Image Enhancement Using Adaptive Neuro-Fuzzy Inference System

R.Pushpavalli, G.Sivarajde

Abstract: This paper presents a hybrid filter for denoising and enhancing digital image in situation where the image is corrupted by salt and pepper noise. Image denoising and enhancement are important preprocessing and post processing steps in image analysis. Successful results of image analysis extremely depend on image enhancement. There are several filters have been illustrated till date. But they are highly sensitive to noise. The structure of the proposed hybrid filter, to make the process robust against noise, is a combination of nonlinear switching median filter and neuro-fuzzy network. The internal parameters of the neuro-fuzzy network are adaptively optimized by training. The most distinctive feature of the proposed operator offers excellent line, edge, and fine detail preservation performance while, at the same time, effectively removing noise from the input image. The proposed filter is evaluated under different noisy condition on several test images and also compared with already existing filters for performance evaluation.

Index Terms: Adaptive Neuro-fuzzy Inference System, Image denoising, image enhancement, Nonlinear switching median filters.

1 Introduction

IMAGES are often corrupted by impulse noise during image acquisition and transmission over communication channel. Noise elimination and enhancement are essential features in digital image processing. Because the performances of subsequent image processing tasks are strictly dependent on the success of the noise removal operation. However, this is a difficult task because the noise removal operator is imposed with the requirement of preserving useful information in the image while efficiently removing the noise. Digital images are valuable sources of information in many research and application areas including astronomy, biology, medicine, remote sensing, materials science, etc. During image acquisition, digital images are frequently corrupted by noise due to number of imperfections in the imaging process. The image corruption is usually introduced by a nonideal imaging system (sensor noise, limited system accuracy, finite precision, quantization of image data, etc.) or an imperfect medium between the original scene and the imaging system (random scattering, absorption, etc.). The currently available nonlinear filters cannot simultaneously satisfy both of these criteria. The existing filters either suppress the noise at the cost of reduced noise suppression performance. Neural networks and fuzzy systems had been investigated to the problems in digital signal processing. 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 (classifier, controller). 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. The proposed work is carried in two stages. In first stage, noisy image (i.e. received or captured by camera) is denoised by new tristate switching median filter. The denoised image is further enhanced by ANFIS. . The structure of the proposed hybrid filter, to make the process robust against noise, is a combination of nonlinear switching median filter and neuro-fuzzy network. The internal parameters of the neuro-fuzzy network are adaptively optimized by training. The proposed filter is evaluated under different noisy condition on several test images and also compared with already existing filters for performance evaluation. 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 and remarks.

2 Proposed Operator

Fig. 1 shows the structure of the proposed impulse noise removal operator. The operator is a hybrid filter obtained by appropriately combining a new switching median filter and a neuro-fuzzy network. The proposed filter is obtained by appropriately combining output images from new tristate switching median filter and neuro-fuzzy network. Learning and understanding aptitude of the network congregate information from a new switching median filter to compute output of the system which is equal to the restored value of noisy input pixel. The neuro-fuzzy network utilizes the information from this switching median filter to compute the output of the system, which is equal to the restored value of the noisy input pixel. The new tristate switching median filter 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 conventional filtering procedure respectively.

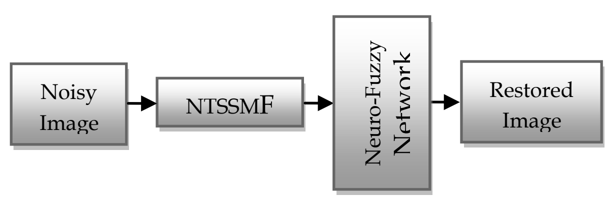

Fig.1 Proposed Hybrid Filter

2.1 New Tristate Switching Median Filter

The filtering operation in this section is experimented by the way of impulse noise detection and elimination performed at the current pixel within the sliding window on digital image. Decision based median filter, called new *tri-state median* (NTSM) filter, is discussed in this section. Impulse noise detection is realized by an impulse detector, which takes the outputs from the Decision Based Filter 1 (DBF1) [22] and

Decision Based Filter 2 (DBF2)[23] and compares them with the origin or center pixel value within the filtering window on given contaminated digital image in order to make a tri-state decision. The switching logic as shown in Fig. 2 is controlled by a threshold T (T = 24; [0 - 255] for gray-scale images).

