A Salt and Pepper Noise Removal and Restoration Refinement Algorithm

Carlos A. JUNEZ-FERREIRA
Facultad de Ingeniería Eléctrica, Universidad Michoacana de San Nicolás de Hidalgo
Morelia, Michoacan, ZIP 58040, Mexico

Fernando A. VELASCO-AVALOS
Facultad de Ingeniería Civil, Universidad Michoacana de San Nicolás de Hidalgo
Morelia, Michoacan, ZIP 58040, Mexico

and

Nelio PASTOR-GOMEZ
Facultad de Ingeniería Civil, Universidad Michoacana de San Nicolás de Hidalgo
Morelia, Michoacan, ZIP 58040, Mexico

ABSTRACT

Noise removal is an important task inside the image processing area. In this paper, an algorithm for reducing salt and pepper noise and improving the restoration quality through refinement is presented. This algorithm proposes a double screen. As a first step, the algorithm computes an estimation of the denoised image by using an adaptive median filter. Then, the Non-Local Means algorithm is used in order to have a better quality of reconstitution. Obtained results show that the implementation of this proposal gives considerable noise suppression, even with high noise densities, and it could prepare the image for other processes like image segmentation and object recognition.

Keywords: Image Denoising, Salt and Pepper Noise, Adaptive Median Filter.

1. INTRODUCTION

Frequently, digital images are corrupted by undesirable random variations in intensity values, called noise. The presence of noise is due to several factors, among which are found the process of acquisition, compression, and transmission of data, as well as occurring phenomena at scene of interest. A common type of noise is impulse noise, widely known as salt and pepper. This kind of noise randomly changes intensities of some pixels to the maximum or minimum values of the intensity range on the image. The model of this kind of noise used in the present work is described below.

Let $x_{i,j}$, for $(i,j)\in A$, where $A\equiv\{1,\ldots,M_1\}\times\{1,\ldots,M_2\}$, the intensity value of a pixel at position (i,j) of an image $\boldsymbol{x}$ of size $M_1\times M_2$, and let $[v_{\min}, v_{\max}]$ the dynamic range of $\boldsymbol{x}$, i.e., $v_{\min}\le x_{i,j}\le v_{\max}$ for all $(i,j)\in A$. $\boldsymbol{y}$ is the salt and pepper noise corrupted version of $\boldsymbol{x}$, then, the observed intensity value at position (i,j) of image $\boldsymbol{y}$ is given by

$$y_{i,j}=\begin{cases} v_{\min} & \text{with probability } p \\ v_{\max} & \text{with probability } q \\ x_{i,j} & \text{with probability } 1-p-q \end{cases} \tag{1}$$

where $r=p+q$ defines noise density. In this work, it is considered that $p=q$.

The suppression of noise is an important task in the computer vision area, with the objective of recovering the original image (or the closest approximation) from its noisy version. The reduction of noise prepares the image for other processes such as segmentation and object recognition.

In order to reduce noise in digital images, a great number of algorithms have been presented. One of the most common ways to remove noise is convolving the image with a mask that represents a low-pass filter (e.g. gaussian filter), performing a smoothing operation through a weighted average of neighbors, where the weights decrease with distance from the central pixel on filter window. Often, the use of smoothing filters cause significant blurring of edges. This problem was addresed by Perona and Malik [1], where the image is processed with a smoothing partial differencial equation similar to heat equation by using diffusion coefficients designed to detect edges. Bilateral filtering, presented by Tomasi and Manduchi [2], has become a popular method that combines pixel values based on geometric closeness and intensity similarity. Recently, Buades et al. [3] proposed the Non-Local Means algorithm, supported on the idea that images contain repeated structures, and averaging this structures, noise can be reduced.

The median filter has been widely used for impulse noise suppression due to its ability to preserve edges. However, this does not always happen in images with high noise density, and because of that reason there have been numerous proposals on this issue, as the one presented by Brownrigg [4], which gives bigger weights to certain pixels in the filtering window. Wang and Zhang [5] proposed an iterative algorithm focused on the detection of pulses, just filtering pixels considered as noise. Moreover, Balasubramanian et al. [6] proposed a methodology divided into two stages, the first one is the use of a median filter based on decisions and the second one in determining the midpoint of a vector, obtained after eliminating extreme values. Yuan and Tan [7] proposed a noise detector based on the difference of the corrupted image and an estimate of the restored image, which is obtained by applying the standard median filter on the corrupted image, then this algorithm filters candidate pixels to be noise, through an adaptive median filter. Chan et al. [8] presented an interesting work which proposes the removal of salt and pepper noise by using a two-phase scheme. At the first phase an adaptive median filter is used in order to identify pixels that can be considered as noise. In the second phase, the image is restored by a regularization method which eliminates noise and preserve edges by minimizing a functional which consists of a data fidelity term as well as a regularization term that preserves edges.

