Enhancement of Digital Images by Combinational Neuro-Fuzzy Logic

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Abstract— Combinational Neuro-Fuzzy (NF) logic is the mixed technique generated by the combination of artificial neural network and fuzzy-logic. Various methods are proposed in the literature to restore the image degraded by impulse noise using soft computing technique where all methods have their own advantages and disadvantages. A novel idea is proposed in this paper where the ANFIS is used to detect the impulse noise and mean of the median of 3x3 window of noisy image is taken for the removal process. Experimental result shows the effectiveness of the proposed method by visual illustration and quantitative analysis.

Index Terms— Image processing, Fuzzy logic, Neural Network, ANFIS, Fused Neuro-Fuzzy Logic, Impulse Noise, Nonlinear Filters

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1 INTRODUCTION

IMAGES are usually degraded by noise during image acquisition and transmission process. The main purpose of the noise reduction technique is to remove impulse noise by retaining the important feature of the images. Noise occurs in the images when the pixels are randomly failed and replaced by other values in an image. The image model containing impulse noise can be described as:

$$X_{ij} = \begin{cases} N_{ij}, & with\ probability\ p \\ S_{ij}, & with\ probability\ 1-p \end{cases}$$

Where, Sij represents the noiseless image pixel and Nij represents the noise substituting for the original pixel. The fixed and random-valued impulse noises are mostly discussed in a variety of impulse noise models for images. Fixed-valued impulse noise, known as the "salt-and-pepper" noise, is made up of corrupted pixels whose values are replaced with values equal to the maximum or minimum (255 or 0) of the allowable range with equal probability (p/2). The random-valued impulse noise is made up of corrupted pixels whose values are replaced by random values uniformly distributed in the range within [0, 255]. The noise removal nonlinear filtering techniques tend to blur fine details and destroy edges while removing corrupted pixels. To overcome these issues several modifications have been applied in conventional filtering techniques [1]-[5].

In recent arena, research is growing in the field of digital image processing with conjunction of soft computing technique. Fusion of Adaptive Neural Network (ANN) and Fuzzy Inference System (FIS) (such as ANFIS) is frequently applied by researchers in various scientific and engineering research areas to solve real world problems. When the classic techniques are not sufficient to produce an easy and accurate solution these two techniques: neural networks and fuzzy logic are applied many times together to the problems in digital image processing [6]-[8]. As both paradigms have their own advantages, so it is a good idea to combine their ability and make a strong tool to solve complex problems.

Suo et al. discussed few advantages of neural network technology such as parallel calculating abilities, nonlinear

mapping and adaptive ability for visual image processing [9]. Monireh has reviewed the application of ANFIS as a classifier in medical image classification [10]. Training procedure of neural network for resolving problems related to medical imaging is analysed by J.Jiang [11]. A novel adaptive neuro-fuzzy inference system (ANFIS) is proposed by Jhang for edge detection in digital images [12]. Saenko et al. has used fuzzy technique for image enhancement and image quality analysis [13]. The role of the fused neuro-fuzzy system is attracting researchers due to the significant enhancement in results over traditional methods.

A combinational neuro-fuzzy filter is proposed in this paper where fused NF logic is used to detect the impulse noise and a mean of the median of the window size is used to restore the noisy image. This paper is organized as section II describes the working of neuro-fuzzy model; section III contains the description of the proposed model. Experimental results are shown in section IV which shows the significant improvement over the traditional method.

2 NEURO-FUZZY MODEL

Neuro-fuzzy systems are those fuzzy systems which are based on Artificial Neural Network (ANN) theory in order to determine their properties by processing data samples. ANNs have greater predictive power than signal analysis techniques and Fuzzy set theory plays an important role in dealing with uncertainty. Neuro-Fuzzy can be defined as a type of system where the fuzzy sets and rules are adjusted using neural network techniques in iterative manner with the set of pair of input and output data vectors. The combination of Fuzzy Inference System (FIS) and ANN can be classified into three categories as:
(a) Concurrent Neuro-Fuzzy model
(b) Cooperative Neuro-Fuzzy model
(c) Fully Fused Neuro-Fuzzy model
In Concurrent model the neural network and the fuzzy systems work together continuously to determine the required parameters specially if the input variables of the controller cannot be measured directly. A Cooperative model can be considered as a preprocessor wherein the artificial learning mechanism determines the fuzzy inference system member-

ship functions or fuzzy rules from the training data. In Fully Fused Neuro-fuzzy model, neural network learning algorithms are used to determine the parameters of fuzzy inference system.

