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Improved Adaptive Impulsive Noise Suppression

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***Abstract*— In this work an improved scheme for eliminating impulsive noise of varying strengths from corrupted images is proposed. A neural network is employed to classify the corrupted and non-corrupted pixels. Filtering is only carried out on corrupted pixels keeping the non-corrupted ones intact. Emphasis has been put on selection of relevant input and training patterns. With appropriate choice of patterns the assiduous task of training has become effortless as well as the noise detection become reliable. Comparative analysis with competent schemes on standard images at different noise conditions shows that the proposed scheme outperforms its counterparts.**

I. Introduction

Noise reduction is one of the major concerns in the field of computer vision and image processing. Images are often contaminated by impulsive noise due to noisy sensors or channel transmission errors or faulty storage hardware. The goal of removing impulsive noise is primarily to suppress the noise as well as to preserve the integrity of edges and detailed information. Most of the classical digital filters, such as averaging filters have low pass characteristics and therefore they tend to blur the edges and other fine image details. But nonlinear filtering techniques [1], [2] have been reported to perform better and produce satisfactory results. One of the most popular nonlinear filters is the Standard Median (SM) filter [3] which falls under the category of order statistics filter. This filter is popular due to its simplicity in implementation and efficient noise removal characteristics. However, the median filter with larger window size destroys finer details of an image, even though it reduces the noise to a greater extent. The shortcomings of these filters are alleviated by Weighted Median (WM) filters [4], [5], [6], which provide more weightage to some pixels in the test window. One of such filters is the Center Weighted Median (CWM) filter [7], which gives more emphasis to the center pixel to remove the high-density impulsive noise. This scheme works well under *Salt & Pepper Noise* but yields unsatisfactory performance under *Random Valued Impulsive Noise*. The main drawback of median filter and its variations is that they alter the non-corrupted pixels as they are applied across the image.

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This problem is eased with recent filtering schemes. These schemes consists of two stages: (i) detection of impulsive noise and (ii) filtering of the corrupted pixels. Few reported such schemes are Second Order Differential Impulse Detector [8], Decision Directed Median Filter [9], ANN based Adaptive Thresholding [10] and FLANN based Adaptive Threshold Selection [11] etc. These schemes are based on second derivative of pixels, which reduces the noise free pixels to zero while that of the noisy pixels remain high. Another scheme based on the two stage process is Tri-State Median Filtering (TSM) [12]. This combined filter comprises of Standard Median filter, identity filter, Center Weighted Median filter and a switching logic. Noise detection is realized by an impulse detector, which takes the outputs from the standard median filter and center weighted median filter and compares them with the center pixel value in order to make a tri-state decision. The switching logic is controlled by a threshold value. Depending on this threshold value, the center pixel value is replaced by the output of either SM filter or CWM filter or identity filter. Pixel-Wise MAD (PWMAD) is another technique based on modified median of absolute deviation from median (MAD). MAD is used to estimate the presence of image details. An iterative pixel wise modification of MAD is used in [13], that provides a reliable removal of impulses with an amplified computational cost. Rank-Ordered Absolute Difference (ROAD) is another scheme that measures the closeness of a test pixel with its surroundings [14]. Another technique which suppresses impulsive noise significantly is the Signal-Dependent Rank Ordered Mean (SDROM) [4]. This algorithm replaces the identified noisy pixel with rank ordered mean of the surroundings.

Most of the reported impulse detection schemes exploit neighborhood correlation of pixels. In this paper we propose one such novel impulsive noise detection scheme. Accurate detection of noisy pixels followed by median filtering are the two prime jobs of the proposed scheme.

Rest of the paper is organized as follows: Section II describes the impulsive noise model followed by the proposed scheme. Computer simulation study has been described in Section III. Finally, Section IV provides the concluding remarks.

