

An Effective Image De-noising Alternative Approach Based on Third Generation Neural Networks

Manuel Mejía-Lavalle^(✉), Estela Ortiz, Dante Mújica, José Ruiz, and Gerardo Reyes

Departamento de Ciencias Computacionales, Centro Nacional de Investigación y Desarrollo Tecnológico (CENIDET), Cuernavaca, Mexico

{mlavalle, estela_or, dantemv, josera, greyes}@cenidet.edu.mx

Abstract. Searching to reduce the noise effect in gray scale digital images, an efficient and effective alternative approach that combines a kind of Pulse-Coupled Neural Network and the Median estimator is proposed to remove Salt and Pepper noise. The proposed approach is based on a simplified Third Generation Neural Network called Intersection Cortical Model (ICM). Using the ICM output images, we can detect which pixel position corresponds to Salt and Pepper noise. Then, a selective Median filter is used for suppressing the Salt and Pepper noise only over the previously detected noisy pixels. The performance of the proposed approach is evaluated by simulating different impulsive noise densities. Simulation results show that method's effectiveness is 32 % better and 225 % faster than conventional Median filter noise suppression. Results are measured by the Peak Signal to Noise Ratio, Mean Absolute Error and Normalized Mean Square Error metrics.

Keywords: Image de-noising · Third Generation Neural Networks · Pulse-Coupled Neural Network · Intersection Cortical Model · Salt and Pepper noise

1 Introduction

Noise in digital images causes problems in its analysis, recognition, classification and interpretation. Salt and Pepper noise is an impulse noise type that commonly affects digital images and is the result of defective sensors or poor transmission channels. The pixels that present this error are visually different from their neighbors, since their gray values tend to be extremely high or low (gray level 0 or 255).

The Median filtering can suppress Salt and Pepper noise successfully; in this well-known technique, the central pixel of the filtering window is replaced by the median value. Despite its simplicity, its main disadvantage is that, when remove the noise also removes image details [1]. Other better techniques are known, but they are more sophisticated and more computer time consuming, for example by using fuzzy techniques [2], or variants of the median filter [3–5]. A different or alternative way of addressing this problem has begun to be explored experimentally; such is the case of the Third Generation Neural Networks, also called Pulse-Coupled Neural Networks (PCNN).

PCNN is a simplified mathematical model proposed by Eckhorn [6], and it is based on the timing of the pulses released in the visual cortex of the mammals

(with this research, John C. Eccles, Alan L. Hodgkin and Andrew F. Huxley won the 1963 Medicine Nobel Prize [6]). The pulse timing of the PCNN is used especially for the detection of noisy pixels because these are activated before or after the not noisy pixels [7].

Different simplified models of PCNN have been developed to work in Artificial Intelligence and Computer Vision context; two of the main variations are the Intersection Cortical Model (ICM) and the Spiking Cortical Model (SCM). In [8] they are used these methods combining them with local Median filter, morphological filter and Wiener filter to reduce Salt and Pepper and Gaussian noises.

The alternative approach proposed in this paper consists of two general phases: (a) the ICM model detects the pixels affected by Salt and Pepper noise, and (b) a Median filter selectively suppresses the previously detected noise pixels. The rest of the paper is organized as follows: in Sect. 2 they are described PCNN and ICM Third Generation Neural Networks; Sect. 3 is devoted to present our proposed alternative de-noising approach; Sect. 4 details experiments and discuss results; Sect. 5 concludes and address future research directions.

2 PCNN and ICM Paradigms

PCNN is a neural network paradigm that emulates biological neurons in the visual cortex of mammals and has been applied in a variety of domains of digital image processing such as noise removal, object detection, feature extraction, image fusion, optimization, image thinning, segmentation, shadows removing, among others.

There are relevant differences between traditional Artificial Neural Networks and PCNN, both in configuration and operation. The PCNN not requires training and its only function is to classify pixels by levels of intensity; in this model every pixel of the digital image corresponds to one neuron. The neurons firing threshold is dynamic and each neuron receives inputs from other neurons through synapses (linking process). These characteristics make neighboring neurons with similar intensity to fire at the same time in certain regions, phenomenon called “synchronous pulse firing” [9]. Each neuron corresponds to a pixel, for this reason the feeding, the linking and the threshold are of the same size of the processed image.