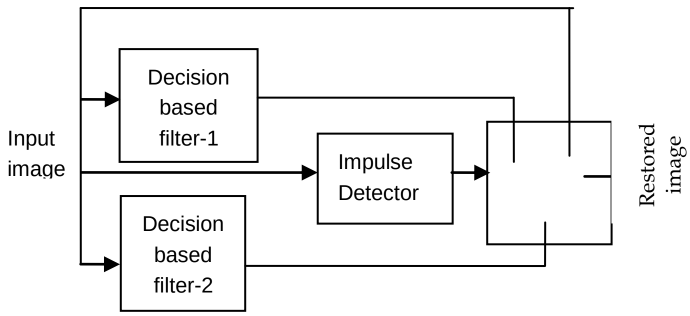

Fig. 2 Tri state based median impulse detector

Fig.2 Illustrate the switching logic for newly proposed tristate decision based median filter. Here, there are two types of comparison is involved to improve the noise reduction. First one is based on decision based median filter1 and second one is based on decision based median filter2. The absolute difference between original pixel value and center pixel value from filtered image is compared with the threshold value. This comparison is based on the following condition:

$$d1 = \left| A(i,j) - Y_{DBF1}(i,j) \right| \quad (2.1)$$

$$d3 = \left| A(i,j) - Y_{DBF2}(i,j) \right| \quad (2.2)$$

where, *d1* is an Absolute difference between original pixel value and decision based median filter1 (DBF1), *d3* is an Absolute difference between original pixel value and decision based median filter2 (DBF2), *X(i,j)* is the Noisy image, $Y_{DBF2}(i,j)$ is the decision based median filtered (DBF2), output, $Y_{DBF1}(i,j)$ is the decision based median filter1 (DBF1) output. If the central processing pixel is uncorrupted, it is left unaltered. If it is corrupted based on the image absolute difference and threshold values, decision based filter is selected. If T is less than d3 then central pixel is replaced by DBF1. If T is less than d1 and greater than d3, then central pixel is replaced by DBF2. T is the threshold value and the tristate decision depends on fixing the threshold value. Based on the quantitative performance evaluation, suitable threshold value is selected. In this work, T=24 gave optimum solution for the proposed filter and also superior performance than existing filtering technique. Some of the above filters have a number of tuning parameters. This tuning parameter is nothing but fixed threshold value (T). This threshold value is selected based on filtering algorithm and the range of T decided by intensity of image (from 0 to 255). However, this T is not suitable with particular filtering algorithm for different nonstaionary digital images. Unfortunately, there is no analytical method to determine the optimal values for these parameters that yield the best results for a given filtering experiment. Hence, the values of these parameters are heuristically determined and experimentally verified for each individual simulation experiment

2.2. Neuro-Fuzzy Network

The neurofuzzy 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 new *tri-state median* (NTSM) filter. The rules of mixture are represented by the rules in the rule base of the neuro-fuzzy network and the mixture process is implemented by the fuzzy inference mechanism of the neuro-fuzzy network. These are described in detail later in this subsection. The neuro-fuzzy network is a first order Sugeno type fuzzy system [49] with one input and one output. In neuro-fuzzy network, there are two types of fuzzy inference systems are widely used. 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 they are very suitable for tuning by optimization and they employ polynomial type output membership functions, which greatly simplifies defuzzification process. The input-output relationship of the neuro-fuzzy network is as follows. Let A_1 denote the inputs of the neuro-fuzzy network and Y denote its output. The new *tri-state median* (NTSM) filter is performed on the noisy input image pixel by pixel. Each noisy pixel is independently processed by the new *tri-state median* (NTSM) filter before being applied to the neuro-fuzzy network. Each possible combination of inputs and their associated membership functions is represented by a rule in the rule base of the neuro-fuzzy network. Since the neuro-fuzzy network has one input and has twenty five membership functions, the rule base contains a total of 25 (25^1) rules, which are as follows.

