A SCIENTIFIC APPROACH FOR GENERATION OF RANDOM FIELDS FOR IMAGE ENHANCEMENT AND RECONSTRUCTION

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ABSTRACT

Noise Suppression from images is one of the most important concerns in digital image processing. Impulsive noise is one such noise, which may corrupt images during their acquisition or transmission or storage etc. A variety of techniques are reported to remove this type of noise. It is observed that techniques which follow the two stage process of detection of noise and filtering of noisy pixels achieve better performance than others. In this work such schemes of impulsive noise detection and filtering thereof are proposed. Two models of impulsive noise are considered in this work. The first one is *Salt & Pepper Noise* (SPN) model, where the noise value may be either the minimum or maximum of the dynamic gray scale range of the image. And, the second one is *Random Valued Impulsive Noise* (RVIN) model, where the noise pixel value is bounded by the range of the dynamic gray scale of the image. This work deal with SPN model and deal with RVIN model of noise. The first scheme is based on second order difference of pixels in order to identify noisy pixels. The second scheme for SPN model uses fuzzy technique to locate contaminated pixels. The contaminated pixels are then subject to median filtering. This detection–filtration is done recursively so that filtered pixels take part in the detection of noise in the next pixel. In the propose schemes for adaptive threshold selection is emphasizing. Incorporation of adaptive threshold into the noise detection process may be leads to more reliable and more efficient detection of noise. Based on the noisy image characteristics and their statistics, threshold values are selected. It may be observed, in general, that the proposing schemes are better in suppressing impulsive noise at different noise ratios than their counterparts.

Keywords: cmf,vmf,smf,msmf.

Introduction

Noise removal from a contaminated image signal is a prominent field of research and many researchers have suggested a large number of algorithms and compared their results. The main thrust on all such algorithms is to remove impulsive noise while preserving image details. These schemes differ in their basic methodologies applied to suppress noise. Some schemes utilize detection of impulsive noise followed by filtering whereas others filter all the pixels irrespective of corruption. In this section an attempt has been made for a detail literature review on the reported articles and studies their performances through computer simulation. We have classified the schemes based on the characteristics of the filtering schemes. first one is Filtering without Detection, In this type of filtering a window mask is moved across the observed image. The mask is usually of size $(2N+1)^2$ where

N is a positive integer. Generally the center element is the pixel of interest. When the mask is moved starting from the left-top corner of the image to the right-bottom corner, it performs some arithmetical operations without discriminating any pixel. Second one is Detection followed by Filtering, This type of filtering involves two steps. In first step it identifies noisy pixels and in second step it filters those pixels. Here also a mask is moved across the image and some arithmetical operations are carried out to detect the noisy pixels. Then filtering operation is performed only on those pixels which are found to be noisy in the previous step, keeping the non-noisy intact. And third one is Hybrid Filtering, in such hybrid schemes; two or more filters are suggested to filter a corrupted location. The decision to apply a particular filter is based on the noise level at the test pixel location or performance of the filter on a filtering mask.

Motivation

Most of the traditional reported schemes work well under SPN but fails under RVIN, which is more realistic when it comes to real world applications. Even though some of the reported methods claim to be adaptive, they are not truly adaptive for the simple reason of not considering the image and noise characteristics. These schemes generally use a threshold value for the identification of noise. A predefined parameter is compared with this threshold value. If it exceeds, the pixel is marked as contaminated otherwise not. Usually the threshold value used is either a constant or a set of four/five values. A threshold, which is optimal in one environment, may not be good at all in a different environment. By environment we mean, the type of image, characteristic and density of noise. Further, there has been little or no usage of soft computing techniques in the reported schemes. Soft computing methodologies mimic the remarkable human Capability of making decision in ambiguous environment. It embraces approximate reasoning, imprecision, uncertainty and partial truth. There exists scope for improving the detector's performance using soft computing techniques. These facts motivated us

• To work towards improved and efficient detectors for identifying contaminated pixels.
• To devise adaptive thresholding techniques so that noise detection would be more reliable.
• To exploit the computational power of soft computing techniques in predicting the threshold value by adapting to the environment with a greater ease.

In this work all the existing filters will be analysed and based on the limitations innovative methods will be suggested for Images Enhancement and restorations which will produce better results.

