A HYBRID FILTERING TECHNIQUE FOR ELIMINATING UNIFORM NOISE AND IMPULSE NOISE ON DIGITAL IMAGES

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ABSTRACT

A new hybrid filtering technique is proposed to improving denoising process on digital images. This technique is performed in two steps. In the first step, uniform noise and impulse noise is eliminated using decision based algorithm (DBA). Image denoising process is further improved by an appropriately combining DBA with Adaptive Neuro Fuzzy Inference System (ANFIS) at the removal of uniform noise and impulse noise on the digital images. Three well known images are selected for training and the internal parameters of the neuro-fuzzy network are adaptively optimized by training. This technique offers excellent line, edge, and fine detail preservation performance while, at the same time, effectively denoising digital images. Extensive simulation results were realized for ANFIS network and different filters are compared. Results show that the proposed filter is superior performance in terms of image denoising and edges and fine details preservation properties.

KEYWORDS

Adaptive Neuro-fuzzy Inference System, Decision based Algorithm, Image denoising.

1. INTRODUCTION

Digital images are often contaminated by impulse noise and uniform noise during image acquisition and/or transmission over communication channel. Detection and removal of impulse noise from digital images have been of high research interest in the last few years. Majority of the existing filtering methods comprise order statistic filters utilizing the rank order information of an appropriate set of noisy input pixels. These filters are usually developed in the general framework of *rank selection filters*, which are nonlinear operators, constrained to output an order statistic from a set of input samples. The difference between these filters is in the information used to decide which order statistic to output. The *standard median filter* (MF) [1]–[3] is a simple rank selection filter and attempts to remove impulse noise from the center pixel of the analysis window by changing the luminance value of the center pixel with the median of the luminance values of the pixels contained within the window. This approach provides a reasonable noise removal performance with the cost of introducing undesirable blurring effects into image details even at low noise densities [4-25].

The great majority of currently available noise filters cannot simultaneously satisfy both of these criteria. The existing filters either suppress the noise at the cost of reduced noise suppression performance. Indeed, Neuro-Fuzzy (NF) systems offer the ability of neural networks to learn from examples and the capability of fuzzy systems to model the uncertainty, which is inevitably encountered when processing noisy signals. Therefore, NF systems may be

DOI : 10.5121/sipij.2013.4207

utilized to design efficient signal and image processing operators with much less distortion than the conventional operators. A Neuro-Fuzzy System is a flexible system trained by heuristic learning techniques derived from neural networks can be viewed as a 3-layer neural network with fuzzy weights and special activation functions is always interpretable as a fuzzy system uses constraint learning procedures is a function approximation.

In this paper, Adaptive Neuro-fuzzy Inference System (ANFIS) is presented, which is a fuzzy inference system implemented in the framework of adaptive network. This ANFIS training algorithm is suggested by Jang. By using hybrid learning procedure, the proposed ANFIS can construct an input-output mapping which is based on both human knowledge (in the form of fuzzy if-then rules) and learning. This technique is performed in two steps. In the first step, uniform noise and impulse noise is eliminated using decision based algorithm (DBA). Image denoising process is further improved by an appropriately combining DBA with Adaptive Neuro Fuzzy Inference System (ANFIS) at the removal of uniform noise and impulse noise on the digital images. Three well known images are selected for training and the internal parameters of the neuro-fuzzy network are adaptively optimized by training. This technique offers excellent line, edge, and fine detail preservation performance while, at the same time, effectively enhancing digital images. Extensive simulation results were realized for ANFIS network and different filters are compared.

The rest of the paper is organized as follows. Section II explains the structure of the proposed operator and its building blocks. Section III discusses the application of the proposed operator to the test images. Results of the experiments conducted to evaluate the performance of the proposed operator and comparative discussion of these results are also presented in this Section IV, which is the final section, presents the conclusions.