1. If (A_1 is M_1), then $Y_1 = MF_1(A_1)$
2. . If (A_1 is M_2), then $Y_1 = MF_2(A_1)$
3. . If (A_1 is M_3), then $Y_1 = MF_3(A_1)$

⋮

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

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

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

and the output membership function are linear

$$MF_{ij} = d_{k1}x_1 + d_{k2} \quad (2.4)$$

where x and x_1 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 yields better performance; but higher complexity and much longer training time. It has been experimentally determined that twenty five membership functions offer a very good balance. The output of the neuro-fuzzy 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:

$$
\begin{aligned}
W_1 &= M_1(A_1)\\
W_2 &= M_2(A_1)\\
W_3 &= M_3(A_1)\\
&\vdots\\
W_{25} &= M_{25}(A_1)
\end{aligned}
$$

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

$$Yo = \frac{\sum\limits_{k=1}^{125} wKYk}{\sum\limits_{k=1}^{125} wk} \qquad (2.5)$$

2.3. Training of the Neuro-Fuzzy Network

The internal parameters of the neuro-fuzzy network are optimized by training. Fig.3 represents the neuro fuzzy network architecture for the proposed hybrid filtering technique. Here, the parameters of the neuro-fuzzy network are iteratively optimized so that its output converges to original noise free image by which the definition, completely removes the noise from its input image. The ideal noise filter is *conceptual* only and does not necessarily exist in reality. Fig.4 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 filterd (NTSMF) images are considered as *training images* and are obtained by corrupting the original training image by impulse noise of 50% noise density. The image in Fig.4 ($c_{1,2\ \mathrm{and}\ 3}$) are the trained images by neuro-fuzzy network.

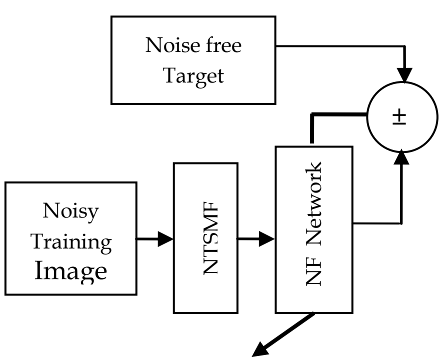

Fig.3 Training of the neuro-fuzzy network

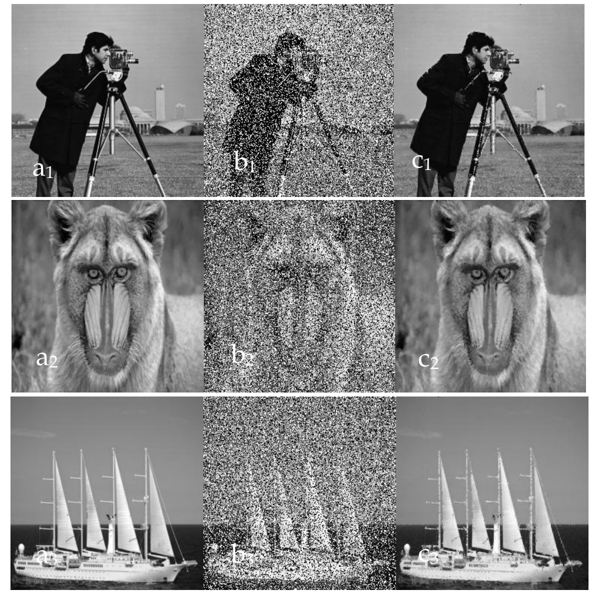

Fig.4 Performance of Training images: ($a_{1,2\ \mathrm{and} 3}$) original images ($b_{1,2\ \mathrm{and}\ 3}$) image corrupted with 50% of noise ($c_{1,\ 2\ \mathrm{and}\ 3}$) trained images

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 impulse noise with a wide range of noise densities provided that the noisy training image has a noise density around 50%. 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 neuro-fuzzy network are then iteratively tuned. Once the training of the neuro-fuzzy network is completed, its internal parameters are fixed and the network is combined with the NTSMF to construct the proposed hybrid filter, as shown in Fig. 1.

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 45% impulse noise 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 of 0.4, 0.45, 0.5 and 0.6. Noise density with 0.45

gave optimum solution for both lower and higher level noise corruption. Therefore images are corrupted with 45% of impulse 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.

