Image Denoising Using A New Hybrid Neuro-Fuzzy Filtering Technique

R. Pushpavalli, G. Sivarajde

Abstract:- Digital images are often contaminated by impulse noise during image acquisition and/or transmission over communication channel. A new Hybrid Neuro-Fuzzy (HNF) filter for restoring digital images corrupted by impulse noise is proposed in this paper. The proposed filter is a hybrid filter obtained by aptly combining a Nonlinear Filter (NF), Canny Edge Detector (CED) and an Adaptive Neuro-Fuzzy Inference System (ANFIS). The internal parameters of the neuro-fuzzy network are adaptively optimized by training of well known images. 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. Extensive simulation results show that the proposed hybrid filter can be used for efficient restoration of digital images corrupted by impulse noise without distorting the useful information in the image. The performance of the proposed hybrid filter is compared with median based filters and hybrid filter [16] and shown to be more effective in terms of eliminating impulse noise and preserving edges and fine details of digital images.

Index Terms: - Adaptive Neuro-fuzzy Inference System, Decision Based Filter, Hybrid Filter, Impulse noise, Image denoising, Nonlinear filters.

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1 INTRODUCTION

Detection and removal of impulse noise from digital images have been of 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 standard median filter (MF) [4] is a simple rank selection filter and attempts to remove impulse noise from the center pixel of the processing 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. Since its application to impulse noise removal, the median filter has been of research interest and a number of rank order-based filters trying to avoid the inherent drawbacks of the standard median filter have been proposed. Weighted order statistic filters, such as the *weighted median filter* (WMF)[4] and the center-weighted median filter (CWMF) [5], employ a mechanism for appropriately weighting pixels of the analysis window to control the tradeoff between the noise suppression and detail preservation.

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These filters yield better detail preservation performance than the median filter at the expense of reduced noise suppression. Conventional order statistic filters usually distort the uncorrupted regions of the input image during restoration of the corrupted regions, introducing undesirable blurring effects into the image. In switching median filters, the noise detector aims to determine whether the center pixel of a given filtering window is corrupted or not. If the center pixel is identified by the noise detector as corrupted, then the output of the system is switched to the output of the noise filter, which has the restored value for the corrupted pixel. If the center pixel is identified as uncorrupted, which means that there is no need to perform filtering, the noise removal operator is bypassed and the output of the system is switched directly to the input. This approach has been employed to significantly improve the performance of conventional median filtering and a number of median based filters exploiting different impulse detection mechanisms have been proposed [6]–[11]. Multiple Decision Based Switching Median (MDSM) Filtering scheme has been proposed to eliminate impulse noise using global and local statistics [12]. Determining the right value of threshold for a given image is a challenging task in single threshold Switching Median Filtering. Besides, the single threshold value cannot be expected to yield optimal performance over the entire image since the images are nonstationary processes. In order to avoid computational complexity, Multiple Threshold Switching Median Filtering Scheme (MTSMFS) has been proposed [13]. A good noise filter is required to satisfy two criteria of (1) suppressing the noise while at the same time (2) preserving the useful information in the signal. Unfortunately, a 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. In the last few years, there has been a growing interest in the applications of soft computing techniques, such as neural networks and fuzzy systems, to the problems in digital signal processing. Neural networks are low-level computational structures that perform well when dealing with raw data although neural networks can learn; they are opaque to the user. In Fuzzy Systems, fuzzy logic deals with reasoning on a higher level, using linguistic information acquired from domain experts. Fuzzy systems lack the ability to learn and cannot adjust themselves to a new environment. Integrated neuro-fuzzy systems can combine the parallel computation and learning abilities of neural networks with the humanlike knowledge representation and explanation abilities of fuzzy systems. As a result, neural networks become more transparent, while fuzzy systems become capable of learning. 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 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 (classifier, controller). Neuro-Fuzzy filtering techniques had been proposed for eliminating impulse noise and preserving edges and fine details of images [14]-[15]. A Hybrid Neuro-Fuzzy Filter for Edge Preserving Restoration of Images Corrupted by Impulse Noise has been recently proposed [16]. This filter is efficiently eliminates impulse noise up to 25% and preserve edges and fine details of images. However this hybrid filter performance deteriorates the image quality for higher level impulse noise. Although these already existing hybrid filters suppresses impulse noise satisfactorily, it is found to exhibit inadequate performance in terms of preserving edges and fine details of images at higher level impulse noise. In order to improve the performance of hybrid filter, a new hybrid filter is proposed. In this paper, Adaptive Neuro-fuzzy Inference System (ANFIS) is considered for hybrid filter, which is a fuzzy inference system implemented in the framework of adaptive network. The ANFIS learning procedure is used for the proposed hybrid filter and ANFIS can construct an input-output mapping which is based on both human knowledge (in the form of fuzzy if-then rules) and learning. ANFIS network is trained using well known images and network structure is fixed. Noisy image (input image), Decision Based Switching Median Filter (DBSMF), Canny Edge Detector (CED) output image are considered as three inputs for ANFIS network and noise free image is considered as a target image for Training of the neural network. While training an ANFIS network, network structure is fixed and the unknown images are tested for the given fixed ANFIS network structure respectively. The performance evaluation is obtained through simulation results and shown to be superior performance to other existing filtering techniques in terms of impulse noise elimination and edges and fine detail preservation properties. The rest of the paper is organized as follows. Section II explains the structure of the proposed filter and its building blocks. Section III discusses the result of the proposed hybrid filter to the test images. Results of the experiments conducted to evaluate the performance of the proposed hybrid filter and comparative discussion of these results are also presented in this Section. IV is the final section, presents the conclusions.

