A Hybrid Approach for Efficient Removal of Impulse, Gaussian and Mixed Noise from Highly Corrupted Images using Adaptive Neuro Fuzzy Inference System (ANFIS)

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ABSTRACT
The aim of the paper is to remove the noise in the images and at the same time to preserve the edges, fine details and texture in the image. This paper proposes a novel Adaptive Neuro Fuzzy Inference System (ANFIS) filter to remove impulse, Gaussian and mixed noise without affecting edges and texture of an image. It is a hybrid filter constructed by combining an appropriate noise filter, an edge detector and ANFIS. Different edge detectors are implemented such as canny, sobel and prewitt. The performance of the proposed filter is tested for impulse, Gaussian and mixed noise in Lena image. As a result, it is observed that the proposed hybrid filter effectively removes the noise in the following order: impulse > Gaussian > mixed noise with canny edge detector.

General Terms
Noise Filter, Adaptive Neuro Fuzzy Inference System , Edge Detector

Keywords
Adaptive Neuro Fuzzy Inference System, Median Filter, Wiener Filter, Image Processing.

1. INTRODUCTION
Digital images are often corrupted by different kinds of noise while transmitting and acquisition of images due to errors produced by noisy sensors, faulty CCD elements and dust on the lens or communication channels. This noise could degrade the image quality and cause loss of image details. The performances of the subsequent image processing tasks such as segmentation, feature extraction and object recognition are severely degraded by noise [1]. Noise removal process is one of the pre-processing steps in image processing. So it is a very paramount important to remove noise from digital image. This paper presents a noise removal technique to suppress the noise and at the same time preserve thin lines, fine texture and image details. This paper takes into account to remove impulse noise, Gaussian noise and mixed noise (combination of impulse and Gaussian noise). Impulse noise may occur due to sudden fluctuations in image signals. It is like white and black dots over the image. So that it is called Salt and Pepper noise, i.e., dark pixels in the bright region and bright pixels in the dark region. Gaussian noise is an idealized form of white noise which is caused by random fluctuations in the signal.

There are many different filtering methods has been proposed in the literature to remove impulse and Gaussian noise. One of the most popular non linear filters is median filter to remove impulse noise which utilizes the rank order information of the pixels contained in the filtering window [2]. It replaces the centre pixel value of the filtering window with the median of the pixels in the window. It removes some reasonable noise at low noise density. But at high density it will not work effectively. Thus the output is blurred image. To overcome this drawback the following filters are used: Weighted Median (WM) filter [3] and Centre Weighted Median filter (CWM) [4] have been proposed. Weights are given to only centre pixel value of the filtering window [4]. Switching Median filter (SM) [5], if the centre pixel is corrupted, the window is filtered by standard median filter, otherwise window is not filtered. Here impulse noise detector is employed. The Tri-State median filter [6] performs better than switching median filter.

Recently, the application of artificial intelligence based non linear technique such as fuzzy systems and neural network are alternative for median based noise detection and reduction. Fuzzy inference rule by else action filter (FIRE) [7] which uses fuzzy rules to estimate degree of noisy pixels and calculates a correction term based on this estimation. The weighted fuzzy mean filter (WFM) [8] and the iterative fuzzy control based filter (IFCB) [9] are able to outperform rank order filter.

Indeed, fuzzy systems are very well suited to model the uncertainty that occurs when both noise cancellation and detail preservation are required. When the images are highly corrupted, the rule-base structure becomes quite difficult. So combinations of neural network and fuzzy systems have been shown to be very promising field for nonlinear filtering of noisy image data [10-11]. In order to overcome above mentioned problems Adaptive Neuro Fuzzy Inference System (ANFIS) is proposed which has ability to learn from examples. Hence ANFIS filter represents a very powerful tool in order to deal with image highly corrupted by noise.

In this present paper, we propose a new hybrid filter constructed by combining an appropriate noise filter, an edge detector and ANFIS. An edge detector is used to extract edges from highly corrupted images [12]. The advantages of proposed hybrid filter are its simplicity and accuracy.