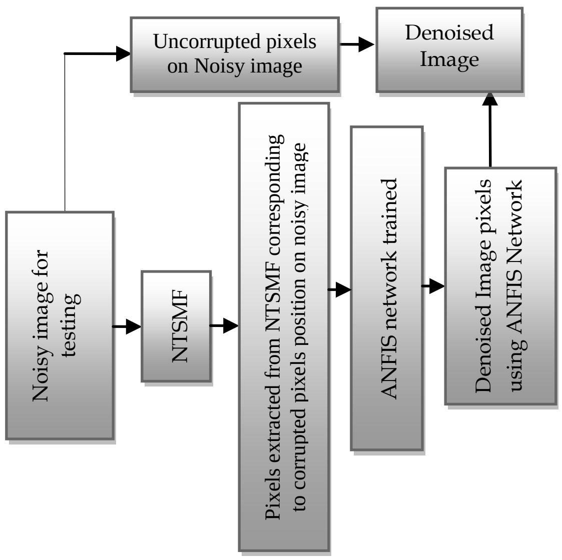

Fig.4 Testing of the images using optimized feed forward adaptive neural network structure

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, new tristate switching median filter is applied on unknown images and then pixels (data) from filtered output NTSMF'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 hybrid filter while these outputs are combined with the network. Since, networks need certain pattern to learn and understand the given data.

2.5 Filtering of the Noisy Image

The noisy input image is processed by sliding the 3x3 filtering window on the image. The filtering 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 new tristate median filter in the structure. Next, the center pixel of the filtering window and the output of the new tristate median filter is applied to the appropriate input of the neuro fuzzy network. Finally, the restored luminance value for the center pixel of the filtering window is obtained at the output of the neurofuzzy network by using the fuzzy inference mechanism.

3. Results

The proposed hybrid impulse noise removing technique is discussed in the previous section is implemented. The performance of the proposed filter 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 impulse noise 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

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

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

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

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. The experimental procedure to evaluate the performance of a given operator is as follows: The noise density is varied from 10% to 90% with 10% increments. For each noise density step, the four test images are corrupted by impulse noise with that noise density. These images are restored by using the operator under experiment, and the PSNR values are calculated for the restored output images. This produces ten 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. This procedure is separately repeated for all noise densities from 10% to 90% to obtain the variation of the average PSNR value of that operator as a function of noise density. 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 ten times yielding ten different PSNR values for the same experiment are summarized in Table1.

TABLE.1
PSNR VALUES OBTAINED USING PROPOSED FILTER AND COMPARED WITH DIFFERENT FILTERING TECHNIQUES ON LENA IMAGE CORRUPTED WITH VARIOUS DENSITIES OF IMPULSE NOISE

Filtering Techniques	10	30	50	70	90
MF	31.74	23.20	15.28	9.98	6.58
WMF	23.97	22.58	20.11	15.73	8.83
CWMF	28.72	20.28	14.45	10.04	6.75
TSMF	31.89	23.96	15.82	10.33	6.58
DBF1	40.8	31.0	22.6	13.42	7.06
DBF2	38.42	30.47	24.92	18.84	10.03
NTSSMF	42.57	35.38	29.34	19.52	10.13
IPPT	45.36	37.56	31.63	22.17	12.68
Proposed NF filter	44.82	37.01	31.89	22.85	13.89

For comparison, the corrupted experimental images are also restored by using several conventional and state-of-the-art impulse noise removal operators including the standard Median Filter (MF), the Weighted Median Filter (WMF), the Center Weighted Median Filter (CWMF), the Tri State median Filter(TSMF), Decision Based Filter 1(DBF1), Decision Based Filter 2(DBF2), New Tri State median Filter(NTSMF), Intellligent Post processing Technique (IPPT) and the proposed technique are subjectively evaluated on Lena test image in Fig.4 and graphically illustrated in Fig.5. These filters are representative implementations of different approaches to the impulse noise filtering problem. Fig.4 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 noise densities up to 90%. The new nonlinear filter outperforms the improved decision making algorithm for the noise densities up to 50%.