2.1 Artificial Neural Network

The ANN can be viewed as weighted directed graphs in which artificial neurons are nodes and directed edges are connections between neurons. It is an information processing system, which analyses data by passing it through several simulated processors. By designing training algorithms we can adjust the weights of ANN in order to obtain the desired output from the network. The backpropagation algorithm is used in layered feed-forward ANNs. Artificial neurons send their signals "forward", and the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer, the difference between actual and expected results is calculated. There may be one or more intermediate hidden layers. The idea of the backpropagation algorithm is to reduce this difference, until the ANN learns the training data. The backpropagation algorithm uses supervised learning and the training begins with random weights. Since the time for training the network grows exponentially therefore for practical reasons ANNs implementing the backpropagation algorithm do not have too many layers [14].
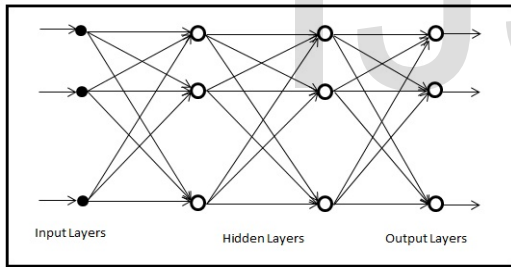

Fig.1 Standard three-layer feed-forward network architecture

2.2 Fuzzy Rule Based Inference System

Fuzzy sets and fuzzy sets operations are the subjects and verbs of fuzzy logic. If-Then rule statements are used to formulate the conditional statements that comprise fuzzy logic. Fuzzy if-then rules or fuzzy conditional statements are expressions of the form IF A THEN B, where A and B are labels of fuzzy sets characterized by appropriate membership functions [15]-[17]. Fuzzy Rules can be categorized into two types:

1) Fuzzy Mapping Rules- It describes a functional mapping relationship between inputs and an output using linguistic terms

2) Fuzzy Implication Rules- It describes a generalized logic implication relationship between two logic formula in volving linguistic variable and imprecise linguistic terms.

Fuzzy Inference Systems (FIS) are also known as fuzzy-rule based systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers. A fuzzy inference system is composed of a set of fuzzy if – then rules, a database containing membership functions of linguistic labels, and an inference mechanism called fuzzy reasoning. A rule base consisting of two fuzzy if- then rules of Takagi and Sugeno's type is:

Rule 1: If x1 is A1 and x2 is B1, then f1 = a1x1 + b1x2 + c1,

Rule 2: If x1 is A2 and x2 is B2, then f2 = a2x1 + b2x2 + c2,

This fuzzy reasoning mechanism is illustrated in Fig.2 where the firing strength (or weight) of ith rule is obtained as T norm (usually multiplication or min. operator) of the membership values on the premise part.

$$w_i = \mu_{A_i}(x_1)\mu_{B_i}(x_2), or$$
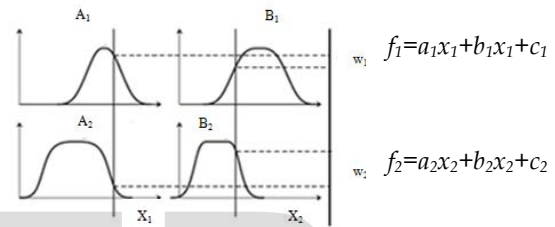$$= \min\{\mu_{A_i}(x_1), \mu_{B_i}(x_2)\}$$

Fig.2. Fuzzy reasoning

The overall output can be chosen either as the weighted sum of each rule's output.