The rest of the paper is organized as follows. Section 2 explains the schematic representation of proposed hybrid filter for impulse, Gaussian and mixed noise. Section 3 explains the implementation of appropriate proposed filter to test image. Simulation results and discussion and conclusion are presented in this section 4 and 5, respectively.

2. SCHEMATIC REPRESENTATION OF PROPOSED HYBRID FILTER

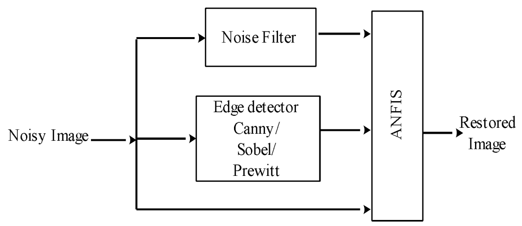

Fig 1: Schematic representation of proposed hybrid filter

The proposed operator is a hybrid filter obtained by appropriately combining a noise filter, an edge detector and ANFIS. The ANFIS network utilizes the information from the noise filter, an edge detector and the noisy input image to find the output of the system, which is equal to the restored value of the noisy input pixel. In noise filter, median, wiener and both median and wiener filters are used to remove impulse noise, Gaussian noise and mixed noise. Before using noise filter an average filter is used for getting sharp edges. Three edge detectors (canny, sobel and prewitt) are used in the proposed approach.

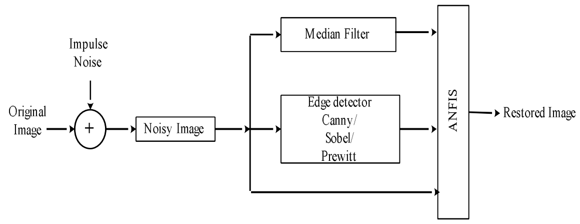

Fig 2: Schematic representation of Impulse Noise Removal

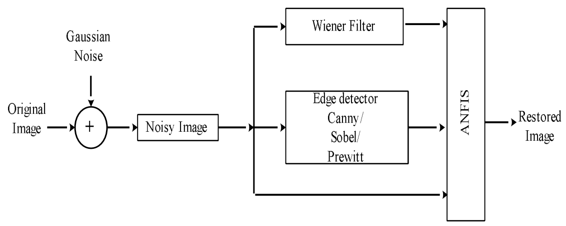

Fig 3: Schematic representation of Gaussian Noise Removal

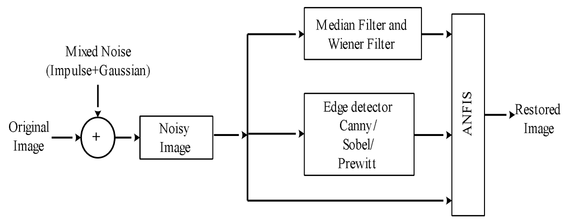

Fig 4: Schematic representation of Mixed Noise Removal

2.1 Median Filter

The median filter is a simple rank selection filter that outputs the median of the pixels contained in its filtering window [2]. The input-output relationship of the median filter may be defined as follows:

Let x[r,c] denote the luminance value of the pixel at location (r,c) of the noisy input image. Here, r and c are the row and the column indices, respectively, with $1 \leq r \leq R$ and $1 \leq c \leq C$ for an input image having a size of R by C pixels. Let $W_N[r,c]$ represent the group of pixels contained in a filtering window centered at location (r,c) of the noisy input image and having the size of (2N+1) by (2N+1) pixels.

$$W_N[r,c] = (x[r + p, c+q]);(p,q)= -N,\ldots,N \quad (1)$$

Where N is a positive integer number related with the size of the filtering window and p,q are integer indices each individually ranging from –N to N.