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 standard median filter, an edge detector and a NF network. The NF network utilizes the information from the median filter, the edge detector and the noisy input image to compute the output of the system, which is equal to the restored value of the noisy input pixel.

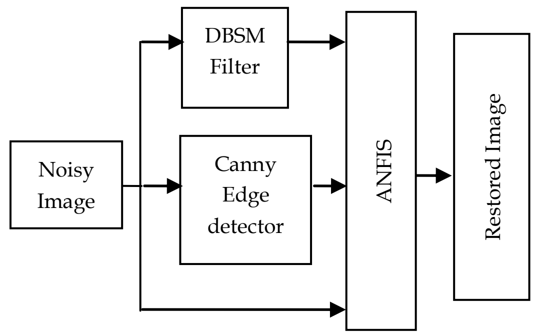

Fig.1 Proposed Hybrid Filter

2.2 New Decision Based Switching Median Filter

The impulse noise detection is based on the assumption that a corrupted pixel takes a gray value which is significantly different from its neighboring pixels in the filtering window, whereas noise-free regions in the image have locally smoothly varying gray levels separated by edges. In widely used Standard Median Filter (SMF) and Adaptive Median Filter (AMF), only median values are used for the replacement of the corrupted pixels. In switching median filter, the difference between the median value of pixels in the filtering window and the current pixel value is compared with a threshold to determine the presence of impulse. If the current pixel is detected to have been corrupted by impulse noise then the pixel is subjected to filtering; otherwise, the pixel is left undisturbed. The filtering technique proposed in this paper detects the impulse noise in the image using a decision mechanism. The corrupted and uncorrupted pixels in the image are detected by comparing the pixel value with the maximum and minimum values in the selected window. If the pixel intensity lies between these minimum and maximum values, then it is an uncorrupted pixel and it is left undisturbed. If the value does not lie within the range, then it is a corrupted pixel and is replaced by the median pixel value or already processed immediate neighboring pixel in the current filtering window. Consider an image of size M×N having 8-bit gray scale pixel resolution. The steps involved in detecting the presence of an impulse or not are described as follows:

Step 1) A two dimensional square filtering window of size 3 x 3 is slid over a highly contaminated image as shown in below.

