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An Efficient Impulse and Blur Noise Removal Based on Total Variational Algorithm

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***Abstract*— The impulsive noise removal for color or grey images usually employs many existing filters example vector median filter, switching median filter, and edge-preserving regularization. These approaches, however, often introduce excessive smoothing and can result in extensive visual feature blurring and thus are suitable only for images with low density noise. Another problem is artificial neural network take more time for analysis the noise pixel. This propose a total variation method approach to restore images corrupted by blur or impulse noise. The median-type filter is a perfect noise detector to identify the outlier pixel (noise value) the pixels that are expected to be corrupted by random-valued impulse noise or blur images. Edge-preserving restoration based on the information on the location of noise-free pixels, by a total variation method by using the essentially outlier-free data. The experimental results prove the new method to be a significantly advance over several state-of-the art techniques with respect to restoration capability and computational efficiency. The results designate that the proposed method provides significant improvement over comparison existing techniques especially for high noise densities.**

***Index Terms*— Impulsive noise, Restore images, Edge-preserving restoration, Total variation.**

I. INTRODUCTION

Image processing is used in many scientific fields such as astronomy, aerospace, photogrammetry, particle physics, biology, medical sciences, geology, and science of materials. Removing noise in an image is important for improving image quality. Some filters like H-infinity filter have been applied to practical industrial systems. Usually, noise originates from taking pictures through a defective sensor or transmitting images through a noisy channel. Such noise can be categorized into many different types by probability distributions, such types being impulsive noise, Gaussian noise, Rayleigh noise, and Laplacian noise.

Digital Image Processing is a promising area of research in the fields of electronics and communication engineering, consumer and entertainment electronics, control and instrumentation, biomedical instrumentation, remote sensing, robotics and computer vision and computer aided manufacturing (CAM). ‘Image restoration and filtering’ is one of the prime areas of image processing and its objective is to recover the images from degraded observations. The techniques involved in image restoration and filtering are oriented towards modeling the degradations and then applying an inverse procedure to obtain an approximation of the original image. Removing noise from digital images is very essential area for research. It is considered to be backbone process in image segmentation, analyses, pattern recognition etc. The sources of noise in digital images arise during image acquisition (digitization) and transmission.

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Impulse noise is characterized by replacing a portion of an image's pixel values with random values, leaving the remainder unchanged. Such noise can be introduced due to transmission errors. The most noticeable and least acceptable pixels in the noisy image are then those whose intensities are much different from their neighbors.

The Gaussian noise removal methods mentioned above cannot adequately remove such noise because they interpret the noise pixels as edges to be preserved. For this reason, a separate class of nonlinear filters have been developed specifically for the removal of impulse noise; many are extensions of the median filter, or otherwise use rank statistics. The common idea among these filters is to detect the impulse pixels and replace them with estimated values, while leaving the remaining pixels unchanged. When applied to images corrupted with Gaussian noise, however, such filters are not effective, and in practice leave grainy, visually disappointing results.

In this proposed paper justify a much simpler alternative approach which overcomes the above-mentioned systematic errors and leads to much better results. First identify the outlier candidates the pixels that are likely to be corrupted by the impulse noise, and we remove them from our data set. In a second phase, the image is deblurred and denoised simultaneously using essentially the outlier-free data. The resultant optimization stage is much simpler in comparison with the current full variation methods and the outlier contamination is more accurately corrected.

II. RELATED WORK

The Cluster-based Adaptive Fuzzy Switching Median (CAFSM), is composed of a cascaded easy-to- implement impulse detector and a detail preserving noise filter. Initially, the impulse detector classifies any possible impulsive noise pixels. Subsequently, the filtering phase replaces the detected noise pixels. Removing impulse noise from images is presented in which the nature of the filtering operation is conditioned on a state variable defined as the output of a classifier that operates on the differences between the input pixel and the remaining rank-ordered pixels in a sliding window. As part of this framework, several algorithms are examined, each of which is applicable to fixed and random-valued impulse noise models. First, a simple two-state approach is described in which the algorithm switches between the output of an identity filter and a rank-ordered mean (ROM) filter.

The existing median-based filter, progressive switching median (PSM) filter, is proposed to restore images corrupted by salt-pepper impulse noise. The algorithm is developed by the following two main points: 1) switching scheme-an impulse detection algorithm is used before filtering, thus only a proportion of all the pixels will be filtered; and 2) progressive methods-both the impulse detection and the noise filtering procedures are progressively applied through several iterations. Another existing system combine it with the weighted median filter to get a new directional weighted median (DWM) filter. Extensive simulations show that the proposed filter not only can provide better performance of suppressing impulse with high noise level but can preserve more detail features, even thin lines. In order to restore data corrupted with outliers and impulsive noise, we focus on cost-functions composed of an $\ell 1$ data-fidelity term and an edge-preserving regularization term.