II. Proposed Scheme

Let z_{ij} be the gray level of an original image Z at pixel location (i,j) and $[n_{min}, n_{max}]$ be the dynamic range of Z. Let x_{ij} be the gray level of the noisy image X at pixel (i,j) location. *Impulsive Noise* of density p may then be defined

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as:

$$x_{ij} = \begin{cases} z_{ij} & \text{with } 1-p \\ \eta_{ij} & \text{with } p \end{cases} \quad (1)$$

where, η_{ij} is the substitute for the original gray scale value at the pixel location (i, j). When $\eta_{ij} = [n_{min}, n_{max}]$, the image is said to be corrupted with *Random Valued Impulsive Noise* (RVIN) and when $\eta_{ij} \in \{n_{min}, n_{max}\}$, it known as *Fixed Valued Impulsive Noise* or *Salt & Pepper Noise* (SPN). Pixels replaced with RVIN and their surroundings exhibit very similar behavior. These pixels differ less in intensity, making identification of noise in RVIN case far more difficult than in SPN. In this work only the RVIN noise model is considered.

The proposed scheme is also one such scheme that is based on estimation–elimination strategy. It decides the sanctity of a pixel based on the output of an Artificial Neural Network (ANN). The network is first trained with a set of training patterns. Two different parameters are used for training. The first parameter is the pixel wise median of the absolute deviation from the median [13] and the second parameter is the rank ordered absolute difference [14]. The first parameter helps in separating the noise from the image details, while the second parameter concentrates on detecting small impulses that are replaced with the true image during contamination. Sections II-A and II-B describes the first and second parameters respectively. Section II-C presents the underlying algorithm.

A. Pixel-Wise MAD (PWMAD)

Let x_{ij}, m_{ij} and d_{ij} represent pixels with coordinates (i, j) of noisy image, median image and absolute deviation image, respectively. Also, let X_{ij}, M_{ij} and D_{ij} denote matrices centered around x_{ij}, m_{ij} and d_{ij}, respectively within a $(2N+1) \times (2N+1)$ size window W, for some non-negative integers N. The median image and absolute deviation image may then be defined as in (2) and (3) respectively.

$$m_{ij} = \text{median}(\mathrm{X}_{ij}) \quad (2)$$

$$d_{ij} = \mid x_{ij} - m_{ij} \mid \quad (3)$$

Pixel-Wise MAD is defined as in (4).

$$\begin{aligned} PWMAD_{ij} &= d_{ij} - \text{median}(\mathrm{D}_{ij}) \\ &= d_{ij} - \text{median}(\mid \mathrm{X}_{ij} - \mathrm{M}_{ij} \mid) \end{aligned} \quad (4)$$

B. Rank-Ordered Absolute Difference (ROAD)

Let $x = x_{ij}$ be the location of the pixel under consideration, and let X_x be the set of pixels in a $(2N+1) \times (2N+1)$ neighborhood centered at x for some non-negative integers N.

Let the set of pixels excluding the center pixel be defined as:

$$\mathrm{X}_x^{(0)} = \mathrm{X}_x - \{x\} \quad (5)$$

For each pixel $y \in \mathrm{X}_x^{(0)}$, let the absolute difference between gray value I of the pixels x and y be defined as:

$$s_{x,y} = |\mathrm{I}_x - \mathrm{I}_y| \quad (6)$$

Then find rank of the eight $s_{x,y}$ values such that $s_{x,y}^{(r)} \leq s_{x,y}^{(r+1)}$, $r = 1, \cdots, 7$. Hence, *Rank-Ordered Absolute Differences* (ROAD) may then be defined as:

$$\text{ROAD}_m(x) = \sum_{r=1}^{m} s_{x,y}^{(r)} \quad (7)$$

where, $2 \leq m \leq 7$. In our simulation m is taken as 4 to find $\text{ROAD}_4(x)$. The following is an example of ROAD statistic generation.

$$\text{Original Neighborhood} = \begin{pmatrix} 154 & 183 & 83 \\ 160 & 210 & 222 \\ 115 & 190 & 75 \end{pmatrix}$$

$$\text{Absolute Differences} = \begin{pmatrix} 56 & 27 & 127 \\ 50 & - & 12 \\ 95 & 20 & 135 \end{pmatrix}$$

Four smallest absolute differences:

$s_{x,y}^{(1)} = 12$, $s_{x,y}^{(2)} = 20$, $s_{x,y}^{(3)} = 27$, and $s_{x,y}^{(4)} = 50$

$$\begin{aligned} \text{ROAD} &= \text{ROAD}_4(x) \\ &= \sum_{r=1}^{4} s_{x,y}^{(r)} = 12 + 20 + 27 + 50 = 109 \end{aligned}$$

This statistic provides a measure of how close a pixel value is to its four similar neighbors.