Families of Common Nonlinear Filters

Boolean, stack, OS and morphological filters. Many nonlinear signal processing methods have their origin in statistics. In fact, the median filter was first introduced in statistics for smoothing economical time series [24]. It soon became evident that the median filter performs very well especially in image processing applications where sharp transitions are common. Especially in urban or other "man-made" scenes we almost always have sharp edges and these edges usually are the most important information in the image. Attempts to retain sharp edges in linear filtering lead to "ringing" effects that are often more disturbing than noise. In applications involving images, image sequences and color images, order statistics and their close kin morphological filters have by far been the most prominent and successful classes of nonlinear techniques, see [1], [3], [5], [6], [17], and [21].One of the greatest limitations of order statistics filters is the fact that they are "smoothers". Without additional processing or combinations, their use remains limited to restoration applications, in which they excel especially in the presence of heavy-tailed noise (to be removed) and important signal details (to be preserved). General Boolean filters and morphological filters with non-flat structuring elements do not suffer from such a shortcomings; however, they do not benefit from the stacking property which unifies all subclasses of stack filters; ranked order, median and weighted median and weighted order statistics filters. The stacking property says that the Boolean function that defines the filter is positive (or increasing as is the standard term in mathematical morphology). There is usually no underlying physical model that would demand the filter to be increasing. The power of increasing filters comes from the fact that concept narrows the filter class in a way that fits well to design processes. For instance, if we have information of the possible desired signal form expressed in Boolean vectors in such a form that it does not conflict the positivity of the defining Boolean function, designing optimal increasing filter becomes straightforward, see [4], [11], [13], [26], and [28]. In some problems, notably in document image processing, noise is loosely speaking signal dependent binary union and intersection noise and increasing filters turn out to perform quite badly [14]. Here one must give up positivity and the penalty is that the large number of parameters and non-robust behavior of an unconstrained Boolean function makes the design of filters with large window sizes impossible. Recently there have emerged new ways to constrain the function leading to much better performance for large window sizes [20].

Challenges in Filter Design

A unified and efficient framework for nonlinear filter design remains one of the most challenging tasks in this field. Even though we can not hope to obtain a framework as powerful as the techniques for designing linear filters we should be able to build a methodology that would tie together the conditions and assumptions of the problem, the major nonlinear filter classes, relevant cost functions and accessible optimization algorithms. It is clear that the methodology must be able to deal with both statistical and deterministic aspects of the problem and filters. This framework cannot be obtained by one step (leap) but it will emerge as the result of incremental steps from the joint efforts of the signal processing community. However it is good to keep the ultimate goal in mind while solving problems for more immediate demands.Few attempts have been made to this end, see for instance [8] and [29]. Here we consider some problems whose solutions will clearly take us forward on this path. We all agree that it would be important to be able to devise a feasible optimization procedure with a suitable cost function, even for a specific application, e.g. image restoration. The unification of two or more existing filter classes will un-doubtfully increasethe modeling power of the framework. Therefore, it would of great interest to determine the class of problems (signals) that can be solved (represented) by the new framework.

A related problem is that of the filter structure, or more specifically, the filter size. An often asked question is how large should the filter size be. Most of the answers have been “try and see” type. In [22], we proposed a solution to this problem, in which we combined both the optimization and the filter structure in a recursive manner. Another equally important challenge to the nonlinear signal and image processing community is to develop new and attracting applications. Next to a mature theory (still developing), interesting applications would be the driving force to open up new frontiers in the field. Most of the current applications remain in the areas of signal (1- and M-D) restoration, enhancement, edge detection and interpolation. Recently, stack and Boolean filters were successfully used as predictors in a DPCM lossless image compression scheme, [16]. More such endeavors are needed in other areas such as speech analysis and processing, telecommunications and data analysis and communication.

We will assume that a degradation function exists, which, together with additive noise, operates on the input image $f(x,y)$ to produce a degraded image $g(x,y)$.

The objective of restoration is to obtain an estimate for the original image from its degraded version $g(x,y)$ while having some knowledge about the degradation function H and the noise $\eta(x,y)$.