This paper presents a two-phase algorithm for removing salt and pepper noise. At the first phase, an estimate of the denoised version is computed by using an adaptive median filter. In the second phase this estimation is improved through applying a refinement based on the Non-Local Means proposal. This paper is organized as follows, in Section 2, a brief review of the Non-Local Means algorithm is done. Section 3 describes the noise removal proposal. Finally, Section 4 shows experimental results.

2. NON-LOCAL MEANS ALGORITHM

Buades et al. [3] proposed the Non-Local Means algorithm, based on the idea that images contain repeated structures and, averaging these structures, the noise of an image can be reduced. In other words, instead of using averages of similar pixel intensity values, this method averages neighbours with similar neighbourhoods.

Given a discrete image with noise $\boldsymbol{y}$, the restored value $\hat{x}_{m,n}$, for the pixel at location $(m,n) \in A$, is computed as the weighted average of all pixels of the image,

$$\hat{x}_{m,n} = \sum_{(i,j)\in A} w_{i,j}^{m,n} y_{i,j} \tag{2}$$

where the family of weights $\left\{w_{i,j}^{m,n}\right\}$ depends on the similarity between pixels at positions $(m,n) \in A$ and $(i,j) \in A$. These weights must satisfy the conditions $0 \le w_{i,j}^{m,n} \le 1$ and $\sum_{(i,j)\in A} w_{i,j}^{m,n} = 1$.

Similarity between $y_{i,j}$ and $y_{m,n}$ depends on the similarity between vectors $V(\Omega_{i,j})$ and $V(\Omega_{m,n})$, where $\Omega_{k,l}$ denotes a fixed size neighbourhood. This neighbourhood is defined as the set of pixels within a window of size $W \times W$, centered at the position $(k,l) \in A$, that can be expressed as

$$\Omega_{k,l} = \{y_{i,j} : i-(W-1)/2 \le k \le i+(W-1)/2, \\ j-(W-1)/2 \le l \le j+(W-1)/2\} \tag{3}$$

$V(\Omega_{k,l})$ represents a vector containing the pixels that belong to the neighbourhood $\Omega_{k,l}$.

Similarity between the above mentioned vectors is measured by a decreasing function of Euclidean distance, $d_{i,j}^{m,n} = \left\| V(\Omega_{m,n}) - V(\Omega_{i,j}) \right\|^2$. Pixels with similar neighbourhood to $V(\Omega_{m,n})$ will have large weights, which are defined as

$$w_{i,j}^{m,n} = \frac{1}{Z_{m,n}} e^{-\left(\frac{d_{i,j}^{m,n}}{H^2}\right)} \tag{4}$$

where $Z_{m,n}$ is the normalization constant

$$Z_{m,n} = \sum_{(i,j)\in A} e^{-\frac{d_{i,j}^{m,n}}{H^2}} \tag{5}$$

and the parameter H acts as a filtering degree, that is, it controls the decay of weights as a function of distances. The implementation of the original proposal of the Non-Local Means algorithm involves a high computational cost. This trouble can be reduced by using a window of size W_1, used to compute the average with a limited number of neighbours, instead of averaging all pixels of the image; and a window of size W_2 which defines the structure of the neighbourhood and the size of vector $V(\Omega_{k,l})$. Some improvements for this algorithm have been presented, as the one proposed by Mahmoudi and Sapiro [9]. In general, the Non-Local Means algorithm gives good results in terms of noise reduction and edge preservation. However, this does not always happen especially in images with impulse noise as shown in Figure 1.

3. SALT AND PEPPER NOISE REMOVAL

Our proposal is divided into two stages. At the first one, an estimation $\hat{\boldsymbol{y}}$ of the denoised image of N pixels is computed through an adaptive median filter. According to the model defined in (1), noisy pixels take its values from the set $\{v_{\min}, v_{\max}\}$. Then, the adaptive median filter will be applied only to pixels at positions of the set $\Gamma = \{(i,j) : y_{i,j} \in \{v_{\min}, v_{\max}\}\}$, i.e. Γ is the set of corrupted pixels candidates. Then Γ^C will be defined as the set of uncorrupted pixels. The intensity values of these pixels are kept without any modification.