Step2) The pixels inside the window are sorted out in ascending order.

Step 3) Minimum, maximum and median of the pixel values in the processing window are determined. In this case, the minimum, maximum and median pixel values, respectively, are 0, 255 and 255.

Step 4) If the central pixel lies between minimum and maximum values, then it is detected as an uncorrupted pixel and the pixel is left undisturbed. Otherwise, it is considered a corrupted pixel value. In the present case, the central pixel value 255 does not lie between minimum and maximum values. Therefore, the pixel is detected to be a corrupted pixel.

Step 5) The corrupted central pixel is replaced by the median of the filtering window, if the median value is not an impulse. If the median value itself is an impulse then the central pixel is replaced by the already processed immediate top neighbouring pixel Xi-1,j in the filtering window. In the present case, the median value is also an impulse and therefore, the pixel is replaced by its already processed top nearest neighbouring pixel value 214.

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. This Impulse noise detection and filtering is based on the following condition:

```
if Xmin < Xi,j < Xmax
{Xi,j is a noiseless pixel;
 no filtering is performed on Xi,j }
 else
{Xi,j is a noisy pixel;
 determine the median value}
if  median 0 and median 255
{Median filter is performed on Xi,j }
Xi,j = Xmed
else
{Median itself is noisy}
Xi,j = Xi-1,j
end;
end;
```

where, $X_{i,j}$ is the intensity of central pixel inside the filtering window, Xmin, Xmax and Xmed are the minimum , maximum and median pixel value in filtering window of noisy image. Xi-1,j is the intensity of the already processed immediate top neighboring pixel. In order to process the border pixels, the first and last columns, respectively are replicated at the front and rear ends of the image matrix; similarly, the first and last rows, respectively, are replicated at top and bottom of the image. The first row pixels of the image are processed using the same algorithm described above except that in step 5, if the median value is also detected to be an impulse it is replaced by one of the uncorrupted nearest neighbourhood pixel values in the processing window.

2.3 Edge Detector

There are a number of different edge detectors in the literature [20]. However, a major drawback of almost all of these edge detectors is that their detection performance is significantly degraded by noise, which makes them in appropriate for use in the structure of the proposed hybrid filter. In this paper, canny edge detector is used to identify the edges of the image. The canny edge detector is considered for training and testing of the images in Hybrid Neuro-Fuzzy Filtering (HNFF) operator. Usually, edge detector output pixels of the images are described by means of binary values 1 and 0. Edges of the image are represented using binary value 1 and homogeneous regions of the image are represented using binary value 0. The three inputs are noisy image; NDBSM Filtered image and Canny edge detector output image are considered as input for Adaptive Neuro-Fuzzy Inference System (ANFIS). Normalized values of these three inputs are given to the ANFIS. This ANFIS structure already explained in Fig.1. After normalizing the input datas, the noisy image datas and edge detector output datas are approximately similar data values. Because normalized noisy image datas contain binary values of 1 and 0 for corresponding to the salt and pepper noise, Those 1 and 0 depending on the percentage of noise contaminated the received image from communication channel. An Canny edge detected output datas contain binary values of 1 and 0 corresponding to edges and homogenous region of the given input image. Therefore ANFIS entails difficulties to learn the error datas from the given input. In order to overcome this issue, canny edge detector is performed on original image and its edges are replaced by original intensity values of its corresponding noise free image for training. Example for training edge detector output is as follow:

68	69	128
67	129	65
130	64	64

⇨

0	0	1
0	1	0
1	0	0

⇨

0	0	128
0	129	0
130	0	0

NDBSM Filter is applied on noisy image and this filtered image is considered as input for Canny edge detector and then edges from Canny edge detector are replaced by original intensity values of its corresponding NDBSM Filtered image data for testing. Example for testing edge detector output is as follow:

0	69	12 8
67	12 9	65
25 5	64	64

⇨

69	65	12 8
67	12 9	65
12 6	64	64

⇨

0	0	1
0	1	0
1	0	0

⇨

0	0	12 8
0	12 9	0
12 6	0	0

In this way, learning performance of ANFIS network is improved

2.4 Neuro-Fuzzy Network

The NF 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 median filter, the edge detector and the noisy input image. 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 NF network is a first order Sugeno type fuzzy system [49] with three inputs and one output. In NF 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 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 NF network is as follows. Let A_1, A_2, A_3 denote the inputs of the NF 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 Decision Based Switching Median Filter(DBSMF) and the canny edge detector before being applied to the NF network. Hence, in the structure of the proposed operator, A_1 represents the noisy input pixel, A_2 represents the output of the DBSMF for the noisy input pixel and represents the output of the canny edge detector for that filtered image pixel. Each possible combination of inputs and their associated membership functions is represented by a rule in the rule base of the NF network. Since the NF network has three inputs and each input has three membership functions, the rule base contains a total of 125 (5^3) rules, which are as follows.

1. If (A_1 is M_{11}) and (A_2 is M_{21}) and A_3 is M_{31}), then $Y_1 = MF_1(A_1,A_2,A_3)$
2. If (A_1 is M_{11}) and A_2 is M_{21}) and (A_3 is M_{32}), then $Y_2 = MF_2(A_1,A_2,A_3)$
3. If A_1 is M_{11}) and (A_2 is M_{21}) and (A_3 is M_{33}), then $Y_3 = MF_3(A_1,A_2,A_3)$
4. If (A_1 is M_{11}) and (A_2 is M_{21}) and (A_3 is M_{34}), then $Y_4 = MF_4(A_1,A_2,A_3)$
5. If (A_1 is M_{11}) and A_2 is M_{21}) and (A_3 is M_{35}), then $Y_5 = MF_5(A_1,A_2,A_3)$
6. If (A_1 is M_{11}) and (A_2 is M_{22}) and (A_3 is M_{31}), then $Y_6 = MF_6(A_1,A_2,A_3)$
7. If (A_1 is M_{11}) and (A_2 is M_{22}) and (A_3 is M_{32}), then $Y_7 = MF_7(A_1,A_2,A_3)$

⋮

125. If (A_1 is M_{11}) and (A_2 is M_{25}) and (A_3 is M_{35}), then $Y_{125} = MF_{125}(A_1,A_2,A_3)$

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 = 1,2,3; j=1,2,3 and k = 1,2 3,…..125. The input membership functions are generalized gaussian membership type. The Gaussian function depends on two parameters σ and c as given by

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

and the output membership functions are linear

$$MF_{ij} = d_{k1}x_1 + d_{k2}x_2 + d_{k3}x_3 + d_{k4} \quad (2)$$

where x, x_1, x_2 and x_3 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 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:

$$W_1 = M_{11}(A_1).M_{21}(A_2).M_{31}(A_3)$$

$$W_2 = M_{11}(A_1).M_{21}(A_2).M_{32}(A_3)$$

$$W_3 = M_{11}(A_1).M_{21}(A_2).M_{33}(A_3)$$

$$W_4 = M_{11}(A_1).M_{21}(A_2).M_{34}(A_3)$$

$$W_5 = M_{11}(A_1).M_{21}(A_2).M_{35}(A_3)$$

$$W_6 = M_{11}(A_1).M_{22}(A_2).M_{31}(A_3)$$

$$W_7 = M_{11}(A_1).M_{22}(A_2).M_{32}(A_3)$$

⋮

$$W_{125} = M_{11}(A_1).M_{25}(A_2).M_{35}(A_3)$$

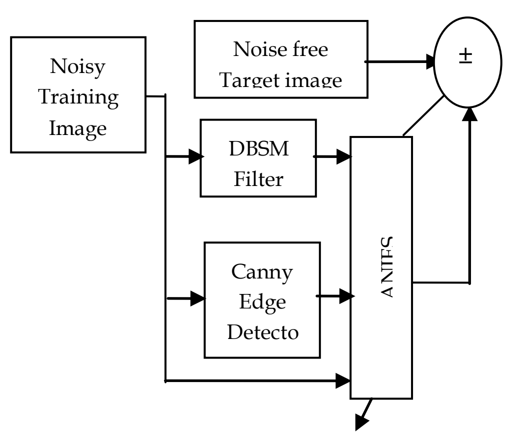

Fig.2 Training of the neuro-fuzzy network

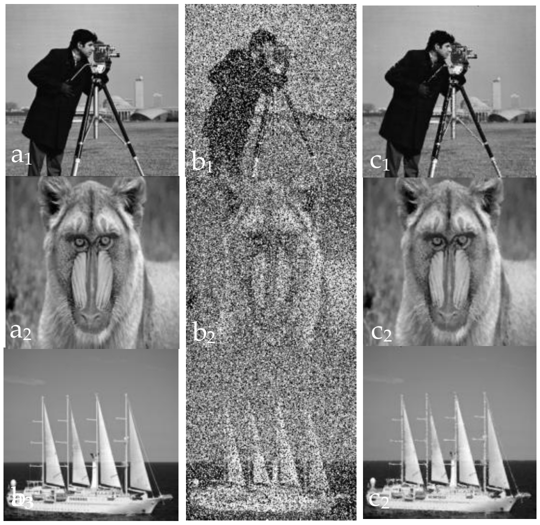

Fig.5 Performance of training image: ($a_{1,2 \text{ and } 3}$) original images, ($b_{1,2 \text{ and } 3}$) images corrupted with 45% of noise and ($c_{1,2 \text{ and } 3}$) trained images

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

$$Y_0 = \frac{\sum_{k=1}^{125} w_k Y_k}{\sum_{k=1}^{125} w_k}$$

2.5 Training of the Neuro-Fuzzy Network

The internal parameters of the NF network are optimized by training. Fig. 2 represents the setup used for training. Here, the parameters of the NF 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. 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($a_{1,2 \text{ and} 3}$) are the *original training image: Lake*, ship and pepper. The size of the training images is 256 x 256. The image in Fig.4 ($b_{1,2 \text{ and } 3}$) are the *noisy training images* and is obtained by corrupting the original training image by impulse noise of 50% noise density. The image in Fig.4 ($b_{1,2 \text{ and } 3}$) 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 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 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 DBSM filter and the edge detector to construct the proposed hybrid filter, as shown in Fig. 1.

2.6 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 median filter and the edge detector in the structure. Next, the center pixel of the filtering window and the outputs of the median filter and the edge detector are applied to the appropriate inputs 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 Results

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 ten popular test images from the literature including *Baboon, Boat , Cameraman, lilyflower, ship, Lena, lotus* 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. 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), a New Impulse Detector(NID), Multiple Decision Based Median Filter(MDBMF) [20], Multiple Threshold Switching Median Filter(MTSMF)[19], already existing hybrid neuro-fuzzy filter and DBSM filter. These filters are representative implementations of different approaches to the impulse noise filtering problem. Some of the above filters have a number of tuning parameters. These 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. Several experiments are performed to measure and compare the noise suppression and detail preservation performances of all operators. The experiments are especially designed to reveal the performances of the operators for different image properties and noise conditions. The performances of all operators are evaluated by using the *peak signal-to-noise ratio* (PSNR) criterion, which is defined as

$$PSNR=10\log_{10}[(255^2/MSE)]$$

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

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

Here, M and N represents the number of rows and column of the image and $x(i,j)$ and $y(i,j)$ represents the original and the restored versions of a corrupted test image, respectively. Since all experiments are related with impulse noise. The experimental procedure to evaluate the performance of a proposed filter is as follows: The noise density is varied from 10% to 90% with 10% increments. For each noise density step, the seven test images are corrupted by impulse noise with that noise density. This produces seven different experimental images, each having the same 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. This procedure is separately repeated for all noise densities from 10% to 90% to obtain the variation of the average PSNR value of that proposed filter as a function of noise density.