C. The IAINS Algorithm

Each of the two statistical measures described above can separate noisy and noise-free pixels. However, the separation performance can be further improved by combining them together with an artificial neural network. The proposed Improved Adaptive Impulsive Noise Suppression (IAINS) algorithm is described below.

1. Compute the PWMAD statistic for each pixel of the noisy image as described in Sections II-A.
2. Compute the ROAD statistic for each pixel of the noisy image as described in Sections II-B.
3. For each pixel x_{ij} of the noisy image perform the following steps.
   3.1. Feed the input pair of PWMAD and ROAD statistics corresponding to the test pixel to the neural detector in order to decide the healthiness of x_{ij}.
   3.2. Corrupted pixels are subjected to median filtering (2) leaving the non-corrupted pixels intact.

III. Simulations and Results

The proposed IAINS algorithm uses an ANN, which needs two parameters as inputs to decide the healthiness of a pixel. To train the neural detector, 600 patterns (300 noisy and 300 noise-free) are selected at random from a *Lena* image corrupted with RVIN of 15% noise density. Each pattern consists of statistics obtained from Section II-A and II-B assuming the window size to be 3×3 and their noise status i.e. *noisy* or *noise-free*. The 2–4–4–1 ANN (Figure 1) is then trained with the training patterns by feeding them at random.

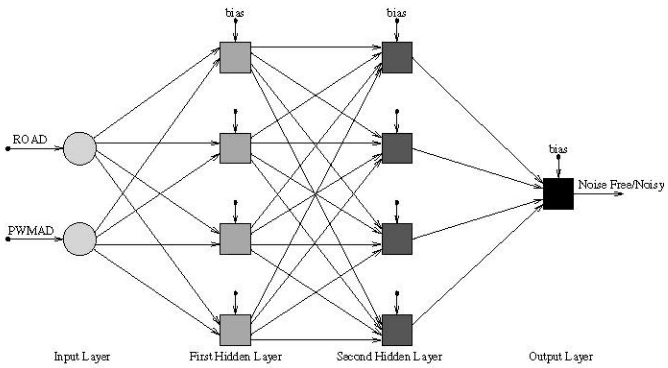

Fig. 1. Back-Propagation Network structure for noise identification.

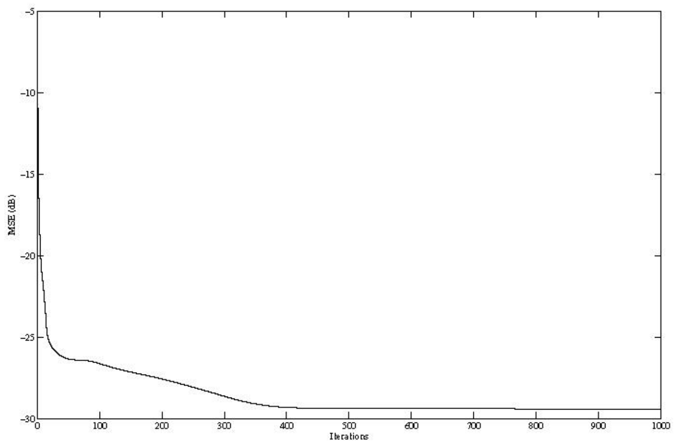

Fig. 2. Convergence characteristics of the network.

The convergence characteristics of the network is shown in Figure 2. It can be seen from the plot that the convergence rate is very fast. For 400 iterations it takes 25 seconds of time in MATLAB in Pentium IV, 2.40GHz machine.

Subsequently, the proposed IAINS scheme, with the trained neural detector, is simulated on some standard images like *Lena*, *Lisa*, *Girl*, *Clown*, *Gatlin*, *Bridge*, *Boat* and *Peppers* etc. To compare the efficacy, few best performing recently reported schemes such as Signal Dependent-Rank Ordered Mean (SD-ROM) [4], Tri-State Median (TSM) [12], Pixel Wise MAD (PWMAD) [13] and FLANN based Adaptive Threshold Selection (FLANN-ATS) [11] are simulated under similar condition. The performance metric used for comparison is Peak Signal to Noise Ratio (PSNR) as defined in (8).

$$\text{PSNR} = 10\log_{10}\left(\frac{255^2}{\frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(z_{i,j}-\hat{x}_{i,j}\right)^2}\right) \tag{8}$$

where,

$(M \times N)$ is the size of the image,

$z_{i,j}$ and $\hat{x}_{i,j}$ represent the pixel values at $(i,j)^{th}$ location of original and restored image respectively.