The original model of PCNN has some limitations in practice, when is used for image processing; for example, the great number of connections among neurons can result in a computer memory problem; another difficulty is related with the adequate operating parameters tuning.

For this reason in [10] it is proposed a simplified PCNN iterative model for image processing. In this paper Intersection Cortical Model (ICM) is used; its diagram is showed in Fig. 1. The ICM is a case of the PCNN when there are no linking neurons; the neuron’s feeding inputs are composed of the feedback input F_{ij} and the last output Y_{ij} , where F_{ij} only accepts the external stimulus S_{ij} (gray level of each pixel normalized between 0 and 1). When F_{ij} is greater than dynamic threshold T_{ij} , the ICM neuron iteratively outputs sequential binary pulse series Y_{ij} . Each entry retains its previous state attenuated by a decay factor.

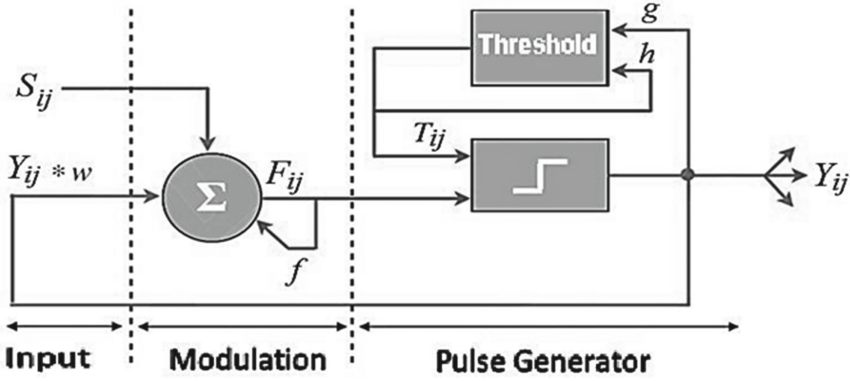


Fig. 1. ICM model diagram [10]

Based on the simplified PCNN model, the iterative computing formulations of the ICM can be simulated with the following functions [10]:

$$F_{ij}[n] = fF_{ij}[n-1] + \sum_{kj} w_{ijkl} Y_{ij}[n-1] + S_{ij} \quad (1)$$

$$Y_{ij}[n] = \begin{cases} 1 & \text{si } F_{ij}[n] > T_{ij}[n] \\ 0 & \text{in other case} \end{cases} \quad (2)$$

$$T_{ij}[n] = gT_{ij}[n-1] + hY_{ij}[n-1] \quad (3)$$

where $[n]$ denotes the current iteration, w is a synaptic weighting matrix that links a neuron with its neighbors, and finally f , g and h are adjust parameter coefficients, typically $g < 1.0$, $f < g$ and h is a large value (20 is a value normally used-recommended in specialized literature).

3 Alternative ICM De-noising Approach Proposed

In our work, all of the ICM neurons are linked mutually in the same mode and their outputs only have two states: firing or non-firing (0 or 1). This model is faster than PCNN model and the noisy pixel's gray values can be adjusted to reduce the noise effect without affect image borders. The main procedure of the proposed de-noising approach has four steps, as follows:

Step 1. Input the normalized noisy digital image to the ICM neural network, obtain the Y_{ij} output and find the high light areas according to firing synchronously. The light pixels in the output image are considered Salt noise.

Step 2. Find the location of correspondent salt noise pixels in this ICM output image and adjust them applying a Median filter.

Step 3. Duplicate the original image and invert its pixels gray value, then repeat step 1 and step 2 with this “negative” image, in order to detect Pepper noise.

Step 4. Find the neurons fired in advance in each ICM output iterative procedure and modify the gray values of their corresponding pixels applying Median filter.

Figure 2 depicts our alternative ICM de-noising approach.