TABLE 1
PERFORMNCE OF MSE FOR PROPOSED HYBRID NEURO-FUZZY FILTERING TECHNIQUE ON DIFFERENT IMAGES

Noise %	Lena	Baboon	Pepper	Rice
10	5.91	18.32	2.76	5.1
20	13.59	39.53	6.74	12.1
30	27.48	70.08	14.86	22.8
40	43.71	101.87	28.11	40.1
50	81.57	150.14	48.25	65.1
60	124.8	208.75	78.93	119.5
70	236.1	298.10	172.85	239.5
80	386.6	415.84	309.02	440.1
90	803.6	640.57	702.15	858.5

Table I and II lists the variations of the MSE and PSNR values of the operators as a function of noise density for different filtering techniques on Baboon image. Table III AND IV lists the variations of the MSE and PSNR values of the operators as a function of noise density for proposed Hybrid Neuro-Fuzzy (HNF) filtering image technique on different 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.

TABLE 2
PERFORMNCE OF PSNR FOR PROPOSED HYBRID NEURO-FUZZY FILTERING TECHNIQUE ON DIFFERENT IMAGE

Noise %	Lena	Baboon	Pepper	Rice
10	40.41	35.50	43.72	41.08
20	36.79	32.16	39.84	37.32
30	33.73	29.67	36.40	34.54
40	31.72	28.04	33.64	32.10
50	30.61	26.36	31.29	29.99
60	27.16	24.93	29.15	27.35
70	24.40	23.38	25.75	24.33
80	22.25	21.94	23.23	21.69
90	19.08	20.06	19.66	18.79

TABLE 3
PERFORMNCE OF MSE FOR DIFFERENT FILTERING TECHNIQUES ON BABOON IMAGE

Noise %	10	30	50	70	90
MF	195.9	265.1	492.4	1.42e+003	7.8e+003
WMF	312.9	400.6	691.2	1500	7.4e+003
CWMF	159.8	632.8	2.2e+003	6.1e+003	1.3e+004
TSMF	69.2	346.1	1.7e+003	5.8e+003	1.4e+004
NID	31.54	138.4	361.9	2.2e+003	1.0e+004
MDBSMF	34.29	241.7	1.3e+003	4.4e+003	1.23e+004
HNFF	31.06	106.1	257.1	480.6	1.1e+003
NDDBSMF	23.56	93.2	206.8	395.3	986.0
Proposed NHNFF	18.32	70.08	150.1	298.1	640.5

TABLE 4
PERFORMNCE OF PSNR FOR DIFFERENT FILTERING TECHNIQUES ON BABOON IMAGE

Noise %	10	30	50	70	90
MF	25.20	23.89	21.20	16.48	9.19
WMF	23.17	22.10	19.73	16.16	9.42
CWMF	26.09	20.11	14.64	10.31	6.90
TSMF	29.72	22.73	15.68	10.43	6.65
NID	33.14	26.71	22.54	14.62	7.99
MDBSMF	32.77	24.29	16.91	11.65	7.30
HNFF	33.20	27.87	24.02	21.31	17.38
NDDBSMF	34.41	28.43	24.97	22.16	18.19
Proposed NHNFF	35.50	29.67	26.36	23.38	20.06

