jeopardizing image fine details and textures. We also channel our attention to develop a fast and automated algorithm. The proposed filter does not require any tedious tuning or time consuming training of parameters as well. In addition, simulation results show that the SCM filter outperforms other state-of-the art impulse noise filters in terms of subjective and objective qualities in the filtered images when applied recursively and iteratively. Furthermore, the proposed SCM filter consistently shows excellent restoration results in denoising color images.

1.1 Impulsive Noise Models :

Before we venture forth, we define the types of impulse noise models in this section for clarity. For an image of size $M \times N$ stored as an 8-bit grayscale pixel resolution, the pixel intensities lie in the dynamic range [$Lmin$, $Lmax$], where $Lmin$ and $Lmax$ are the lowest and highest intensities, respectively. Regardless of its origin, impulse noise exhibits nonstationary statistical characteristics and only a certain percentage of pixels in the image are contaminated by impulse noise Based on this fact, the model for impulse noise with probability is defined as:

$$x(i,j) = \begin{cases} o(i,j) & \text{: with probability } 1-\rho \\ f(i,j) & \text{: with probability } \rho \end{cases}$$

where $x(i,j)$ represents the pixel at location (i,j) with intensity x, $o(i,j)$ and $f(i,j)$ denote the original and noisy image, respectively. There are two types of impulse noise models commonly used in image processing literature: the fixed-valued impulse noise, also known as the salt-and-pepper (SNP) noise, and the random-valued impulse noise, also known as the uniform (UNIF) noise. The simplest impulse noise model is the SNP noise, where noise pixels are assumed to take the minimal and maximal intensities, i.e., $fsnp(i,j)$□$(Lmin, Lmax)$. On the other hand, impulsive noise pixels for the UNIF noise model can take any value within the image dynamic range, i.e., $funif(i,j)$□$[Lmin, Lmax]$. In both cases, $fsnp(i,j)$ and $funif(i,j)$ corrupt an image with equal probability. In addition, impulse noise similar to the SNP noise model, except with more than two intensities, can also be found in some contemporary literature. Since we neither have *a priori* knowledge about the noise amplitudes nor the densities of impulse noise corruption in reality, it is more appropriate to consider a more general impulse noise model. In real-world applications, impulse noise is resulted from interference of noise signals with random amplitudes. Consequently, the impulsive amplitude could either fall within the image dynamic range or out of that range. When the impulsive amplitude lies within the dynamic range, the corresponding pixel appears as UNIF noise in the image. Conversely, if the impulsive amplitude lies outside of the dynamic range, the corresponding pixel will be saturated and thresholded to the maximal or minimal intensity of the image dynamic range and appears as SNP noise. Obviously, real impulse noise is some mixture between the SNP and UNIF noise. As a result, Petrovi and Crnojevi have proposed a more realistic impulse noise model which contains both SNP and UNIF noise models. This general impulse noise model is given here as:

$$x(i,j)=\begin{cases} o(i,j) & \text{: with probability } 1-\rho \\ f^{unif}(i,j) & \text{: with probability } \rho/2 \\ f^{snp}(i,j) & \text{: with probability } \rho/2 \end{cases}$$

In this way, half of the noise pixels are corrupted by SNP noise, while the remaining half by the UNIF noise. This model 2 Impulse noise probability and density both refer to the percentage of corrupted pixels; thus, these two terms are used interchangeably in literature. is deemed more suitable for testing the performance of impulse noise filter. For this reason, we will pay special attention to the impulse noise model described although the proposed SCM filter can also produce impressive results when applied independently on images corrupted with SNP or UNIF noise.

2. SEGMENT BASED CONSTRUCTIVE MEDIAN (SCM)

In this framework, we propose an constructive median-based filter called the *Constructive median mechanism* binary decision map $b(t)(i,j)$ acts as a "switch" by turning on the filter when a noise pixel is detected, i.e., $b(t)(i,j) = 0$. Otherwise, the filtering action is skipped when $b(t)(i,j) = 1$ and the noise-free pixel is retained. The filtering algorithm adopts an adaptive size filtering window $Wf(i,j)$ of the dimensions

$(2Lf+1)\times(2Lf+1)$, given here as:
$Wf\,(i, j) = x(i + p, j + q)$ v p, q E$\{-Lf , Lf\}$

where Lf is a nonzero positive integer. For every noise pixel detected, Lf is initialized to one, i.e., $Wf(i,j)$ begins the filtering process with a square window of size 3×3, before being expanded to a larger size. The algorithmic description of the proposed filter is summarized as follows:

1. Determine the number of noise-free pixels $G(i,j)$ by computing the number of '1s' in $B^{(t)}(i,j)$:

   $$G(i,j)=\sum_{p,q\in\{-L_f,L_f\}} B^{(t)}(i+p,j+q)$$

2. Expand $W_f(i,j)$ by one pixel at each of its four sides (i.e., $L_f \leftarrow L_f + 1$) if $G(i,j) < 1$. Repeat Steps 1 and 2 until the criterion $G(i,j) \geq 1$ is satisfied.
3. Compute the median pixel $M(i,j)$ using all noise-free pixels in the current $W_f(i,j)$. The median pixel $M(i,j)$ is given as:

   $$M(i,j)=\text{median}\{\,x(i+p,j+q)\,\}\ \forall\ p,q \quad \text{with } B^{(t)}(i+p,j+q)=1$$

4. Extract the local information $D_I(i,j)$ from $W_f(i,j)$ according to:

   $$D_I(i,j)=\max\{D^1(m)\}=D_S((2L_d+1)^2-1)$$

5. Compute the fuzzy membership value $F(i,j)$ based on the local information $D_I(i,j)$:

   $$F(i,j)=\begin{cases} 0 & : D_I(i,j)<T_1 \\ \dfrac{D_I(i,j)-T_1}{T_2-T_1} & : T_1\leq D_I(i,j)<T_2 \\ 1.0 & : D_I(i,j)\geq T_2 \end{cases}$$

   where T_1 and T_2 are two predefined thresholds.
6. Compute the restoration term $y(i,j)$ as follows:

   $$y(i,j)=F(i,j)\cdot M(i,j)+[1-F(i,j)]\cdot x(i,j)$$

We note that, although noise-free pixels are relatively easy to be selected by utilizing the binary decision map $B(t)(i,j)$, the number of noise-free pixels to be used as candidates for restoration posed as a problem. This is especially true for median-based filters because the median pixel selected from only noise-free pixels of a large window is very likely belonged to a nonlocal neighbor. Restoring a noise pixel with a nonlocal noise-free pixel could lead to loss of image details. Consequently, the restored image is blurred and jittering appears at objects' edges. Furthermore, a large number of noise-free pixels in a sample will consume higher computational time . Therefore, we set a limit for *Wf*(*i*,*j*) to contain a minimum number of pixels and we choose the minimum number of pixel as one in Step2 before *Wf*(*i*,*j*) stops enlarging its window size. In Step4, the proposed filter extracts the local information from the noisy image using the MAX-operator. The local information must contain information such as image fine details, edges, thin lines, and textures even after the image has been degraded with noise. As an illustration, Figure 1 below shows the examples of local information extracted from original and noisy 'Lena' images.

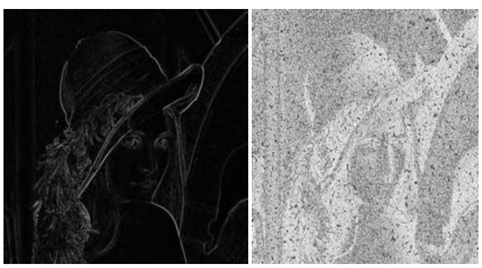


Fig 1 Local information extracted from: (a) original 'Lena' test image and (b) 'Lena' image corrupted with 30% impulse noise.

As part of the filtering mechanism, the proposed filter adopts fuzzy reasoning in Step5 to deal with uncertainties present in the local information. These uncertainties, e.g. thin lines or pixels at edges being mistaken as noise-pixels, are caused by the nonlinear nature of impulse noise. Therefore, the fuzzy set in processes the local information *DI*(*i*,*j*) by producing a suitable fuzzy membership value *F*(*i*,*j*). Subsequently, *F*(*i*,*j*) is used to assist the restoration of a noise pixel by approximating an accurate restoration term *y*(*i*,*j*). Instead of replacing the noise pixel *x*(*i*,*j*) with the median pixel *M*(*i*,*j*) as practiced by median-based filters *F*(*i*,*j*) lends a weight on whether more of *x*(*i*,*j*) or *M*(*i*,*j*) will be restored . As a result, image details are very well preserved after filtering.