2. PROPOSED OPERATOR

Fig.1 shows the structure of the proposed impulse noise removal operator. The proposed filtering technique is obtained by appropriately combining and Decision Based Algorithm (DBA) and a neuro-fuzzy network. The proposed filter is obtained by an appropriately combining output images from decision based algorithm, corrupted images and neuro-fuzzy network. Learning and understanding aptitude of the network congregate information from these two image data to compute output of the system which is equal to the restored value of the noisy input pixel. The neuro-fuzzy network utilizes the information from the Decision Based Algorithm and the noisy input image to compute the output of the system, which is equal to the restored value of the noisy input pixel. The decision based algorithm is discussed in section 2.1. Section 2.2 presents the neuro-fuzzy network and section 2.3, 2.4 and 2.5 discuss the neuro-fuzzy training, testing and conventional filtering procedure respectively.

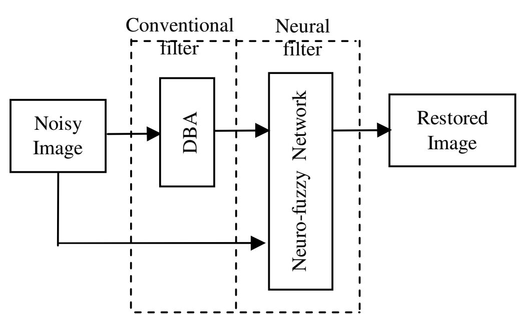

Fig.1 Proposed Hybrid Filter

2.1 Decision Based Algorithm

The filtering technique [25] is discussed this paper employs a decision mechanism to detect the presence of impulse noise on the test image. The pixels inside the sliding window are identified as corrupted or not. If the pixel is corrupted, based on the type of noise the corrupted central pixel is replaced by either median filter or midpoint filter. This is called unsymmetric trimmed midpoint filter. Median filter is defined as

$$MF = [med\{F(i,j)\}], \quad (i,j) \in S_{mn} (s,t) \in S_{mn} \tag{2.1}$$

where, *MF* represents median filter, *F(i,j)* represents processing pixel, S_{mn} represents the filtering window. Midpoint filter simply computes the midpoint between the maximum and minimum values in the area covered by filter or mask. So midpoint filter is defined as

$$MPF = (1/2)[\max\{F(i,j)\} + \min\{F(i,j)\}], \quad (i,j) \in S_{mn} (s,t) \in S_{mn} \tag{2.2}$$

where, *MPF* represents midpoint filter, *F(i,j)* represents processing pixel, S_{mn} represents the filtering window. This filter is a combination of statistics and midpoint. It is very useful for enhancement if image is corrupted with impulse noise and uniform noise. In this paper, Pixel inside the window is separated as impulse noise and remaining pixels. The remaining pixels (without impulse noise) inside the filtering window are arranged in ascending order and average values of maximum and minimum is taken for filtering. This new midpoint filter is called as Unsymmetric trimmed midpoint filter.

Consider an image of size M×N having 8-bit gray scale pixel resolution. The proposed filtering algorithm as applied on noisy image is described in steps as follows:

Step 1) A two-dimensional square filtering window of size 3 x 3 is slid over the noisy image.

Step 2) As the window move over the noisy image, at each point the central pixel inside the window is checked whether it is a corrupted pixel or not.

Step3) If the pixel is detected as a corrupted by fixed impulse noise, the median filter is performed on it. Otherwise it is replaced by unsymmetric trimmed midpoint filter.

Then the window is moved to form a new set of values, with the next pixel to be processed at the centre of the window. This process is repeated until the last image pixel is processed. It may be noted that the filtering is performed by either taking the median or the unsymmetric midpoint value of the pixels of the filtering window. Moreover, the unsymmetric midpoint filtering on the remaining pixels (without impulse noise) sample is performed only on processing pixels. As a result, the pixels in the filtered image do not cause any noticeable visual degradation. The performance of the proposed filter is superior to other existing filters in terms of eliminating multiple noise and preserving edges and features of images. This filter output is one of the inputs for ANFIS training.