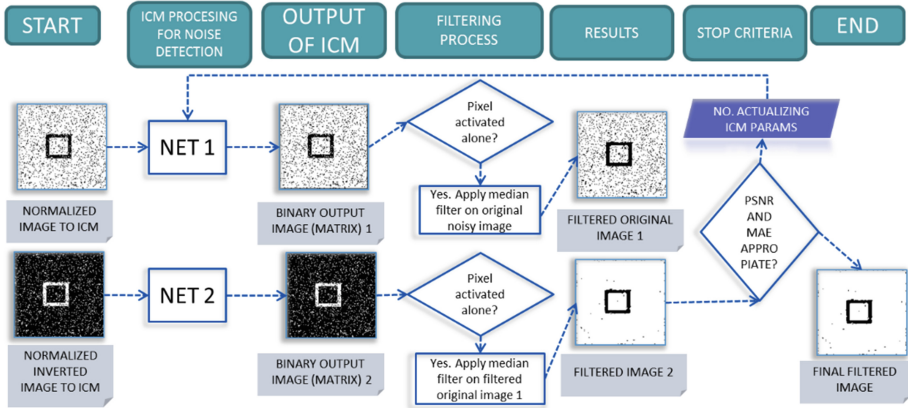


Fig. 2. Alternative ICM de-noising approach proposed

4 Experiments and Results

Experimental evaluation were carried out on the well-known gray scale digital images Lena, Peppers and Baboon, with sizes of 128×128 and 512×512 pixels, just as Fig. 3 shows. During the experimental process, the images were corrupted with impulsive noise densities of 5 %, 10 %, 15 %, 20 %, 25 %, 30 %, 40 %, 50 %, 60 % and 70 %. Then the normalized image from 0 to 1 enters to the ICM model as S_{ij} . The $F_{ij}[n-1]$, $Y_{ij}[n-1]$ and $T_{ij}[n-1]$ values were initially set to 0.



Fig. 3. Noisy test images: 10 % Salt and Pepper noise

The other parameters were empirically selected as follows in simulation.

- Internal-weighting matrix w formed with Gaussian weights as a function of the neuron neighbor distance:

$$w = \begin{bmatrix} 0.5 & 1 & 0.5 \\ 1 & 0 & 1 \\ 0.5 & 1 & 0.5 \end{bmatrix}$$

- Parameters: $f = 0.9$, $g = 0.8$ y and $h = 20$.
- In *Step 2*, the Median filter is applied. Let x_{ij} denote pixels with coordinates (i, j) in noisy image, and X_{ij} denote the set of pixels in $(2K + 1) \times (2K + 1)$ neighborhood window W centered at x_{ij} . In our case we use $K = 1$ and then W size is 3×3 pixels; this was chosen primarily to ensure better details preservation. Equation (4) resume these concepts.

$$X_{ij} = \{x_{i-K,j-K}, \dots, x_{ij}, \dots, x_{i+K,j+K}\} \tag{4}$$

- Median operator is defined as:

$$m_{ij} = \text{median}(X_{ij}) \tag{5}$$

As can be seen in Fig. 4, using Lena of 128×128 pixels with 30 % Salt and Pepper noise, we can exploit ICM to distinguish noisy and noise-free pixels in an image for processing them.

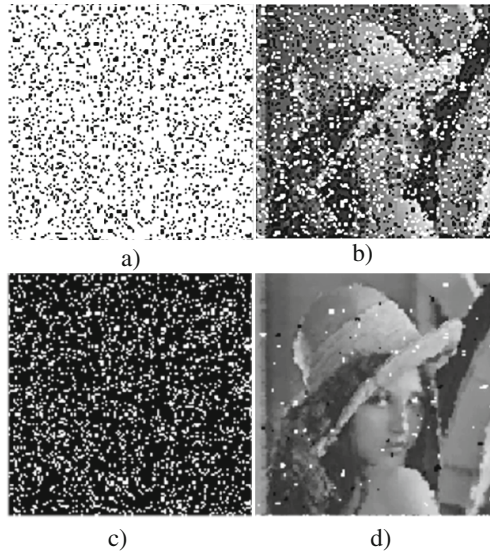


Fig. 4. Lena with 30 % noise (a) First iteration output pattern from ICM, (b) Resulted de-noised image, (c) Third iteration output pattern from ICM, (d) Resulted de-noised image

For the ICM based method it is difficult to wipe off the noise when its pixel value is similar to the background; for that reason we include-contribute the intuitive, useful and

pragmatic idea of processing also the inverse gray level. When noisy pixels are detected for the ICM output, then the Mean filter was applied for de-noising.