2.1 Mechanism For Iterations :

In this paper, the detection and filtering operations are also performed iteratively where impulse noise is successively reduced. The iterations are halted when the stopping criterion defined later in this section is satisfied. In order to shorten the processing time, we do not wish to introduce any lengthy computation involving complex mathematical formulations.

We strive for a simple criterion utilizing the already exist operations in the simplest way. Due to the fact that iterations should be stopped once noise pixels are almost eliminated, we compute the estimated noise density *pe*(*t*) in the image after each iteration from the existing *B*(*t*)(*i*,*j*) using

$$\rho_e^{(t)} = \frac{\sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \neg B^{(t)}(i,j)|}{M \cdot N}$$

where operator ' ~ ' denotes negation operation on *B*(*t*)(*i*,*j*). The estimated noise density gives a rough estimation on the density of unfiltered noise pixels. At each iteration *t*, we apply the threshold *Td* (*t*) in a decreasing manner

$T_d^{(t+1)}$=0.97 $T_d^{(t)}$

to ensure high accuracy of detection. The decreasing impulse noise density after every iteration justifies the reason in lowering *Td* (*t*), which is used to control the sensitivity in impulse detection as well as for detail preservation. At early iterations, our proposed impulse detector only identifies pixels that are likely to be noise candidates with large threshold. Then, we decrease the threshold in the subsequent iterations to include remaining noise impulses disguising as "noise-free" pixels that are more difficult to detect. The manner in which $Td^{(t)}$ is decreased is crucial because the estimator $Pe^{(t)}$ can affect the determination of optimal number of iterations.

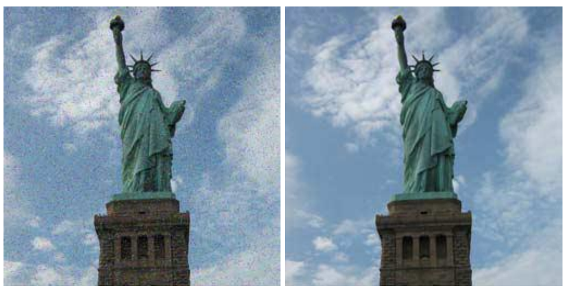
2.2 Application On Color Image

In this paper, the RGB color space is chosen to represent the color images. The noisy color images are generated by injecting the impulse noise model in (2) to each of the R-, G-, and B-channels independently. This means when a color image is contaminated by noise density p then each color plane is being corrupted with p. Consequently, our proposed SCM filter can be straightforwardly extended for filtering corrupted color images simply by applying the proposed algorithm to the R-, G-, and B-channels independently. Thus, three more master binary decision maps are generated that correspond to the R-, G-, and B-channels, and the condition [*x*(*i*,*j*) != *LSALT* and *LPEPPER*] can now be ignored due to the robustness of the cluster-based detection action alone. Simulation results for the 'Statue of Liberty' test image contaminated with 5% impulse noise and the 'Rose' test image corrupted with 15% impulse noise are depicted in Figs. 2(a) and (b), respectively. It is observed that the proposed SCM filter consistently exhibits excellent noise attenuation performances when applied on color images. Loss of image fine details is negligible and subjective sensations of the images are very well reconstructed.

However, the processing time consumed for filtering color images is slightly higher as compared to the filtering of its monochrome counterparts. This is because the filtering process treats each color plane as an independent entity. This process is also known as the *scalar filtering* approach. Intuitively, the processing time of the proposed algorithm can

be sped up by using the *vector filtering* approach, where each pixel is seen as a vector rather than three distinguished color entities. The only drawback in vector filtering is the implementation will result in more image details degradation

since a pixel is considered as corrupted as long as one of its color components is considered as noisy



2 (a) ‘Statue of Liberty’ test image corrupted with 5% impulse noise; PSNR = 19.81dB and MAE = 5.04. (b) Restored ‘Statue of Liberty’ image using the SCM filter through scalar filtering; PSNR = 42.44dB, MAE = 0.18 and processing time = 425.20ms.

CONCLUSION

In this paper, we propose a novel algorithm for impulse denoising based on the Segment based Constructive median (SCM),. One of the advantages of the proposed SCM filter is its capability in handling realistic impulse noise model for real-world applications and, thus, can be regarded as a universal impulse noise filter. The SCM filter is constructed by cascading a powerful impulse detector with a simple Constructive switching median filter. Fuzzy reasoning is embedded as part of its filtering mechanism, which permits us to exploit the effectiveness of fuzzy paradigm in handling imprecise local information

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