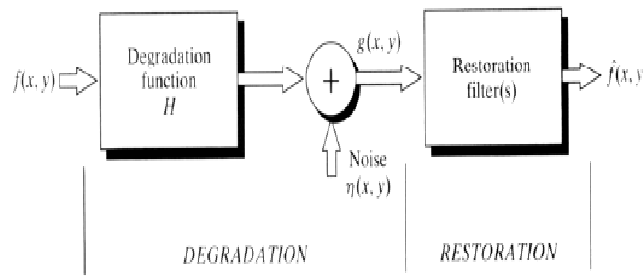
Mean Filter

The Mean Filter is a linear filter which uses a mask over each pixel in the signal. Each of the components of the pixels which fall under the mask are averaged together to form a single pixel. This new pixel is then used to replace the pixel in the signal studied. The Mean Filter is poor at maintaining edges within the image.

$$MEANFILTER(x_1, \ldots, x_N) = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (1)$$

The use of the median in signal processing was first introduced by J. W. Tukey [1]. The Median Filter is performed by taking the magnitude of all of the vectors within a mask and sorting the magnitudes, as defined in (2). The pixel with the median magnitude is then used to replace the pixel studied. The Simple Median Filter has an advantage over the Mean filter in that it relies on median of

Model for image degradation/restoration process



the data instead of the mean. A single noisy pixel present in the image can significantly skew the mean of a set. The median of a set is more robust with respect to the presence of noise.

$$MEDIANFILTER(x_1, \ldots, x_N) = MEDIAN(\|x_1\|^2, \ldots, \|x_N\|^2) \qquad (2)$$

When filtering using the Simple Median Filter, an original pixel and the resulting filtered pixel of the sample studied are sometimes the same pixel. A pixel that does not change due to filtering is known as the root of the mask. It can be shown that after sufficient iterations of median filtering, every signal converges to a root signal [2].

The Component Median Filter, defined in (3), also relies on the statistical median concept. In the Simple Median Filter, each point in the signal is converted to a single magnitude. In the Component Median Filter each scalar component is treated independently. A filter mask is placed over a point in the signal. For each component of each point under the mask, a single median component is determined. These components are then combined to form a new point, which is then used to represent the point in the signal studied. When working with color images, however, this filter regularly outperforms the Simple Median Filter. When noise affects a point in

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a grayscale image, the result is called "salt and pepper" noise. In color images, this property of "salt and pepper" noise is typical of noise models where only one scalar value of a point is affected. For this noise model, the Component Median Filter is more accurate than the Simple Median Filter. The disadvantage of this filter is that it will create a new signal point that did not exist in the original signal, which may be undesirable in some applications.

$$CMF(x_1,\ldots,x_N) = \begin{bmatrix} MEDIAN(x_{1r},\ldots,x_{Nr}) \\ MEDIAN(x_{1g},\ldots,x_{Ng}) \\ MEDIAN(x_{1b},\ldots,x_{Nb}) \end{bmatrix} \quad (3)$$

The Vector Median Filter (VMF) was developed by Astola, Haavisto, and Neuvo in 1990 [3]. In the VMF (4), a filter mask is placed over a single point. The sum of the vector magnitude differences using the *L*2 norm from each point to each other point within the mask is computed. The point with the minimum sum of vector differences is used to represent the point in the signal studied. The VMF is a well-researched filter and popular due to the extensive modifications that can be performed in conjunction with it.

$$VMF(x_1,\ldots,x_N) = MIN\left(\sum_{i=1}^{N}\|x_1 - x_i\|,\ldots,\sum_{i=1}^{N}\|x_N - x_i\|\right) \quad (4)$$

For each of the four algorithms discussed, experimental results will be shown that indicate which algorithm is best suited for the purpose of impulse noise removal in digital color images. Those results will be compared to two new algorithms for noise removal: the Spatial Median Filter and the Modified Spatial Median Filter.

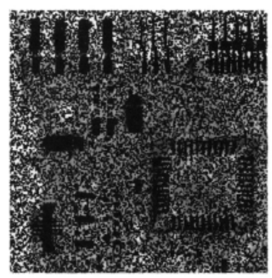
In testing, we consider sets of images containing various amounts of artificial noise. Impulse noise represents random spikes of energy that happen during the data transfer of an image. To generate noise, a percentage of the image is damaged by changing a randomly selected point channel to a random value from 0 to 255. The noise model, *In*, is given by

$$I_n(i,j) = \begin{cases} I(i,j) & & x \geq p \\ (I_r(i,j), I_g(i,j), z) & y < \frac{1}{3} & x < p \\ (I_r(i,j), z, I_b(i,j)) & \frac{1}{3} \leq y < \frac{2}{3} & x < p \\ (z, I_g(i,j), I_b(i,j)) & \frac{2}{3} \leq y & x < p \end{cases} \quad (5)$$