The output of the median filter is equal to the median of the pixels contained in the filtering window $W_N[r,c]$

$$m[r,c] = \text{Median}\ (W_N[r,c]) \quad (2)$$

2.2 Wiener Filter

To remove Gaussian noise Wiener filter is prescribed. The Wiener filter is the Mean Square Error (MSE)-optimal stationary linear filter for images degraded by additive noise and blurring. Calculation of the Wiener filter requires the assumption that the signal and noise processes are second order stationary (in the random process sense). Here power spectrum can be deemed as a constant. Then Wiener filter *H* (ω_1, ω_2) is given

$$\frac{P_f(\omega1,\omega2)}{P_f(\omega1,\omega2)+P_v(\omega1,\omega2)} = \frac{\sigma^2 f}{\sigma^2 f+\sigma^2 v} \quad (3)$$

Where σ^2_f is the local variance of the original image and σ^2_v is the variance of Gaussian noise. Adaptive wiener filter works well for removing Gaussian noise.

2.3 Edge Detector

Edge detector refers to the process of detecting meaningful discontinuities in intensity values. Edge detector detects the outlines of an object and boundaries between objects and the background in the image. An edge-detection filter can also be used to improve the appearance of blurred image. The edge-detection operator is calculated by forming a matrix centred on a pixel chosen as the centre of the matrix area. If the value of this matrix area is above a given threshold, then the middle pixel is classified as an edge. The gradient-based edge detectors are Roberts, Prewitt, and Sobel operators. All the gradient-based algorithms have kernel operators that calculate the strength of the slope in directions which are orthogonal to each other, commonly vertical and horizontal. The following three different edge detectors are used in the proposed approach:

- Sobel
- Prewitt
- Canny

Edge detector is capable of extracting edges from digital images corrupted by noise without requiring a prefiltering of the input image. Therefore, canny, sobel and prewitt edge detectors are employed as the edge detectors in this work.

3. IMPLEMENTATION OF PROPOSED APPROACH

ANFIS is a multilayer feed forward network which uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space. The ANFIS is a first order Sugeno type fuzzy system with three inputs and one output. Sugeno-type fuzzy systems are popular general nonlinear modelling tools because they are very suitable for tuning by optimization. Each input has three gauss type membership function where the output has linear membership function. Using given input/output data set, the MATLAB toolbox function ANFIS constructs a fuzzy inference system (FIS) whose parameters for membership function are tuned using least mean square method and back propagation algorithm. This allows the FIS to learn from the given training data to improve the performance in the case of ANFIS. ANFIS has three inputs and each input has three membership functions. Let V_1, V_2, V_3 denote the inputs of the ANFIS and Y denote its output. Each noisy pixel is independently processed by the noise filter and the edge detector before being applied to the ANFIS. In the structure of the proposed operator, V_1 represents the output of the noise filter for the noisy input pixel, V_2 represents the output of the edge detector for that noisy pixel, and V_3 represents the noisy pixel itself. The rule base contains total of (3^3) 27 rules which are as follows.

1. If (V_1 is M_{11}) and (V_2 is M_{21}) and (V_3 is M_{31}) then, $R_1 = F_1(V_1, V_2, V_3)$
2. If (V_1 is M_{11}) and (V_2 is M_{21}) and (V_3 is M_{32}) then, $R_2 = F_2(V_1, V_2, V_3)$
3. If (V_1 is M_{11}) and (V_2 is M_{21}) and (V_3 is M_{33}) then, $R_3 = F_3(V_1, V_2, V_3)$
4. If (V_1 is M_{11}) and (V_2 is M_{22}) and (V_3 is M_{31}) then, $R_4 = F_4(V_1, V_2, V_3)$
5. If (V_1 is M_{11}) and (V_2 is M_{22}) and (V_3 is M_{32}) then, $R_5 = F_5(V_1, V_2, V_3)$

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27. If (V_1 is M_{13}) and (V_2 is M_{23}) and (V_3 is M_{33}) then, $R_{27} = F_{27}(V_1, V_2, V_3)$ (4)

where, $M_{i,j}$ denotes the j^{th} membership function of the i^{th} input. R_k denotes the output of the K^{th} rule and F_k denotes the k^{th} output membership function, with i = 1, 2, 3; j = 1, 2, 3; and K = 1, 2, 3,.......,27.