(a)

(b)

Figure 1: (a) Noisy image (20%), (b) Denoised image by NL-means algorithm.

Thus, beginning with a minimum window size $W_{\min}$, a neighbourhood $\Omega_{k,l}$ for the corrupted pixel at position (k,l) is defined, then uncorrupted pixels belonging to the neighbourhood are stored in a vector ***VW***, and the central pixel is replaced by the median value of this vector. This kind of filtering considers geometric closeness in restoration. If the mentioned vector is empty, the window size is increased, repeating the procedure above described.

If the size increases to reach a defined window size W_d, and the number of pixels with intensities equal to maximum (*crw*) is bigger than a percentage *P* of the whole window pixels, the central pixel value is replaced by the maximum value of intensity of the image. In the same way, if the number of pixels with intensities equal to minimum (*crb*) is bigger than *P*, the central pixel value is replaced by the minimum value of intensity. These procedures considers the existence of objects whose pixels intensity values are equal to the maximum or minimum values on image, in other words, the presence of black or white objects in the image without noise, for example. If the size increases to reach a maximum size of window $W_{\max}$, central pixel value is replaced by the median value of all pixels in neighbourhood. This procedure is shown as pseudo-code in Figure 2.

```
Algorithm
Estimation(y, v_min, v_max, N, W_d, W_min, W_max, P)
    i ← 1
    do
        if (y_i = v_min) ∨ (y_i = v_max)
            W ← W_min; witness ← 0
            do
                if (y_i = v_min) ∨ (y_i = v_max)
                Y = {y_j : y_j ∈ Ω_i(W)}
                VW ← φ; cr ← 1; crb ← 0; crw ← 0;
                do
                    if (Y_cr ≠ v_min) ∧ (Y_cr ≠ v_max)
                        VW ← VW ∪ Y_cr
                    else
                        if (Y_cr = v_min)
                            crb ← crb + 1
                        else
                            crw ← crw + 1
                            cr ← cr + 1
                while cr ≤ (W × W)
                if VW ≠ φ
                    ŷ_i ← Median(VW)
                    witness ← 1
                else
                    if W ≥ W_d
                        if crb/(W × W) ≥ P
                            ŷ_i ← v_min
                            witness ← 1
                        else
                            if crw/(W × W) ≥ P
                                ŷ_i ← v_max
                                witness ← 1
                            else
                                W ← W + 2
            while (W ≤ W_max) ∧ (witness = 0)
            if (W > W_max) ∧ (witness = 0)
                ŷ_i ← Median(Ω_i(W_max))
        else
            ŷ_i ← y_i
        i ← i + 1
    while i ≤ N
    return(ŷ)
```

Figure 2: Pseudo-code of Estimation function.

After obtaining the image estimation, the second stage of the algorithm is refinement. For this purpose, we use the Non-Local Means algorithm. The idea behind using this proposal lies in the fact that we could take advantage of structural features in neighbourhoods in order to refine previously estimated image. This refinement is performed by calculating the weights of the pixels in the neighbourhood for a corrupt pixel candidate (whose position belongs to the set Γ) according to expression (4). Then, weights greater than an established threshold, *TW*, are stored in a vector ***WV***. Their corresponding intensity values are stored in a vector ***YV***. Later, vector ***WV*** is normalized. Thus, the restored value $\hat{\boldsymbol{x}}_{i,j}$ is the element-wise product of vectors ***WV*** and ***YV***. In this way, only pixels with very similar structures to the pixel in question are involved in the computation of the new intensity value unlike original Non-Local Means algorithm. Figure 3 shows the pseudo-code of this step.

It can be derived that the proposed two-phase algorithm is O(N), where N is the number of pixels on image.

Algorithm Refinement($\hat{\boldsymbol{y}}$, $v_{\min}$, $v_{\max}$, N, W_1, W_2, TW, H)