The exiting median based switching schemes, called multi-state median (MSM) filter. By using a simple Thresholding logic, the output of the MSM filter is adaptively switched among those of a group of centers weighted median (CWM) filters that have different center weights. Partial differential equation (PDE)-based image denoising for random-valued impulse noise. We introduce the notion of ENI (the abbreviation for "edge pixels, noisy pixels, and interior pixels") that denotes the number of homogeneous pixels in a local neighborhood and is significantly different for edge pixels, noisy pixels, and interior pixels. The existing fuzzy switching median (FSM) filter employing fuzzy techniques in image processing. The proposed filter is able to remove salt-and-pepper noise in digital images while preserving image details and textures very well. To detect the impulse noise from the corrupted image using feed forward neural network (FFNN) is presented. A modified version of the arithmetic mean filter is proposed to remove the detected impulse noise. The performance of proposed noise detection approach is analyzed using the performance measures such as False Alarm Ratio (FAR), Missed Noise (MN) pixels and Falsely Detected Noise (FDN) pixels. Another a novel two-stage denoising method for the removal of random-valued impulse noise (RVIN) in images. The first stage of our algorithm applies an impulse-noise detection routine that is a refinement of the HEIND algorithm and is very accurate in identifying the location of the noisy pixels. The second stage is an image inpainting routine that is designed to restore the missing information at those pixels that have been identified during the first stage. One of the novelties of our approach is that our inpainting routine takes advantage of the shearlet representation to efficiently recover the geometry of the original image. This method is particularly effective to eliminate jagged edges and other visual artifacts that frequently affect many RVIN denoising algorithms, especially at higher noise levels.

III. PROPOSED APPROACH

The propose approach is to first detect those possible corrupted pixels and then, at a second phase, to restore the image by using only those pixels that are surely not corrupted. The two-phase idea comes from our two-phase denoising methods. The restoration is done only for corrupted pixels using the restored values of the outliers. Here the inherent illposedeness of deblurring makes it impossible to use any restored values for the outliers since they are likely to be fake. A specialized minimization functional is hence necessary for deblurring.

1. It consists of the following two phases: accurate detection of the location of outliers (the noise candidates) using a median-type filter.
2. Edge-preserving restoration that deblur using only those data samples that are not noise candidates.

A. *Image Noise*

In general terms Impulse Noise (IN) can be defined as intensity value of a single pixel, corrupted by any means and value of signal pixel can be dark or bright spots that are not authentic imagery. Impulse noise can be classified mainly in two categories namely as.

1. Salt and pepper noise (SPN).
2. Random value impulse noise (RVIN).

- Salt & Pepper (SNP)

The consider how to recover a digital image $x \in \mathbb{R}^{m \times m}$ when the observed image y is blurred and corrupted with impulse noise. Degradation by blur is almost unavoidable in imaging systems while corruption with impulse noise comes from bit errors in transmission, wrong pixels and faulty memory locations in hardware. Under this degradation model, the observation y is of the form

$$y = N_P(\tilde{y}) \quad \text{where } \tilde{y} = Hx \qquad (1)$$

Here, N_P represents an impulse noise while H models the blurring effect. Let us assume that the blurring kernel of H is known. Two main models for the impulse noise are used in a wide variety of applications: salt-and-pepper and random valued impulse noise. Denote the dynamic range of $\tilde{y}$ to be $[d_{min}, d_{max}]$, $ie\ d_{min} \le \tilde{y}_{ij} \le d_{max}\ \ for\ all\ (i, j)$.

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The gray level of y at pixel location (i,j) is

$$y_{ij} = \begin{cases} d_{min}, & with\ probability\ s/2 \\ d_{max}, & with\ probability\ s/2 \\ \tilde{y}_{ij} & with\ probability\ 1-s \end{cases} \qquad (2)$$

where s determines the level of the salt-and-pepper noise.

- Random valued impulse noise (RVIN)

Random value impulse noise (RVIN) also known as uniform noise is a type of noise in which pixel value can be closer to the neighboring pixel value. RVIN is harder to detect and remove due to its characteristics. The gray level of y at pixel location (i,j) is

$$y_{ij} = \begin{cases} d_{ij} & with\ probability\ r, \\ \tilde{y}_{ij} & with\ probability\ 1-r \end{cases} \qquad (3)$$

where d_{ij} are identically and uniformly distributed random numbers in $[d_{min}, d_{max}]$ and r defines the level of the random-valued noise.