2.2. Neuro-Fuzzy Network

The neuro-fuzzy network used in the structure of the proposed hybrid filter acts like a *mixture* operator and attempts to construct an enhanced output image by combining the information from the noisy input image data and DBA output image data. The rules of mixture are represented by the rules in the rule base of the NF network and the mixture process is implemented by the fuzzy inference mechanism of the NF network. These are described in detail later in this subsection. The neuro-fuzzy network is a first order Sugeno type fuzzy system with two inputs and one output. In neuro-fuzzy network, the Mamdani method is widely accepted for capturing expert knowledge. It allows us to describe the expertise in more intuitive, more human-like manner. However, mamdani-type fuzzy inference entails a substantial computational burden. On the other hand, the Sugeno method is computationally effective and works well with optimization and adaptive techniques, which makes it very attractive in control problems, particularly for dynamic nonlinear systems.

Sugeno-type fuzzy systems are popular general nonlinear modeling tools because these tools are very suitable for tuning by optimization and employ polynomial type output membership functions, which greatly simplifies defuzzification process. The input-output relationship of the NF network is as follows.

Let A_1, A_2 denote the inputs of the neuro-fuzzy network and Y denote its output. The fuzzy inference is performed on the noisy input image pixel by pixel. Each noisy pixel is independently processed by the noisy input image data and an Decision Based Algorithm before being applied to the NF network. Hence, in the structure of the proposed operator, A_1 represents the output data from the noisy input image data and A_2 represents the output data from an Decision Based Algorithm. Each possible combination of inputs and their associated membership functions is represented by a rule in the rule base of the neuro-fuzzy (NF) network. Since the neuro-fuzzy network has two inputs and each input has twenty five membership functions, the rule base contains total of 25 (5^2) rules, which are as follows.

1. If (A_1 is M_{11}) and (A_2 is M_{21}), then
   $Y_1 = MF_1(A_1,A_2)$
2. If (A_1 is M_{11}) and A_2 is M_{21}), then
   $Y_2 = MF_2(A_1,A_2)$
3. If A_1 is M_{11}) and (A_2 is M_{21}) , then
   $Y_3 = MF_3(A_1,A_2)$
4. If (A_1 is M_{11}) and (A_2 is M_{21}), then
   $Y_4 = MF_4(A_1,A_2)$
5. If (A_1 is M_{11}) and A_2 is M_{21}) , then
   $Y_5 = MF_5(A_1,A_2)$
6. If (A_1 is M_{11}) and (A_2 is M_{22}, then
   $Y_6 = MF_6(A_1,A_2)$
7. If (A_1 is M_{11}) and (A_2 is M_{22}), then
   $Y_7 = MF_7(A_1,A_2)$

⋮

25. If (A_1 is M_{11}) and (A_2 is M_{25}), then
    $Y_{25} = MF_{25}(A_1,A_2)$

where M_{ij} denotes the jth membership function of the ith input, Y_k denotes the output of the kth rule, and MF_k denotes the output membership function, with I = 1,2; j=1,2 and k = 1,2 3,…..25. The input membership functions are generalized gaussian membership type. The Gaussian function depends on two parameters σ and c as given by

$$Mij(x,c,\sigma) = e^{-1/2\left(\frac{x-c}{\sigma}\right)} \qquad (2.3)$$

and the output membership function are linear

$$MF_{ij} = d_{k1}x_1 + d_{k2}x_2 + d_{k3} \qquad (2.4)$$

where x, x_1 and x_2 are formal parameters, and the parameters c and d are constant parameters for input and output membership functions that characterize the shape of the membership functions. The optimal values of these parameters are determined by training the neuro-fuzzy network system. The optimal number of the membership functions is usually determined heuristically and verified experimentally. A smaller number yields lower complexity and shorter training time, but poor performance. On the other hand, a greater number of yields better performance, but higher complexity and much longer training time. It has been experimentally determined that five membership functions offer a very good balance. The output of the NF network is the weighted average of the individual rule outputs. The weighting factor of each rule is calculated by evaluating the membership expressions in the antecedent of the rule. This is accomplished by first converting the input values to fuzzy membership values by utilizing the input membership functions and then applying the *and* operator to these membership values. The *and* operator corresponds to the multiplication of input membership values. Hence, the weighting factors of the rules are calculated as follows:

$$W_1 = M_{11}(A_1).M_{21}(A_2)$$

$$W_2 = M_{11}(A_1).M_{21}(A_2)$$

$$W_3 = M_{11}(A_1).M_{21}(A_2)$$

$$W_4 = M_{11}(A_1).M_{21}(A_2)$$

$$W_5 = M_{11}(A_1).M_{21}(A_2)$$

$$\vdots$$

$$W_{25} = M_{11}(A_1).M_{25}(A_2)$$

Once the weighting factors are obtained, the output of the NF network can be found by calculating the weighted average of the individual rule outputs.

$$Y_o = \frac{\sum_{k=1}^{25} w_K Y_k}{\sum_{k=1}^{25} w_k} \qquad (2.5)$$

2.3. Training of the Neuro-Fuzzy Network

The internal parameters of the neuro-fuzzy network are optimized by training. Fig. 2 represents the setup used for training. Here, the parameters of the neuro-fuzzy network are iteratively optimized so that its output converges to original noise free image which, by definition, completely removes the noise from its input image. The ideal noise filter is *conceptual* only and does not necessarily exist in reality.

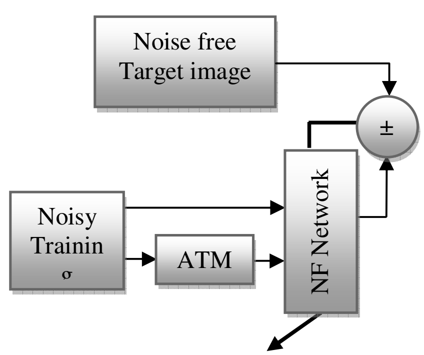

Fig.2 Training of the neuro-fuzzy network

Fig. 3 shows the images used for training. Three different images are used in training, in order to improve the learning capability of neural network. The image shown in Fig. 3($a_{1,2\ \mathrm{and}3}$) are the *original training image: Cameraman, Baboonlion* and ship. The size of the training images is 256 x 256. The performance of the proposed filter is superior to other existing filters in terms of eliminating multiple noise and preserving edges and features of images. Fig.3($b_{1,\ 2\ \mathrm{and}\ 3}$) are the *noisy training images* and is obtained by corrupting the original training image by impulse noise of 10% and unifor m noise with zero mean and σ=200. The image in Fig.3 ($c_{1,2\ \mathrm{and}\ 3}$) are the trained images by neuro-fuzzy network.

Although the density of the corrupting noise is not very critical regarding training performance, it is experimentally observed that the proposed operator exhibits the best filtering performance when the noise density of the noisy training image is equal to the noise density of the actual noisy input image to be restored. It is also observed that the performance of the proposed operator gradually decreases as the difference between the two noise densities increases. Hence, in order to obtain a stable filtering performance for a wide range of filtering noise densities, very low and very high values for training noise density should be avoided since it is usually impossible to know the actual noise density of a corrupted image in a real practical application. Results of extensive simulation experiments indicate that very good filtering performance is easily obtained for all kinds of images corrupted by multiple impulse noise with a wide range of noise densities. The images in Fig. 3(b) and (a) are employed as the *input* and the *target (desired)* images during training, respectively. The parameters of the NF network are then iteratively tuned. Once the training of the NF network is completed, its internal parameters are fixed and the network is combined with the noisy image data and the DBA output image data to construct the proposed hybrid filter, as shown in Fig. 2.