The symmetric Gaussian function depends on two parameters σ and c as given by

$$f(x;\sigma,c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \quad (5)$$

The optimal values of these parameters are determined by training. The structure of an ANFIS is shown in fig. 5

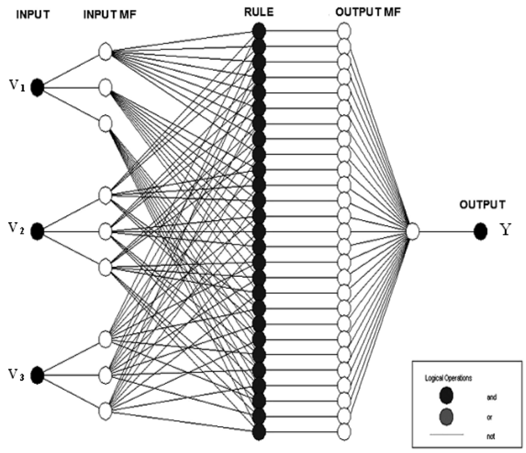

Fig 5: Structure of ANFIS

The output of the ANFIS is the weighted average of the individual rule outputs. The weighting factor w_k of each rule is calculated by evaluating the membership expressions Hence, the weighting factors of the rules are calculated as follows:

$$w_1 = M_{11}(V_1).\ M_{21}(V_2).\ M_{31}(V_3)$$
$$w_2 = M_{11}(V_1).\ M_{21}(V_2).\ M_{32}(V_3)$$
$$w_3 = M_{11}(V_1).\ M_{21}(V_2).\ M_{33}(V_3)$$
$$w_4 = M_{11}(V_1).\ M_{22}(V_2).\ M_{31}(V_3)$$
$$w_4 = M_{11}(V_1).\ M_{22}(V_2).\ M_{32}(V_3)$$

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$$w_{27} = M_{13}(V_1).\ M_{23}(V_2).\ M_{33}(V_3) \quad (6)$$

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

$$Y = \frac{\sum_{k=1}^{27} WkRk}{\sum_{k=1}^{27} Wk} \quad (7)$$

3.1 Training of the ANFIS

Once the neural network has been created it needs to be trained. One way to train ANFIS is first initialize the neural net with random weights and then feed it a series of inputs. For each layer we check the output and adjust the weights accordingly to the desired output. The output like a desired output it outputs 1 otherwise zero. This type of training is called supervised training and the data we feed it is called a Training data. Using back propagation and combination with least squares method are to adjust the weights. The Epoch number, which is the number of times the complete training set has been trained, was selected as 20 for training. Also during training, the output is computed repeatedly and the result is compared to the preferred output generated by the training data. Here the parameters of the ANFIS are iteratively optimized so that its output converges to the output of the noise filter which completely removes the noise from its input image. This is shown in fig 6.

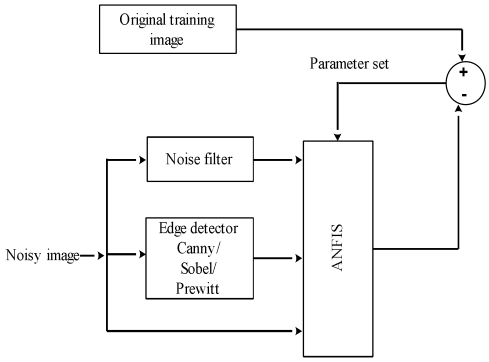
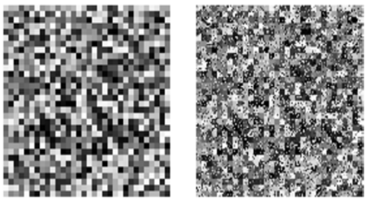


Fig 6: Training of ANFIS



(a) (b)

Fig 7: (a) Original training image. (b) Noisy training image (corrupted by 30% impulse noise).