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B. Noise Detection

The H is a smoothing operator, edges and other high frequency features are not that prominent in the blurred image Hx. This suggests that median-type filtering can efficiently detect the locations of the data pixels corrupted by impulse noise. Which median-type filter is chosen as detector depends on the kind of the impulse noise. The adaptive median filter (AMF) to detect salt-and-pepper noise and the adaptive center-weighted median filter (ACWMF) for random-valued impulse noise. Let us emphasize that any other filter (usually a median-type filter) that provides a good detection of outliers can also be employed in this phase.

Denote by $z \in \mathbb{R}^{m\times m}$ the result obtained by applying the median-type filter to the blurred and noisy image y. The filtered data z will only be used to determine the noise candidate set N the data samples that are likely to be contaminated with impulse noise.

For salt-and-pepper noise:

$$\mathcal{N} = \left\{(i,j) \in \mathcal{A}\ : z_{ij} \neq y_{ij}\ \ and\ y_{ij} \in \{d_{min}, d_{max}\}\right\} \quad (4)$$

For random-valued impulse noise:

$$\mathcal{N} = \left\{(i,j) \in\ \mathcal{A}:\ z_{ij} \neq y_{ij}\right\} \quad (5)$$

The set of data samples that are likely to be uncorrupted is defined as

$$\mathcal{U} = {}^{\mathcal{A}}/_{\mathcal{N}} \quad (6)$$

Clearly random-valued impulse noise is more difficult to detect than salt-and-pepper noise. It can hence expect more difficulties with random-valued noise.

C. Restoration Using a Total Variation

The data samples y_{ij} with (i,j) ∈ N do not carry proper information of the true image. Their estimates z_{ij} provided by any median-type filter combine in some way the values of the neighboring pixels, so they inevitably contain errors that do not fit the model for Gaussian noise in $\tilde{y}$, assumed in (4). Their use in the deblurring stage can only be harmful. Indeed, the harmful effect they produce on the solution can be observed. The best can do is to ignore all y_{ij} with (i,j) ∈ N. The restoration is then done using only the incomplete data set y_{ij} with (i,j) ∈ $\mathcal{U}$.

These data samples may still contain a few outliers of small amplitude as no median-type filter is a perfect noise detector. The resultant inverse problem is heavily ill-posed, but it is based on the most reliable data samples that could find. It solves it by a variational method.

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The functional we minimize is convex and reads.

$$\sum_{(i,j)\in\mathcal{U}} \left|[Hx-y]_{ij}\right| + \beta \sum_{(i,j)\in\mathcal{A}} \sum_{(k,l)\in\mathcal{V}_{ij}} \left|x_{ij}-x_{kl}\right| \qquad (7)$$

It corresponds to choosing ϕ(t) = t with the data fitting term being restricted only to the samples belonging to U which is the crucial difference and also the functionals. A more convenient and equivalent expression for our functional is

$$\sum_{(i,j)\in\mathcal{A}} \left|\mathcal{X}_{ij}[Hx-y]_{ij}\right| + \beta \sum_{(i,j)\in\mathcal{A}} \sum_{(k,l)\in\mathcal{V}_{ij}} \left|x_{ij}-x_{kl}\right| \qquad (8)$$

where $\mathcal{X}$ is the characteristic function of the set $\mathcal{U}$, namely.

$$\mathcal{X}_{ij} = \begin{cases} 1 & if\ (i,j) \in \mathcal{U} \\ 0 & otherwise \end{cases} \qquad (9)$$

The second phase, minimize a functional consisting of an $\ell_1$fidelity and a Mumford-Shah regularization term as follows

$$\sum_{(i,j)\in\mathcal{U}} \left| [Hx-y]_{ij} + \beta \int_{\frac{\Omega}{\Gamma}} |\nabla x|^2 + \alpha \int_{\Gamma} d\sigma \right| \qquad (10)$$

Thus, there exist numerous local minimums of, while any local minimum of is its global minimum.

D. Smooth Regularization

The weak smooth regularization, as it is customarily done

$$\boldsymbol{\mathcal{F}(x)} = \sum_{(i,j)\in\mathcal{A}} \sqrt{\boldsymbol{\mathcal{X}_{ij}[Hx-y]_{ij}^2+\eta}} + \boldsymbol{\beta} \sum_{(ij)\in\mathcal{A}} \sum_{(k,l)\in\mathcal{V}_{ij}} \sqrt{\left|\boldsymbol{x_{ij}-x_{kl}}\right|^2+\boldsymbol{\eta}} \qquad \mathbf{(11)}$$