$i \leftarrow 1$
do
  if $(y_i = v_{\min}) \vee (y_i = v_{\max})$
    $\hat{\boldsymbol{Y}} = \{\hat{y}_j : \hat{y}_j \in \Omega_i(W_1)\}$
    $\boldsymbol{W_i}$ =ComputeWeights($\hat{\boldsymbol{y}}, i, \hat{\boldsymbol{Y}}, W_1, W_2, H$)
    $\boldsymbol{YV} \leftarrow \phi$; $\boldsymbol{WV} \leftarrow \phi$; $ctr \leftarrow 1$; $ctrw \leftarrow 0$;
    do
      if $w_{ctr} \geq TW$
        $\boldsymbol{YV} \leftarrow \boldsymbol{YV} \cup \hat{Y}_{ctr}$
        $\boldsymbol{WV} \leftarrow \boldsymbol{WV} \cup w_{ctr}$
        $ctrw \leftarrow ctrw + 1$
      $ctr \leftarrow ctr + 1$
    while $ctr \leq (W_1 \times W_1)$
    $\boldsymbol{WV} \leftarrow \boldsymbol{WV} \;/\; \sum_{ctr1=1}^{ctrw} WV(ctr1)$
    $\hat{x}_i \leftarrow \boldsymbol{WV}^T \boldsymbol{YV}$
  else
    $\hat{x}_i \leftarrow \hat{y}_i$
  $i \leftarrow i + 1$
while $i \leq N$
return($\hat{\boldsymbol{x}}$)

Figure 3: Pseudo-code of Refinement function.

4. EXPERIMENTAL RESULTS

Experiments show that the results obtained by applying the described algorithm are good. The implementation of the code was made using Matlab 6.5 R13 on a PC 2.8 GHz Dual Core CPU.

The used images were corrupted with salt and pepper noise with different densities using the *imnoise* Matlab function. For image estimation we used $W_{min}=3$, $W_d=7$, $W_{max}=10$, and $P=0.75$. For refinement, we use the values $W_1=3$, $W_2=3$, $TW=0.10$ and $H=10$. Tables 1-3 show the performance of the algorithm for noise reduction measured by Peak Signal-to-Noise Ratio (PSNR), Mean Absolute Error (MAE), and Universal Image Quality Index (UIQI) [10], for images 1 (Figure 4(a)), 2 (Figure 5(a)), and 3 (Figure 6(a)), respectively.

It can be observed that reconstitution is quite good for all experiments. As comparative purposes, we show in table 4 some results reported by Chan et al. [8], applying their proposal to image 3 (Lena). This work is considered as state of the art on salt and pepper noise corrupted images restoration. The results of applying our algorithm are, in general, similar o better than those reported by Chan et al. [8], also they were obtained in less time. In Figure 7(a), a detail of image 3 is shown. Figures 7(b) and 7(c) correspond to the same detail zone of the estimate and the refined images of phase 1 and phase 2, respectively. It can be noticed that borders obtained in phase 2 are smoother than those obtained in phase 1. This smoothing represents the goal of our proposal of using a refinement step.

Table 1: Obtained performance of our noise suppression proposal for image 1.

Noise density	PSNR (dB)	MAE	UIQI	Time (s)
20%	35.29	1.27	0.94	12.59
50%	30.38	3.31	0.83	28.61
80%	26.58	6.37	0.64	45.42

Table 2: Obtained performance of our noise suppression proposal for image 2.

Noise density	PSNR (dB)	MAE	UIQI	Time (s)
20%	33.71	1.02	0.95	12.60
50%	29.05	2.55	0.86	28.25
80%	25.32	5.10	0.70	45.42

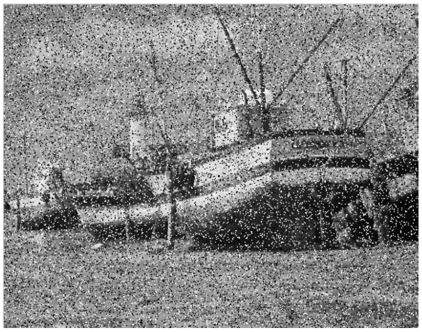
Table 3: Obtained performance of our noise suppression proposal for image 3.

Noise density	PSNR (db)	MAE	UIQI	Time (s)
20%	42.64	0.50	0.98	12.19
50%	36.57	1.52	0.93	27.91
70%	33.39	2.52	0.87	45.74
80%	31.33	3.31	0.81	44.39

Table 4: Reported performance by Chan et al. [8] noise suppression proposal for image 3.

Noise density	PSNR (db)	MAE	Time (s)
20%	39	0.1	-
50%	33	2	-
70%	29.3	4	2009

(a)



(b)

(c)

Figure 4: Image 1, (a) Original image, (b) Noisy image (20%), (c) Denoised image by our proposal.