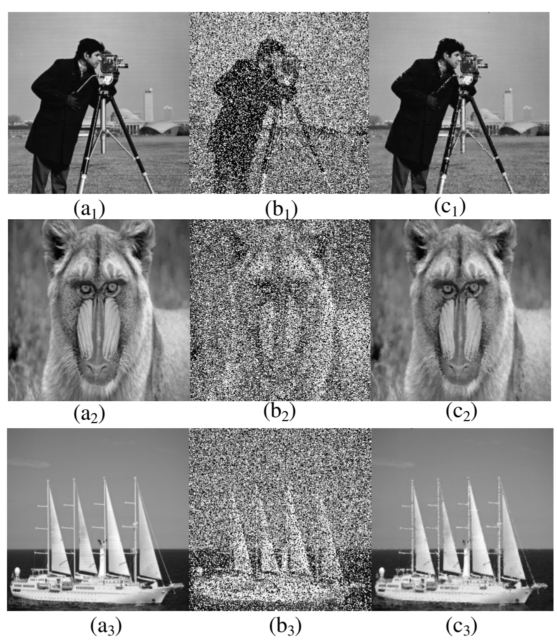

Fig.3 Performance of Training images: ($a_{1,2\ \mathrm{and}3}$) original images, ($b_{1,2\ \mathrm{and}\ 3}$) image corrupted with 45% of random valued impulse noise and ($c_{1,\ 2\ \mathrm{and}\ 3}$) trained images

2.4 Testing of unknown images using trained structure of neural network

The optimized architecture that obtained the best performance for training with three images has 196608 data. The network trained with 10% impulse noise uniform noise with zero mean and σ=200 shows superior performance for testing under various noise levels. In order to get effective filtering performance, already existing hybrid filters are trained with image data and tested using equal noise density. But in practical situation, information about the noise density of the received signal is unpredictable one. Therefore; in this paper, the ANFIS architecture is trained using denoised three well known images which are corrupted by adding different noise density levels. Noise density with 0.1 impulse noise uniform noise with zero mean and σ=200 gave optimum solution for both lower and higher level noise corruption. Therefore images are corrupted with 10% impulse noise uniform noise with zero mean and σ=200 of noise is selected for training. Then the performance error of the given trained data and trained network structure are observed for each network. Among these network structures, the trained network structure with the minimum error level is selected (10^{-3}) and this trained network structures are fixed for testing the received image signal. Also, to ensure faster processing, only the corrupted pixels from test images are identified and processed by the optimized neural network structure. As uncorrupted pixels do not require further processing, they are directly taken as the output.

The chosen network has been extensively tested for several images with different level of impulse noise. Fig.4 shows the exact procedure for taking corrupted data for testing the received image signals for the proposed filter. In order to reduce the computation time in real time implementation; in the first stage, Decision Based Algorithm is applied on unknown images and then pixels (data) from noisy image and DBA's output is obtained and applied as input for optimized neural network structure for testing; these pixels are corresponding to the pixel position of the corrupted pixels on noisy image. At the same time, noise free pixels from input are directly taken as output pixels. The tested pixels are replaced in the same location on corrupted image instead of noisy pixels. The most distinctive feature of the proposed filter offers excellent line, edge, and fine detail preservation performance and also effectively removes impulse noise from the image. Usually conventional filters give denoised image output and then these images are enhanced using these conventional outputs as inputs for hybrid filter while these outputs are combined with the network. Since, networks need certain pattern to learn and understand the given data.

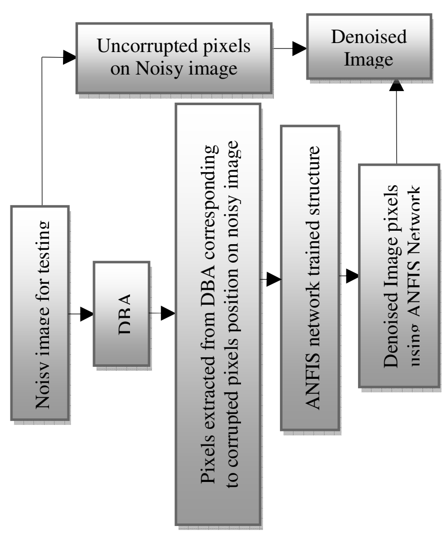

Fig.4 Testing of the images using optimized feed forward adaptive neural network structure

2.5. Filtering of the Noisy Image

The noisy input image is processed by sliding the 3x3 filtering window on the image. This filtering window is also the filtering window for both the median filter and the edge detector.