Fig. 7 shows the images used for training. Only one image (image pair) is used in training. Fig. 7(a) shows the *original training image*, which is a 64 x 64 pixel artificial image that can easily be generated in a computer. Each square box in this image has a size of 4 x 4 pixels and the 16 pixels contained within each box have the same luminance value, which is a random integer number uniformly distributed in [0, 255]. Fig. 7(b) is obtained by original training image corrupted by impulse noise of 30% noise density. The proposed operator shows the best filtering performance when the noise density of the noisy training image is equal to the noise density of the actual input image to be restored. If the difference between two noise densities increases then the performance of proposed operator is decreased. Once ANFIS is trained, its internal parameters are fixed.

4. RESULTS AND DISCUSSION

The performance of the proposed operator is tested for removing impulse, Gaussian and mixed noise on popular Lena image based on Adaptive Neuro Fuzzy Inference System (ANFIS). Noisy image is obtained by contaminating the original image by different noise with an appropriate noise density. The filtering performance was implemented on the well-known software MATLAB on Personal computer. In the present study 64x64 gray scale Lena image is corrupted by impulse noise, Gaussian noise and mixed noise at various noise densities. In the case of salt and pepper, image will be corrupted by "salt" (with value 255) and "pepper" (with value 0) with equal probability. A wide range of salt-and-pepper noise levels varied from 5% to 90% with an increment of 5%. The additive Gaussian white noise is zero mean with varied variance from 0.0005 to 0.90. And for mixed noise, Gaussian white is zero mean and 0.2 variance is fixed, impulse noise varied from 5 % to 90 % with increments of 5%. Restoration performances of the proposed operator is evaluated by using the *peak signal-to-noise ratio* (PSNR) criterion as well as in terms of visual quality of the images, which is defined as

$$\text{PSNR} = 10\, log_{10} \frac{255^2}{MSE} \text{ dB} \tag{8}$$

MSE is the *mean squared error* (MSE) and defined as,

$$\text{MSE} = \frac{1}{RC} \sum_{r=1}^{R} \sum_{c=1}^{C} (s[r,c] - y[r,c])^2 \tag{9}$$

Here, s[r,c] and y[r,c] represent the original image and filtered image of size RC, respectively. All experiments are related with noise and noise is a random process. So the same experiment gives 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. The averages of these values are then taken as the representative PSNR value for that experiment. This procedure is repeated for all noise densities from 5% to 90% for impulse noise. The same procedure employed for Gaussian noise and mixed noise resembles the same.

Initially, Lena image was corrupted by impulse noise at various noise levels varied from 5% to 90% with an increment of 5%. The proposed hybrid filter removes the impulse noise using canny, sobel and prewitt edge detector and produced the restored image of original Lena. In the case of Gaussian noise, Lena image is corrupted by Gaussian white noise at mean zero and the variance is varied from 0.0005 to 0.90. With regard to the mixed noise Lena image is corrupted by Gaussian white with zero mean and variance 0.2 is fixed and impulse noise is varied from 5% to 90% with an increment of 5%

Table 1. MSE and PSNR using canny, sobel and prewitt edge detector in proposed approach for impulse noise

NOISE DENSITY (%)	CPSNR	SPSNR	PPSNR
9	36.5230	35.3638	34.5012
10	31.5542	30.0512	28.5140
15	26.6741	25.1771	24.0611
20	25.2639	24.1836	23.1962
25	25.0445	23.2524	22.5001
30	23.9310	22.8102	22.0142
40	21.5012	20.3810	19.5021
50	20.2001	19.0112	18.0215
60	18.5924	17.6583	16.6234
70	17.1345	16.0241	15.5695
80	16.2742	15.5335	15.4291
90	15.6907	15.4302	15.4112

Table 2. MSE and PSNR using canny, sobel and prewitt edge detector in proposed approach for Gaussian noise