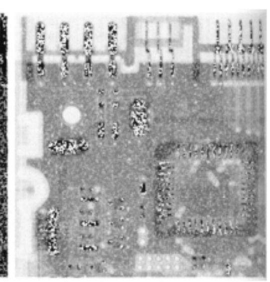
where *I* is the original image, *Ir*, *Ig*, and *Ib* represent the original red, green, and blue component intensities of the original image, *x*,*y* *2* [0,1] are continuous uniform random numbers, *z 2* [0,255] is a discrete uniform random number, and *p 2* [0,1] is a parameter which represents the probability of noise in the image.

Restoration in the presence of noise only – Spatial filtering

Selecting an incorrect sign in contra harmonic filtering may lead to unpleasant results...



Pepper noise: result with $Q = -1.5$ instead of 1.5

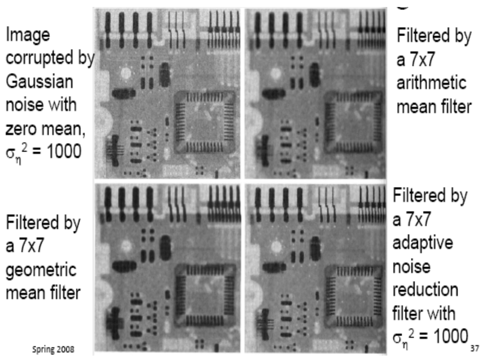


Salt noise: result with $Q = 1.5$ instead of -1.5

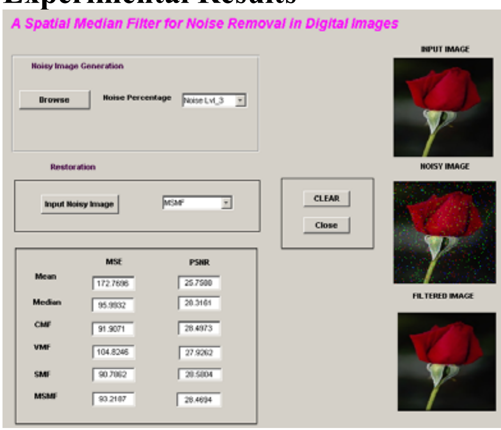
Adaptive local noise reduction filter:

since the mean gives a measure for average intensity in the region and variance characterizes contrast in that region, they both are reasonable parameters to base an adaptive filter.

Considering a local region *Sxy* of a noisy version *g*(*x*,*y*) of the image *f*(*x*,*y*) with the overall noise variance ση2, local mean of pixels in the region *mL* and their local variance σ*L2*, the following rules are to be implemented:

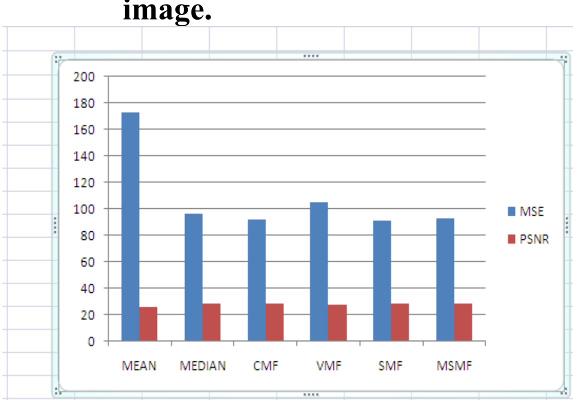


Experimental Results



Method	MSE	PSNR
MEAN	172.7696	25.7588
MEDIAN	95.9932	28.3161
CMF	91.9071	28.4973
VMF	104.8246	27.9262
SMF	90.7862	28.5804
MSMF	93.2187	28.4694

Table : MSE AND PSNR values of the image.



Graph : PSNR and MSE shown in graph

Conclusion

We have introduced two new filters for removing impulse noise from images and shown how they com- pare to four well-known techniques for noise removal. The Spatial Median Filter is proposed based on the Vector Median Filter and the Spatial Median quantile order statistic. Seeing that the order statistic can be utilized to make a judgment as to whether a point in the signal is considered noise or not, a Modified Spatial Median Filter has been proposed. This filter accepts a threshold parameter *T* indicating the estimated number of uncorrupted pixels under the mask.

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