The window is started from the upper-left corner of the noisy input image, and moved rightwards and progressively downwards in a *raster scanning* fashion. For each filtering window, the nine pixels contained within the window are first fed to the DBA in the structure. Next, the center pixel of the filtering window and the output of the DBA is applied to the appropriate input of the NF network. Finally, the restored luminance value for the center pixel of the filtering window is obtained at the output of the NF network by using the fuzzy inference mechanism.

3. RESULT AND DISCUSSION

The proposed hybrid impulse noise removal operator discussed in the previous section is implemented. The performance of the operator is tested under various noise conditions and on four popular test images from the literature including *Baboon, Lena, Pepper and Rice images*. All test images are 8-bit gray level images. The experimental images used in the simulations are generated by contaminating the original images by 10% impulse noise uniform noise with zero mean and σ=200 with an appropriate noise density depending on the experiment. Several experiments are performed on Lena test image to measure and compare the noise suppression and detail preservation performances of all operators. The performances of all operators are evaluated by using the *peak signal-to-noise ratio* (PSNR) criterion, which is defined as

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \qquad (3.1)$$

where *MSE is the mean squared error* and is defined as

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|(x(i,j) - y(i,j)\right|^2 \qquad (3.2)$$

Here, M and N represents the number of rows and columns of the image and $x(i, j)$ and $y(i, j)$ represents the original and the restored versions of a corrupted test image, respectively. The averages of these values are then taken as the representative PSNR value for that experiment. For each noise density step, the four test images are corrupted by 10% of impulse noise and uniform noise with zero mean and σ=200. These images are restored by using the operator under experiment, and the PSNR values are calculated for the restored output images. This produces different PSNR values representing the filtering performance of that operator for different image properties. These values are then averaged to obtain the representative PSNR value of that operator for that noise density.

Fig.5 Subjective performance illustration of the proposed filtering technique compared with existing technique: (a) Original Lena image, (b) Lena image Corrupted by 10% impulse noise and uniform noise with zero mean and σ=200, (c) Restored by median filter, (d) Restored by midpoint filter, (e) Restored by ATMPF (f) Restored by MAATMPF, (g) Restored by NDBN filter and (h) Restored by proposed algorithm.

Finally, the overall experimental procedure is individually repeated for each operator. Since all experiments are related with noise and noise is a random process, every realization of the same experiment yields different results even if the experimental conditions are the same. Therefore, each individual filtering experiment presented in this paper is repeated for several times yielding different PSNR values for the same experiment are summarized in Table1. For comparison, the corrupted experimental images are also restored by using several conventional and state-of-the-art multiple noise removal operators including an Decision Based Algorithm (DBA), Feed forward back propagation algorithm (FFBPA) and the proposed neuro-fuzzy filtering technique are subjectively evaluated on Lena test image in Fig.5 and graphically illustrated in Fig.6. This filter is representative implementations of different approaches to the impulse noise filtering problem. Fig.5 illustrates the performance of proposed filter and compares with that of the different filtering algorithm in terms of PSNR when applied on Lena image contaminated with 10% of impulse noise and uniform noise with zero mean and σ=200.

Table 1
PSNR values obtained using different filtering technique on Lena image corrupted with various densities of 10% of impulse noise and uniform noise

Noise	Uniform noise	100	200	300	400	500	600
	Impulse noise	10%	10%	10%	10%	10%	10%
Filters	Median filter	18.07	16.99	15.65	14.5	13.65	12.62
	MPF	0.59	0.63	0.67	0.72	0.84	0.87
	ATMPF	13.68	14.12	14.06	13.83	13.23	12.95
	Modified AATMPF	25.62	22.62	20.14	18.33	16.76	14.56
	MNE filter	27.14	26.06	25.05	24.91	23.72	19.95
	FFBPA	28.24	26.76	26.43	25.98	24.45	20.56
	Proposed filter	28.95	27.94	27.12	26.76	25.89	22.32