VARIANCE	CPSNR	SPSNR	PPSNR
0.0005	35.1719	34.5853	34.0803
0.001	32.5489	31.4747	31.0080
0.002	30.0304	28.9507	28.0506
0.003	28.6291	28.0241	27.5705
0.004	27.7173	26.5397	25.9620
0.005	26.8007	26.0460	28.4833
0.01	25.2830	24.6696	24.1058
0.015	24.5312	24.0018	23.2589
0.02	23.5660	22.6590	22.0057
0.025	22.6727	21.9813	21.0360

0.03	22.0525	21.4551	20.9856
0.035	21.6611	20.9360	20.6481
0.04	21.3999	20.5347	20.0254
0.045	21.0005	20.0205	19.6712
0.05	20.9020	19.8778	19.0243
0.10	19.5987	19.0298	18.9334
0.20	18.0810	17.7513	17.0560
0.30	17.5297	17.1041	16.5107
0.40	16.7695	16.2280	15.9252
0.50	16.4327	15.8602	15.7195
0.60	16.1125	15.7086	15.5676
0.70	15.9563	15.5514	15.4251
0.80	15.7183	15.4301	15.4105
0.90	15.4523	15.4102	15.3098

Table 3. MSE and PSNR using canny, sobel and prewitt edge detector in proposed approach for mixed noise

IMPULSE NOISE (%)	CPSNR	SPSNR	PPSNR
0.05	34.5324	34.3230	34.0002
0.5	33.9479	33.5796	33.4212
1	33.6781	33.3371	33.0013
5	32.0021	31.2557	30.9417
15	26.9521	21.5147	26.0064
20	24.8972	24.3016	24.0172
25	24.0215	23.8715	23.5201
30	23.1458	23.0577	22.8726
50	20.5641	20.1025	19.5824
60	18.6717	17.5801	17.5737
70	17.6384	16.5261	16.5120
80	15.7469	15.6890	15.4212
90	15.4407	15.3902	15.1027

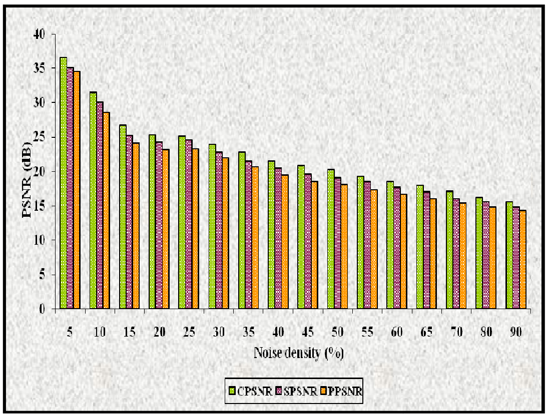


Fig 8: Comparison of PSNR values using canny, sobel and prewitt edge detector for impulse noise

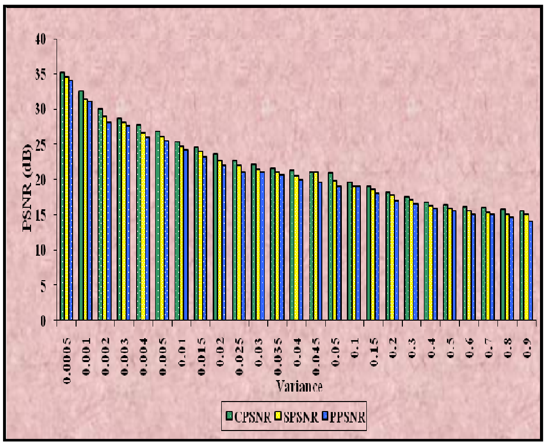


Fig 9: Comparison of PSNR values using canny, sobel and prewitt edge detector for Gaussian noise