Final results were evaluated by means of three well known metrics, which are formulated as follows [11, 12]:

- (a) PSNR (Peak Signal to Noise Ratio in dB), which is used to measure the ability of impulse noise suppression (6): the bigger PSNR is, the effect of de-noising is.

$$PSNR = 10 \log_{10} \frac{f(m, n)^2}{\frac{1}{MN} \sum_{m=1}^M \sum_{n=1}^N [f(m, n) - f'(m, n)]^2} \tag{6}$$

- (b) MAE (Mean Absolute Error), indicating filtering quality (7), that is, preserving fine details must be minimized.

$$MAE = \frac{1}{MN} \cdot \sum_{m=1}^M \sum_{n=1}^N |f(m, n) - f'(m, n)| \tag{7}$$

- (c) NMSE (Normalized Mean Square Error), a better noise image filtering method can often result in the less NMSE (8).

$$SMSE = \frac{\sum_{m=1}^M \sum_{n=1}^N [f(m, n) - f'(m, n)]^2}{\sum_{m=1}^M \sum_{n=1}^N [f(m, n)]^2} \tag{8}$$

In (6) and (7) M, N denote the image’s rows and columns; $f(m, n)$ is the non-processing image and $f'(m, n)$ is the de-noising resulting image.

Figure 5 shows a Lena zoom in order to observe that our approach is visualized better (detail preservation) than when only a Median filter is applied.

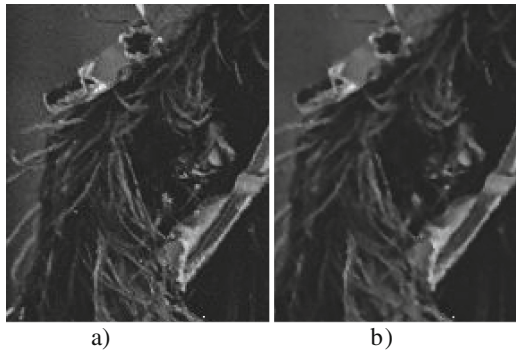


Fig. 5. Detail Lena 10 % noise (a) De-noised image applying our alternative ICM de-noising approach, (b) De-noised image obtained with only traditional median filter method

To determine the ICM iteration number required to perform the noise image filtering, the noise reduction process was measured iteration by iteration. The relation between the de-noising performance denoted by PSNR and MAE (Y axis) vs. the ICM iteration number (X axis) is showed in Fig. 6.

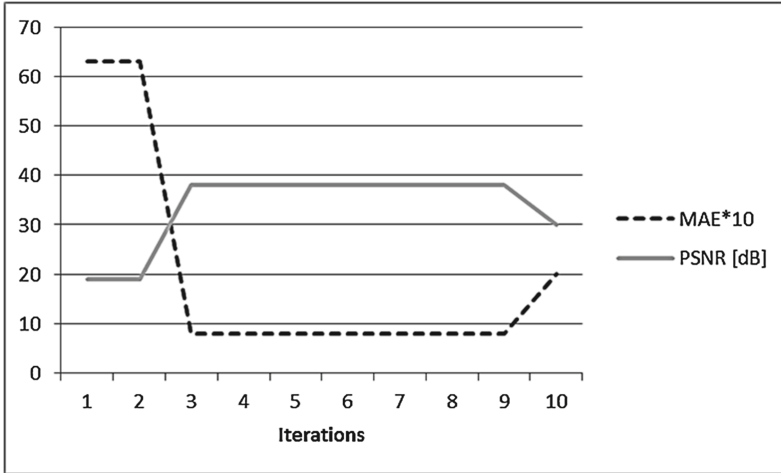


Fig. 6. The effect of ICM’s iterations vs. noise suppression (Lena 10 % noise)

We can see that the PSNR and MAE metrics have no changes after three iterations; therefore, it is not necessary to conduct further ICM iterations and calculations; this observation allows us to reduce effectively computer processing time (225 % faster).

To show the detail preservation performance for each method, various contamination noise levels were applied to Lena, Peppers and Baboon digital images. According to Table 1, the first two rows indicate the images corrupted by Salt and Pepper noise with 5 % and 10 % respectively. Columns show the three metrics obtained results that are used to compare both methods: our alternative ICM approach vs. traditional Median filter; as can be seen, PSNR is upper (better), and MAE and NMSE are lower (again better) using our ICM approach than the traditional Median filter method.