Firstly, *Lena* image is corrupted with RVIN of 1%, 5%, 10%, 15%, 20%, 25% and 30% of noise densities. The seven

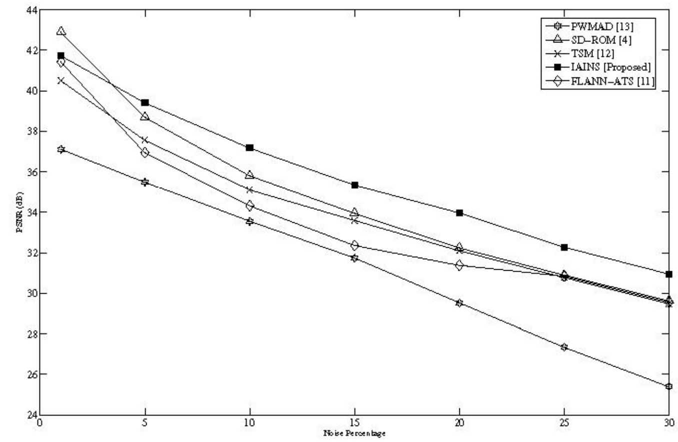

Fig. 3. Variations of PSNR (dB) of Restored *Lena* image corrupted with RVIN of varying strengths.

noisy images thus generated are filtered with the proposed scheme along with other reported schemes. The simulated result of PSNR (dB) variation is plotted in Figure 3.

Secondly, the PSNR (dB) of various images corrupted with 15% and 20% of RVIN is tabulated in Table I. Figure 4 shows the restored results of *Peppers* image.

IV. Conclusions

An efficient noise suppression scheme has been suggested in this paper to combat random valued impulsive noise from images. The scheme works in two phases: detection of faulty pixels followed by filtering of only those pixels using median filter. The detection process utilizes an artificial neural network. The detection is more reliable as relevant input parameters are used in the neural detector. The network proposed here is a generalized one as it works without flaw for a variety of images even though it has been trained with limited number of patterns of one image. Simulation of the proposed scheme along with the recently reported schemes have been carried out under similar environment. It is, in general, observed that the proposed scheme outperforms both qualitatively as well as quantitatively to its counterparts.

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TABLE I
PSNR (dB) OF DIFFERENT SCHEMES AT 15% AND 20% OF NOISE ON DIFFERENT IMAGES

		Lisa	*Girl*	*Clown*	*Gatlin*	*Bridge*	*Boat*	*Peppers*
	PWMAD	30.50	29.28	23.02	30.66	26.07	29.25	31.29
15%	SD-ROM	31.98	31.31	24.33	32.77	27.48	30.75	32.00
RVIN	TSM	32.05	31.05	23.88	32.46	27.08	30.51	33.04
	FLANN-ATS	31.79	30.17	23.59	31.83	27.42	28.93	32.15
	IAINS	**38.65**	**34.94**	**25.45**	**34.71**	**28.62**	**31.56**	**35.14**
	PWMAD	28.26	27.73	22.16	28.77	24.99	27.57	29.04
20%	SD-ROM	30.86	29.92	23.59	31.51	26.55	29.50	31.40
RVIN	TSM	30.95	29.69	23.28	31.30	26.28	29.35	31.41
	FLANN-ATS	30.37	28.14	21.69	29.49	26.64	28.18	30.48
	IAINS	**37.07**	**33.42**	**24.81**	**32.66**	**27.65**	**30.99**	**33.46**

(a) True Image (b) 20% Noisy (c) PWMAD (d) SDROM

(e) TSM (f) FLANN-ATS (g) IAINS

Fig. 4. Magnified portion of restored *Peppers* image corrupted with 20% of RVIN.

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