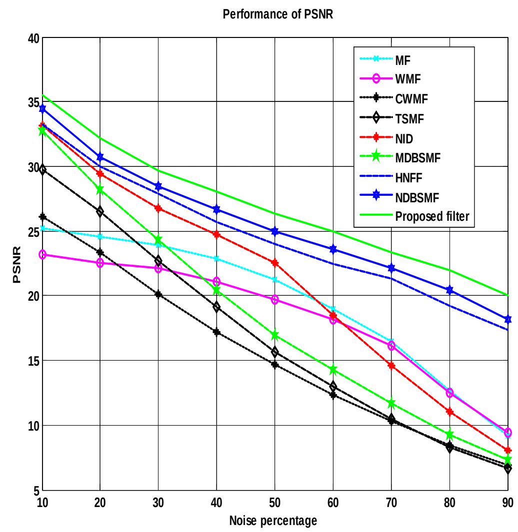

Fig.5 PSNR obtained using proposed HNFF and compared with different filtering techniques on Baboon image corrupted with different densities of impulse noise

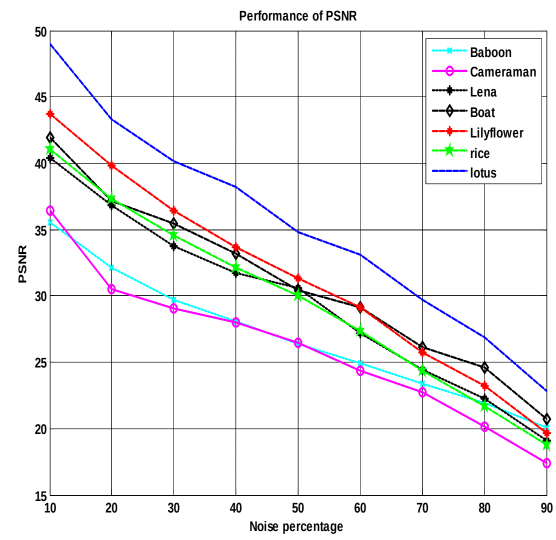

Fig.7 PSNR obtained by applying HNFF for different images corrupted with various densities of mixed impulse noise

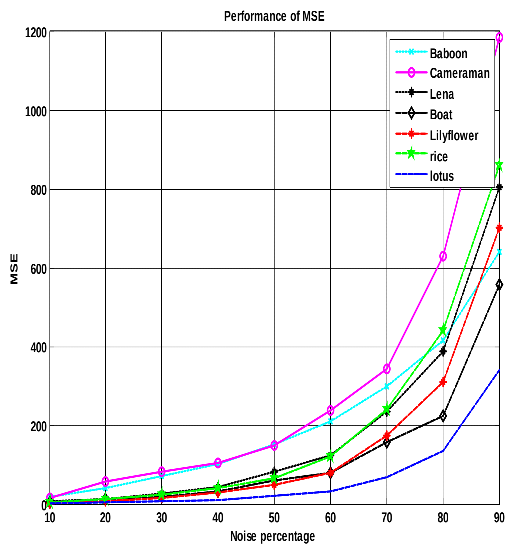

Fig.6 MSE obtained by applying HNFF for different images corrupted with various densities of mixed impulse noise