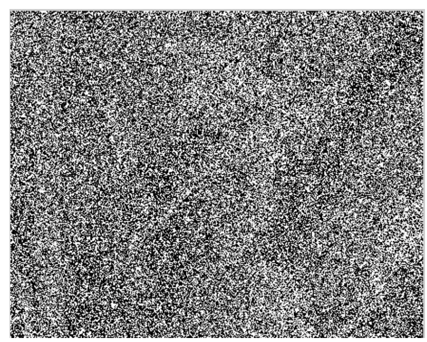
(a)

(b)

(c)

Figure 5: Image 2, (a) Original image, (b) Noisy image (50%), (c) Denoised image by our proposal.

(a)

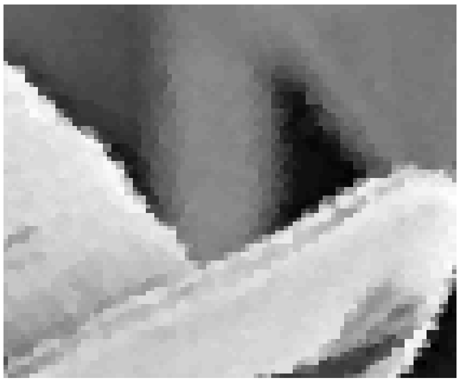


(b)

(c)

Figure 6: Image 3, (a) Original image, (b) Noisy image (80%), (c) Denoised image by our proposal.

(a)



(b)

(c)

Figure 7: Image 3, details, (a) Original image, (b) Estimate of phase 1 (from noisy image (80%)), (c) Denoised image after applying phase 2.

5. CONCLUSIONS

In this paper, an algorithm for removing salt and pepper noise in digital images has been presented. This algorithm is based on a preliminary estimate of the restored image, made by an adaptive median filter. Following this, the Non-Local Means algorithm is used for refinement. Experimental results have shown that the proposed algorithm provides similar (in some cases better) performance, in reasonable operation time, respecting other state of the art denoising algorithms. As future work, we can consider to adapt this algorithm for removing different types of noise and using it as a part of an image pre-processing step, in order to perform tasks such as segmentation and object recognition in a robust way. Also, some research on real time implementation of denoising algorithms must be done, as well as, reassessing the method of weighting on similar pixels, because of the fact that reconstituted images, even with sharp boundaries, are globally faded.

6. REFERENCES

[1] P. Perona, S. Malik, S., "Scale-Space and Edge Detection Using Anisotropic Diffusion", **IEEE Transactions on Pattern Analysis and Machine Intelligence,** Vol. 12, No. 7, 1990, pp. 629-639.

[2] C. Tomasi, R. Manduchi, "Bilateral Filtering for Gray and Color Images", **In proc. IEEE International Conference on Computer Vision**, 1998, pp. 839-846.

[3] A. Buades, B. Coll, J.M. Morel, "A non-local algorithm for image denoising", **In proc. IEEE Computer Society Conference on Computer Vision and Pattern Recognition**, Vol. 2, 2005, pp. 60-65.

[4] D.R.K. Brownrigg, "The weighted median filter", **Communications of the ACM**, Vol. 27, No. 8, 1984, pp. 807-818.

[5] Z. Wang, D. Zhang, "Progressive Switching Median Filter for the Removal of Impulse Noise from Highly Corrupted Images", **IEEE Transactions on Circuits and Systems-II: Analog and Digital Signal Processing**, Vol. 46, No. 1, 1999, pp. 78-80.

[6] S. Balasubramanian, S. Kalishwaran, R. Muthuraj, D. Ebenezer, V. Jayaraj, "An Efficient Non-linear Cascade Filtering Algorithm for Removal of High Density Salt and Pepper Noise in Image and Video sequence", **In Intl. Conf. on Control, Automation, Communication and Energy Conservation**, 2009.

[7] S.Q. Yuan, Y.H. Tan, "Difference-Type noise detector for adaptive median filter", **IEEE Electronic Letters**, Vol. 42, No.8 2006.

[8] R.H. Chan, C.W. Ho, M. Nikolova, "Salt-and-Pepper Noise Removal by Median-Type Noise Detectors and Detail-Preserving Regularization", **IEEE Transactions on Image Processing**, Vol. 14, No. 10, 2005, pp. 1479-1485.

[9] M. Mahmoudi, G. Sapiro, "Fast Image and Video Denoising via Nonlocal Means of Similar Neighborhoods", **IEEE Signal Processing Letters**, Vol. 12, No.12, 2005, pp. 839-842.

[10] Z. Wang, A.C. Bovik, "A universal image quality index", **IEEE Signal Processing Letters**, Vol. 9, No. 3, 2002, pp. 81-84.