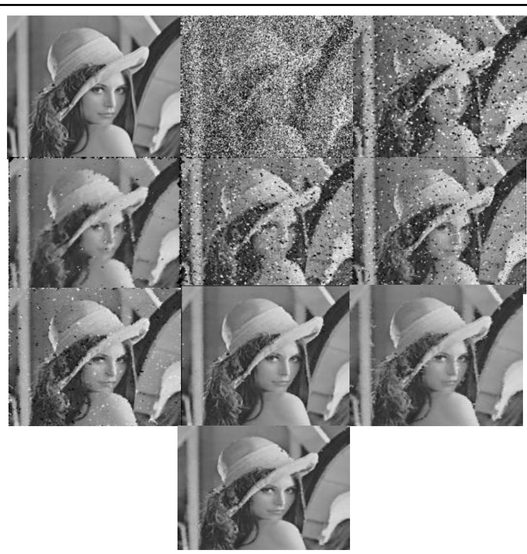

Fig.4 Performance of Test image: Lena (a) Noise free images, (b) image corrupted by 50% impulse noise, (c) images restored by MF, (d) images restored by WMF, (e) images restored by CWMF, (f) images restored by TSMF, (g) images restored by DBF1, (h) images restored by DBF2,(i) images restored by NTSSMF, (j)images restored by IPPT, (k) images restored the proposed filter

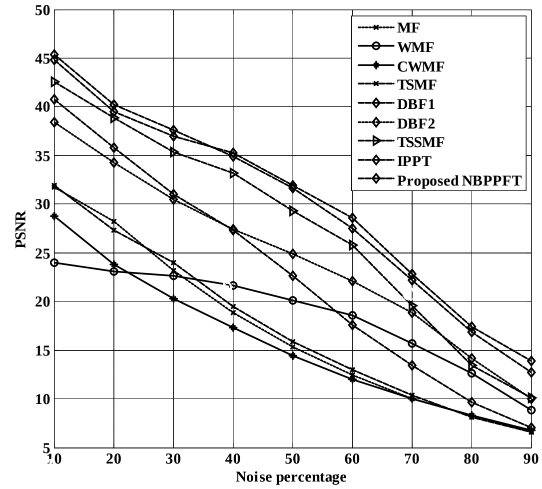

Fig.5 Performance of PSNR for proposed filter compared with different filtering technique on Lena image

Table II lists the variations of the PSNR values of the operators as a function of noise density for the proposed filtering technique on different test images. The proposed operator demonstrates the best filtering performance of all. Its PSNR values are significantly higher than the other filters for all noise densities.

TABLE II
PERFORMANCE OF PSNR FOR PROPOSED HYBRID NEURO-FUZZY FILTER FOR DIFFERENT IMAGES CORRUPTED WITH VARIOUS NOISE DENSITIES

NOISE %	Lena	Baboon	Pepper	Rice
10	44.82	39.04	43.89	42.34
20	39.50	34.56	42.30	37.07
30	37.01	32.21	40.56	35.66
40	35.29	31.07	38.78	33.45
50	31.89	26.78	34.00	29.87
60	28.56	22.05	31.21	26.11
70	22.85	17.00	25.82	20.43
80	17.43	14.87	20.55	15.88
90	13.89	10.44	16.05	11.35

Fig.6 Performance of test images: ($a_{1,2 \text{ and } 3}$) original images,($b_{1,2 \text{ and } 3}$) images corrupted with 50% of noise and ($d_{1, 2 \text{ and } 3}$) images enhanced by proposed filter

Fig.6 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.

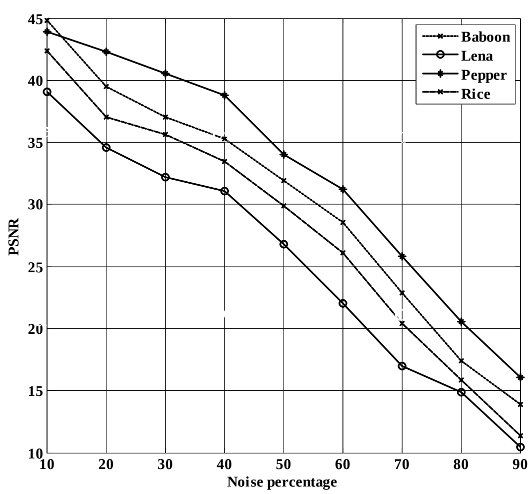

Fig.7 Performance of PSNR for the proposed filter on different test images

Fig.7 presents the noise-free, noisy, and filtered images for objective evaluation. Four different test images corrupted with 50% impulse noise 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.

4. Conclusion

An intelligent two stage hybrid filter is described in this paper. The proposed filter is seen to be quite effective in eliminating the 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 median based filter 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 while preserving the image features intact. Further, the proposed filter is suitable for real-time implementation, and applications because of its adaptive in nature.

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