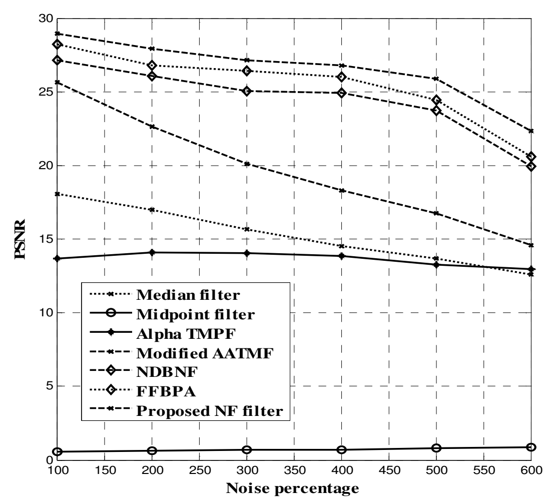

Fig. 6 Performance of PSNR for proposed filter compared with different filtering technique on Lena image

The PSNR performance explores the quantitative measurement. In order to check the performance of the feed forward neural network, percentage improvement (PI) in PSNR is also calculated for performance comparison between conventional filter and proposed neural filter for Lena image and is summarized in Table 2. This PI in PSNR is calculated by the following equation 3.3.

$$PI = \left[\frac{PSNR_{CF} - PSNR_{NF}}{PSNR_{CF}} x100 \right] \quad (3.3)$$

where PI represents percentage in PSNR, $PSNR_{CF}$ represents PSNR for conventional filter and $PSNR_{NF}$ represents PSNR values for the designed neural filter.

Table 2

Percentage improvement in PSNR obtained on Lena image corrupted with different level of impulse noise

Noise %	Proposed filter (PF)	DBA	PI for PF
100	28.95	27.14	6.6691
200	27.94	26.06	7.2063
300	27.12	25.05	8.2764
400	26.76	24.91	7.4410
500	25.89	23.72	9.1355
600	22.32	19.95	11.8690

The summarized PSNR values in Table 2 for the proposed neural filter for percentage improvement in PSNR appears to perform well for human visual perception when images are corrupted up to 10% of impulse noise and uniform noise with zero mean and σ=200. These filters performance are better for quantitative measures when images are corrupted by 10% of impulse noise and uniform noise with zero mean and σ=200. PI is graphically illustrated in Fig.7.

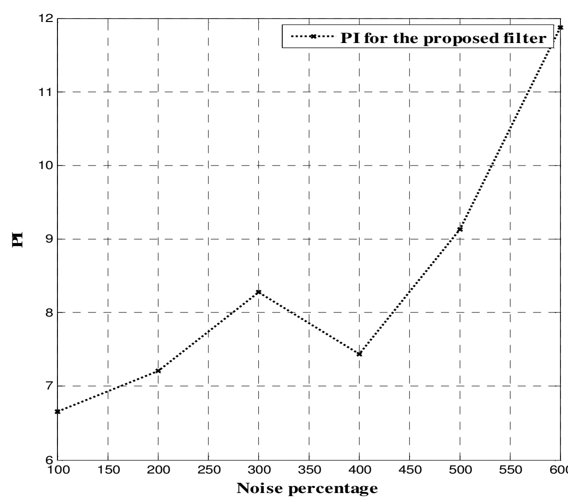

Figure 7 PI in PSNR obtained on Lena image for the proposed filter corrupted with various densities of mixed impulse noise

Table 3 lists the variations of the PSNR values of the operators as a function of noise density for proposed filtering image technique on different test images. The proposed operator demonstrates the best filtering performance of all. Its PSNR values are significantly higher than those of the other filters for all noise densities. Fig.8 detects the subjective performance of proposed filter on different test images. The proposed filter can be seen to have eliminated the impulse noise completely. Further, it can be observed that the proposed filter is better in preserving the edges and fine details than the other existing filtering algorithm. The experiments are especially designed to reveal the performances of the operators for different image properties and noise conditions.