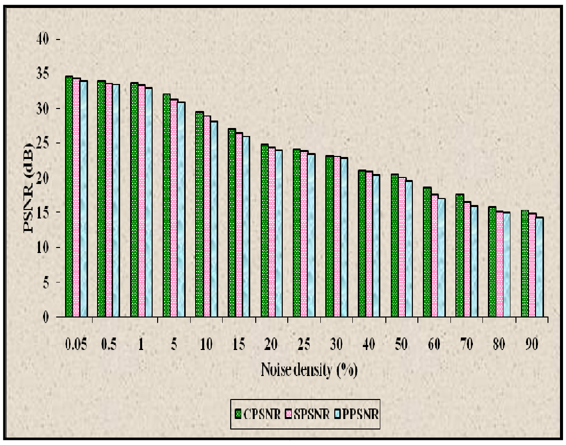


Fig 10: Comparison of PSNR values using canny, sobel and prewitt edge detectors for mixed noise

Table 1 lists the PSNR values using canny, sobel and rewitt edge detector in the proposed approach for impulse noise. It is clearly seen from Table 1 that proposed hybrid filter with canny edge detector removes impulse noise effectively compared to using sobel and prewitt edge detector. At high noise densities (90%) restored image is not visually good in case of canny, sobel and prewitt. However, from their PSNR values canny seemed to be better than sobel and prewitt.

Table 2 and Tables 3 list the average of the PSNR using canny, sobel and prewitt edge detectors for Gaussian and mixed noise in the proposed approach. Fig (8-10) shows the comparison of PSNR values using canny, sobel and prewitt edge detectors for impuse, Gaussian and mixed noise. Lena image is corrupted by impulse noise with 25% and the noisy image is restored by proposed filter with canny, sobel and prewitt edge detector is shown in Fig 11. Gaussian noise with zero mean and variance is 0.2 and for mixed noise, impulse noise is 25% and Gaussian noise is zero mean and variance is 0.2 of the restored image using proposed filter with canny, sobel and prewitt edge detector is shown in Fig.12 and Fig.13 respectively.

(a) (b) (c) (d) (e)

Fig 11: (a) Original lena (b) Lena corrupted by impulse noise with 25 % (c) Restored image using canny (d) Restored image using sobel (e) Restored image using prewitt

(a) (b) (c) (d) (e)

Fig 12: (a) Original lena (b) Lena image corrupted by Gaussian noise mean zero and variance 0.2 (c) Restored image using canny (d) Restored image using sobel (e) Restored image using prewitt

(a) (b) (c) (d) (e)

Fig 13: (a) Original Lena image (b) Lena image corrupted by mixed noise Gaussian noise with zero mean and variance 0.2 and impulse noise is 25 %. (c) Restored image using canny (d) Restored image using sobel (e) Restored image using prewitt

From these tables and graphs it was found that proposed method removes Gaussian and mixed noise using canny edge detector better than the sobel and prewitt. On comparing it could be stated that among three edge detectors canny's performance was best in removal of impulse, Gaussian and mixed noise. Because sobel and prewitt method return edges at those points where the gradient of image is maximum. In the case of canny, it finds edges by looking for local maxima of the gradient of image. The method uses two thresholds, to detect strong and weak edges. It detects the weak edges in the output only if they are connected to strong edges. This method is employed to detect true weak edges. Prewitt and sobel filter have a major drawback of being very sensitive to noise. In prewitt, the size of the kernel filter and coefficients are fixed and cannot be adapted to a given image. The Canny edge is used in finding the most edges by minimizing the error rate, marking edges as closely as possible to the actual edges to maximize localization, and marking edges only once when a single edge exists for minimal response. Therefore, canny edge detector preserves edges than the sobel and prewitt edge detectors.

5. CONCLUSION

In this paper, removal of impulse, Gaussian and mixed noise using ANFIS is proposed. A Median and Wiener filter are preferred because it is a simple and well known impulse and Gaussian noise filter. Hence, the present paper proposes that hybrid filter effectively removes high (90%) density impulse noise from digital images while successfully preserving thin lines, edges, fine details and texture in the original image using canny edge detector than the Gaussian and mixed noise. The advantages of proposed filter are

1. It is a first order sugeno type system with three inputs and one output. It is a simple structure.
2. Internal parameters are tuned using training. So no need to train externally.
3. For training purpose artificial images are generated using a computer.

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