Table 1. De-noising methods performances

Noisy image	Our alternative ICM approach filter			Traditional median filter		
	PSNR [dB]	MAE	NMSE	PSNR [dB]	MAE	NMSE
Lena 5 %	41.9741	0.3614	0.0003	33.2361	3.2268	0.0027
Lena 10 %	37.0746	0.8885	0.0011	32.4863	3.4124	0.0033
Peppers 5 %	41.8626	0.3435	0.0002	34.4246	2.8941	0.0013
Peppers 10 %	36.9480	0.8558	0.0007	33.2819	3.1012	0.0017
Baboon 5 %	32.5673	1.1571	0.0019	23.310	10.8228	0.0162
Baboon 10 %	28.5731	2.7620	0.0048	23.0225	11.1927	0.0173

So, from Table 1, it is observed that our proposed method shows better performance, for experiments when noise density is 5 and 10 %. Additionally, from Fig. 7, it is observed that Baboon and Peppers with 10 % noise density show the proposed approach restoration ability. It is visualized (human eye) that our proposed method preserves the edges and lines of the image while the Median filter has a smoothing effect on all the details. Also Fig. 7 shows that our approach based on ICM Neural Network virtually eliminates image noise.

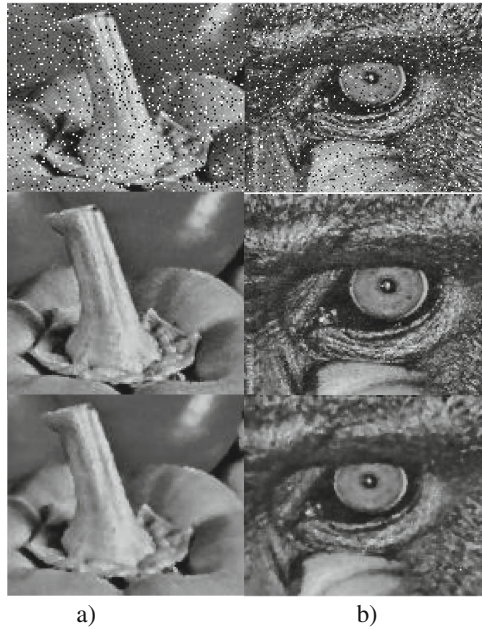


Fig. 7. Preservation details. From up to down, column (a) Noisy Peppers 10 %, de-noised image by our ICM and by median filter; column (b) Noisy Baboon 10 %, de-noised image by our ICM and by median filter.

In order to compare the effectiveness of the proposed ICM de-noising approach vs. traditional Median filter, another series of experiments were carried out varying noise degrees. Lena corrupted by Salt and Pepper noise with various noise densities from 5 % to 70 %, with 5 % and 10 % increments was used for experiments that are presented and resumed in Fig. 8.

The comparative PSNR graphical illustration for each method is showed. In particular, in the case of 5 % corrupted image, the proposed algorithm was approximately 8.74 dB better (32 %) than the Median filter. Additionally, MAE and NMSE scores were measured for each method. The proposed approach produced the lowest (better) MAE and NMSE values with various noise densities under 45 %.

Finally we can observe the behavior of our ICM de-noising approach vs. Median filter when increasing noisy degree beyond 45 % noise: the ICM performance is decreasing according to Fig. 8 (X axis shows noise degree expressed as probability,