Where $\boldsymbol{\eta} > \mathbf{0}$. Let G be the difference matrix such that $(\boldsymbol{Gx})_{ij,kl} = \boldsymbol{x_{ij}-x_{kl}}\quad \boldsymbol{for}\ (\boldsymbol{i},\boldsymbol{j}) \in \boldsymbol{\mathcal{A}}\ \boldsymbol{and}\ (\boldsymbol{k},\boldsymbol{l}) \in \boldsymbol{\mathcal{V}_{ij}}$. Then the gradient of F is given by

$$\boldsymbol{\nabla\mathcal{F}x} = \boldsymbol{H}^* \frac{\boldsymbol{\mathcal{X}^\circ\,(Hx-y)}}{\sqrt{[\boldsymbol{Hx-y}]^2+\boldsymbol{\eta}}} + \boldsymbol{\beta G}^* \frac{\boldsymbol{Gx}}{\sqrt{[\boldsymbol{Gx}]^2+\boldsymbol{\eta}}} \qquad \mathbf{(12)}$$

where °, $[\cdot]^2$ and % are entry wise multiplication, square, and division respectively, and H ∗ and G ∗ are the adjoint of H and G respectively. Since F is convex, minimizing F(x) is equivalent to solving ∇F(x) = 0. This can be minimized by a fixed-point iteration method. The basic idea is to linearize the gradient of F at each iteration. Given xp, get xp+1 by solving x in the equation:

$$H^* \frac{\mathcal{X}^\circ\,(Hx-y)}{\sqrt{[Hx^P-y]^2+\eta}} + \beta G^* \frac{Gx}{\sqrt{[Gx^P]^2+\eta}} = 0 \qquad (13)$$

The linear equation, it can be solved efficiently by linear solvers.

IV. Experiment Results and Comparisons

The proposed algorithm is evaluated and compared with many others existing methods. For this purpose, six popular 512 x 512, -bit gray-level grayscale test Images.

$$PSNR = 10log_{10}\frac{255^2}{\frac{1}{n^2\sum_{(i,j)\in\mathcal{A}}(\hat{x}_{ij}-x_{ij})^2}} \qquad (14)$$

where $\hat{x}_{ij}$ and x_{ij} are the pixel values of the restored image and of the original image, respectively. The test images are all 256-by-256 gray level images. fix $\eta = 1$. The remaining parameter β is chosen empirically such that it gives the best restoration measured in PSNR.

Fig. 1. Lena image blurred with out-of-focus kernel of radius 3, and then corrupted by salt-and-pepper noise with noise levels 30%, 50%, 70%, and 90% respectively.

TABLE I: COMPARISON OF EXISTING AND PROPOSED SYSTEM PSNR VALUE

Method	PSNR			NCC			SSIM		
	20%	40%	60%	20%	40%	60%	20%	40%	60%
NOISY	16.10	13.06	11.33	0.704	0.479	0.294	0.171	0.075	0.037
ACWM-EPR	30.33	23.22	17.71	0.987	0.933	0.759	0.787	0.459	0.204
MPSM-EPR	32.24	25.74	19.78	0.991	0.962	0.843	0.864	0.601	0.301
ROAD-EPR	30.80	28.70	26.26	0.988	0.981	0.967	0.861	0.725	0.510
FIDRM-EPR	30.73	25.26	17.43	0.988	0.957	0.742	0.848	0.637	0.264
DWM-EPR	29.07	28.18	26.91	0.982	0.978	0.971	0.809	0.717	0.587
IAINS-EPR	30.23	29.30	25.43	0.986	0.983	0.959	0.809	0.722	0.509
ANN	31.55	29.46	27.23	0.990	0.984	0.973	0.860	0.753	0.594
Proposed	37.55	35.64	33.03	0.998	0.988	0.979	0.960	0.834	0.658

The experimental results prove the new method to be a significantly advance over several state-of-the art techniques with respect to restoration capability and computational efficiency. The results designate that the proposed method provides significant improvement over comparison existing techniques especially for high noise densities.

V. CONCLUSION

The impulsive noise removal for color or grey images usually employs many existing filters example vector median filter, switching median filter, and edge-preserving regularization. These approaches, however, often introduce excessive smoothing and can result in extensive visual feature blurring and thus are suitable only for images with low density noise. Another problem is artificial neural network take more time for analysis the noise pixel. Thus proposed a two-phase approach to restore images corrupted by blur and impulse noise. The first algorithm to identify the outlier pixel (noise value) the pixels that are expected to be corrupted by random-valued impulse noise or blur images. The second algorithm based on the information on the location of noise-free pixels, by a total variation method by using the essentially outlier-free data. The experimental results prove the new method to be a significantly advance over several state-of-the art techniques with respect to restoration capability and computational efficiency. The results designate that the proposed method provides significant improvement over comparison existing techniques especially for high noise densities. Further, the investigation of noise detectors which exhibit robustness when detecting corrupted pixels for a broad range of noise levels and types still leaves room for improvement in future research.

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