Table 3
Performance of PSNR for proposed hybrid neuro-fuzzy filter for different images corrupted with various noise densities

PSNR					
Uniform noise	Impulse noise	Baboon	Lena	Pepper	Rice
100	10	23.56	28.95	32.03	26. 86
200		21.72	27.94	31.54	24.78
300		19.77	27.12	30.12	24.92
400		18.32	26.76	29.23	24.04
500		17.58	25.89	28.65	22.88
600		13.23	22.32	24.25	19.12

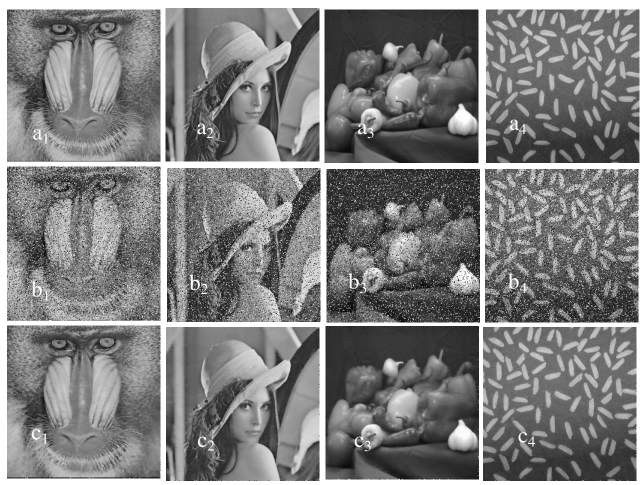

Fig. 8 Performance of test images: ($a_{1,2 \text{ and } 4}$) original images,($b_{1,2 \text{ and } 4}$) images corrupted with 10% of impulse noise and uniform noise with σ=200 and ($d_{1,\ 2 \text{ and } 4}$) images enhanced by proposed filter

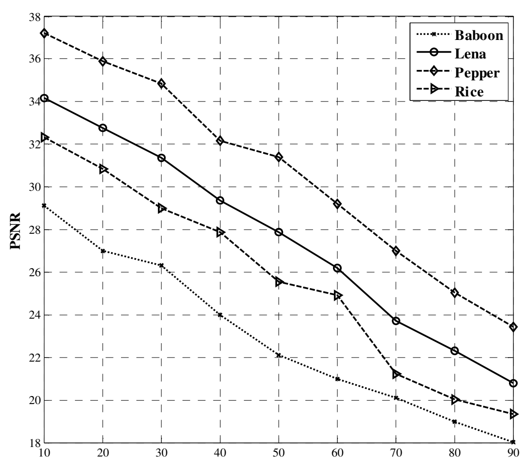

Fig. 9 Performance of PSNR for the proposed filter on different test images

Fig.9 presents the noise-free, noisy, and filtered images for objective evaluation. Four different test images corrupted with 10% impulse noise and uniform noise with σ=200 are used to illustrate the efficacy of the proposed filter. HNF filter is found to have eliminated the impulse noise completely while preserving the image features quite satisfactorily. It can be seen that this filtered images are more pleasant for visual perception.

5. CONCLUSION

A neuro-fuzzy filter is described in this paper. The proposed filter is seen to be quite effective in eliminating the uniform noise and impulse noise; in addition, the proposed filter preserves the image boundaries and fine details satisfactorily. The efficacy of the proposed filter is illustrated by applying the filter on various test images contaminated by different levels of noise. This filter outperforms the existing filters in terms of qualitative and quantitative measures. In addition, the hybrid filtered images are found to be pleasant for visual perception, since the filter is robust against the impulse noise and uniform noise while preserving the image features intact. Further, the proposed filter is suitable for real-time implementation, and applications because of its adaptive in nature. The proposed Hybrid filter, developed using MATLAB functions, is flexible, accurate than existing filtering algorithm and its scope for better real-time applications.

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