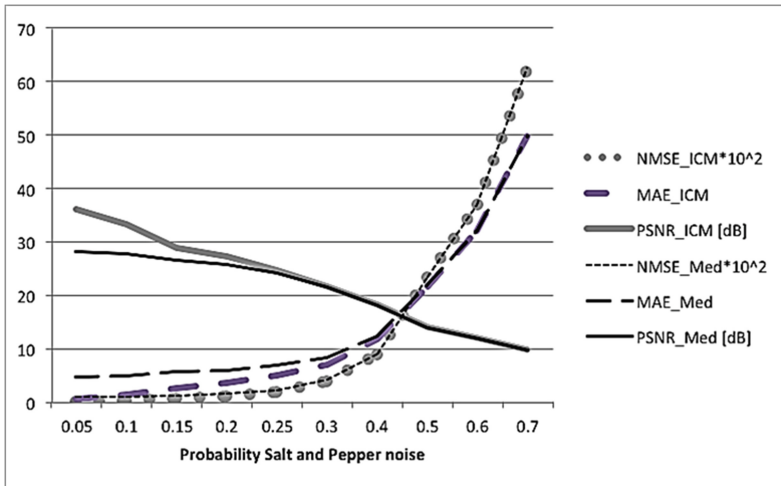


Fig. 8. Filtering performance curves on Lena with several Salt and Pepper noise degrees

and Y axis shows obtained values for the three evaluation metrics). As can be seen, when noise is upper than 70 %, the de-noised image lost important details for both methods, as PSNR, MAE and NMSE depicts: this result is predictable because very high noise density is presented.

5 Conclusion and Future Work

Noise reduction on digital images is essential for processing them. An efficient and effective alternative filtering approach is proposed to reduce the noise of Salt and Pepper; this alternative is based on the integration of the simplified model PCNN called ICM and is used to effectively detect noisy pixels and then combined with a selective Median filter to eliminate-reduce noise.

Experimental results show that the proposed method's effectiveness noise suppression and details preservation for gray scale images is 32 % better than traditional Median filter (as PSNR, MAE and NMSE metrics report) and 225 % faster because the PCNN can be implemented in a parallel processor and the median operator can be applied by an indexed method. Quantitative data show that only three iterations are enough to obtain a de-noised image using ICM for Salt and Pepper noise removing.

For future works, the proposed ICM based approach will also be evaluated on color digital images, with Gaussian and Speckle noise, and on a public collection of thousands of images. We should consider further adjustments and development of the proposed approach to increase its performance and compare it to some of the other selective de-noising methods to ensure is competing with more standard methods and other recent research.

References

1. Sreenivasulu, P., Chaitanya, N.K.: Removal of salt and pepper noise for various images using median filters: a comparative study. *IUP J. Telecommun.* **6**, 54–70 (2014)
2. Gao, G., Liu, Y.: An efficient three-stage approach for removing salt & pepper noise from digital images. *Optik - International J. Light Electron Opt.* **126**(4), 467–471 (2015)
3. Sharma, A., Chaurasia, V.: Removal of high density salt-and-pepper noise by recursive enhanced median filtering. In: *IEEE 2nd International Conference on Emerging Technology Trends in Electronics, Communication and Networking* (2014)
4. Zhang, C., Wang, K.: A switching median–mean filter for removal of high-density impulse noise from digital images. *Optik - International J. Light Electron Opt.* **126**(9–10), 956–961 (2015)
5. Chang, J.: Applying generalized weighted mean aggregation to impulsive noise removal of images. In: *IEEE Proceedings of the 2014 International Conference on Machine Learning and Cybernetics*, pp. 13–16 (2014)
6. Lindblad, T., Kinser, J.M.: *Image Processing Using Pulse-Coupled Neural Networks*, 2nd edn, pp. 11–23. Springer, Berlin (2005)
7. Johnson, J.L., Padgett, M.L.: PCNN model and applications. *IEEE Trans. Neural Netw.* **10**, 480–498 (1999)
8. Ma, Y., Zhan, K., Wang, Z.: *Applications of Pulse-Coupled Neural Networks*, pp. 6–23. Springer, Berlin (2010)
9. Zhang, J.Y., Li, B.Y.: Feature extraction on image smoothness based on PCNNs. *Comput. Simul. Mag.-Room 9*, 103–105 (2003)
10. Ekblad, U., et al.: The intersecting cortical model in image processing. *Nucl. Instrum. Methods Phys. Res.* **525**(1), 392–396 (2004)
11. Lui, C., Zhang, Z.: Sonar images de-noising based on pulse coupled neural networks. In: *Congress on Image and Signal Processing*, pp. 403–406 (2008)
12. Wang, Z., Ma, Y., Cheng, F., Yang, L.: Review of Pulse-Coupled Neural Networks. *Image Vision Comput. J.* **28**, 5–13 (2010). Elsevier