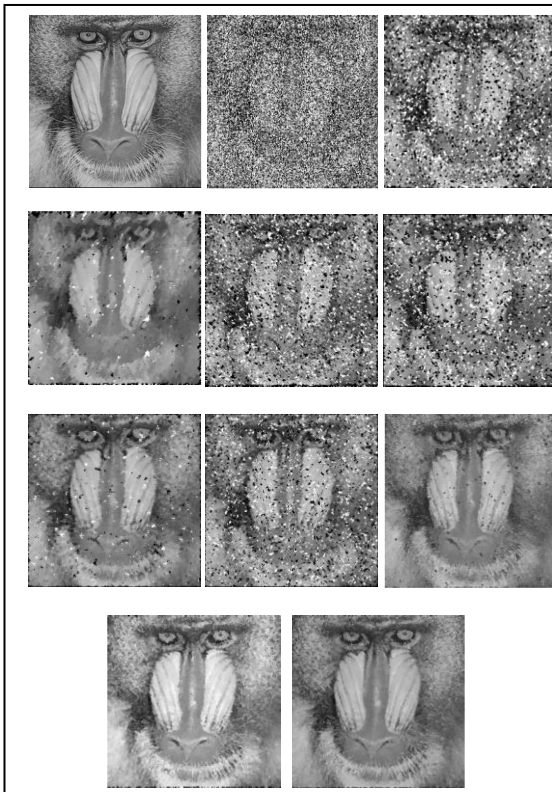

Fig. 8 (a) original Baboon image, (b) image corrupted with 60% impulse noise (c) restored by MF, (d) restored by WMF, (e) restored by CWMF, (f) restored by TSMF, (g) restored by NID, (h) restored by MDBSMF, (i) restored by existing HNFF, (j) restored by NDDBSMF and (k) restored by Proposed HNFF

As it is seen from this table, the performances of the MF, WMF, CWMF and TSMF filters are very poor, the MDBSMF and NID being slightly better than the first four filters. The proposed HNF Filter performs better than the other existing filters. Fig.4 AND Fig.5 illustrates the performance of proposed Hybrid Neuro-Fuzzy Filter(HNFF) and compares with that of the different filtering algorithm in terms of PSNR and MSE when applied on Baboon image contaminated with noise densities up to 90%. The new nonlinear filter outperforms the improved decision making algorithm for the noise densities up to 70%. Fig.2 and Fig.6 and Fig.7 detect the performance of proposed HNFF for different images. The filtered Baboon image is presented for filtering different techniques in Fig.8 for visual perception and subjective evaluation. The proposed new HNF filter can be seen to have eliminated the impulse noise completely. Further, it can be observed that the HNF filter is better in preserving the edges and fine details than the other existing filtering algorithm. Fig.9 presents the noise-free, noisy, and filtered images for subjective evaluation. Seven different test images corrupted with 60% impulse noise are used to illustrate the efficacy of the proposed HNF filter. HNF filter is found to have eliminated the impulse noise completely while preserving the image features quite satisfactorily. It can be seen that the HNF filtered images are more pleasant for visual perception.

Fig.9 Performance of proposed HNF Filter for different images: ($a_{1, 2, 3, 4, 5, 6 \text{ and } 7}$) original images, ($b_{1, 2, 3, 4, 5, 6 \text{ and } 7}$) image corrupted with 60% of noise and ($c_{1, 2, 3, 4, 5, 6 \text{ and } 7}$) corrupted images restored by proposed HNF Filter

The advantages of the new HNF filter may be summarized as follows:

1) It has a very simple structure. It is constructed by appropriately combining a NDDBSM filter, canny edge detector and a NF network. The structure of the NF network is also very simple. It is a first order Sugeno type fuzzy system with three inputs and one output.
2) It does not require user-supplied heuristic tuning parameters. The internal parameters of the proposed operator is adaptively tuned by training.
3) The training is easily accomplished by using very simple images. However, contrary to its simplicity in implementation and convenience in training, the proposed operator may be used for efficiently filtering any image corrupted by impulse noise of virtually any noise density.
4) An even better performance may be obtained by repetitive application of the proposed operator to the corrupted image. The increase in performance is depending on the image properties and the density of the corrupting noise.

It is concluded that the proposed HNF filter can be used as a powerful tool for efficient removal of impulse noise from digital images without distorting the useful information within the image.

4 CONCLUTIONS

A new Hybrid Neuro-Fuzzy (HNF) filter is described in this paper. The proposed filter is seen to be quite effective in eliminating the impulse noise; in addition, the HNF 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. The HNF filter outperforms the existing median based filter in terms of qualitative and quantitative measures. In addition, the HNF 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 HNF filter is suitable for real-time implementation, and applications because of its adaptive in nature.

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