$$f(\bar{x}) = \sum_{i=1}^{R} w_i f_i ,$$

Or the weighted average

$$f(\bar{x}) = \frac{\sum_{i=1}^{R} w_i f_i}{\sum_{i=1}^{R} w_i} ,$$

Where R is the number of fuzzy if- then rules. Thus, the overall weighted output f in terms of consequent parameters (a, b, c) will be-

$$= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2$$
$$= \overline{w_1}(a_1 x_1 + b_1 x_2 + c_1) + \overline{w_2}(a_2 x_1 + b_2 x_2 + c_2)$$
$$= (\overline{w_1} x_1)a_1 + (\overline{w_1} x_2)b_1 + (\overline{w_1})c_1 + (\overline{w_2} x_1)a_2 + (\overline{w_2} x_2)b_2 + (\overline{w_2})c_2$$

2.3 Adaptive Neuro-Fuzzy Inference System(ANFIS)

ANFIS implements a Takagi–Sugeno fuzzy inference system and has a five layered architecture as shown in Fig.3. Backpropagation learning method is used to determine the input membership parameters and for determination of consequent parameters, least mean square method is used [18].

Detailed analyses of different layers of Adaptive network are as follows:

Layer 1: $O_{1,i}$ is the output of the ith node of the layer l. Every node i in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{A_i}(x) \ for \ i = 1, 2 \ or$$
$$O_{1,i} = \mu_{B_{i-2}}(x) \ for \ i = 3, 4$$

x (or y) is the input node i and Ai (or Bi−2) is a linguistic label associated with this node. Therefore $O_{1,i}$ is the membership grade of a fuzzy set (A1, A2, B1, and B2).

Layer 2: Every node in this layer is a fixed node labelled Prod. The output is the product of all the incoming signals.

$$O_{2,i} = w_i = \mu_{A_i}(x).\mu_{B_i}(y), i = 1, 2$$

Each node represents the fire strength of the rule. Any other T-norm operator that perform the AND operator can be used.

Layer 3: Every node in this layer is a fixed node labelled Norm. The ith node calculates the ratio of the ith rulet's firing strengths to the sum of all rulet's firing strengths.

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, i = 1, 2$$

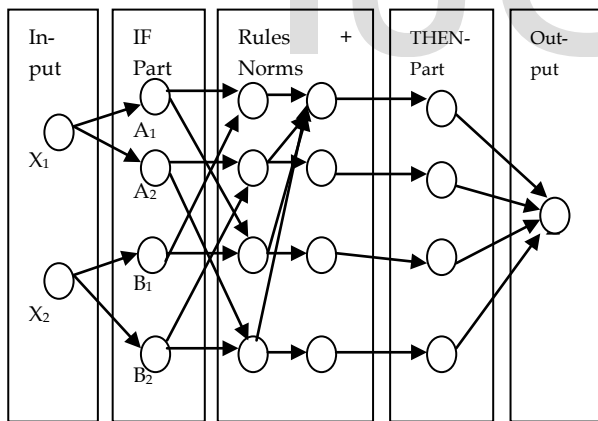Outputs are called normalized firing strengths.

Fig.3 Adaptive Network Representation

Layer 4: Every node i in this layer is an adaptive node with a node function:

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(a_i x + b_i y + c_i)$$

Layer 5: The overall output $O_{5,i}$ is calculated in this last layer as:

$$O_{5,1} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

3 PROPOSED MODEL

In this proposed model, to preserve the important fine details and due to uncertainty in impulse noise ANFIS is used for detection of noise where three input parameters are used to train ANFIS network. The output of ANFIS indicates the presence of impulsive pixel. The 3x3 sliding window has taken into consideration where the centre pixel is noisy one. To reduce the extreme values of impulsiveness the mean of the median of the window has taken into account and the corrupted pixel is replaced by this estimated value whereas the uncorrupted pixel is left unchanged. Flowchart for proposed model is depicted in Fig.4.

$$i(x,y) = \begin{cases} mean(median(w)), & if \ pixel \ is \ corrupted \\ n(x,y), & if \ pixel \ is \ uncorrupted \end{cases}$$

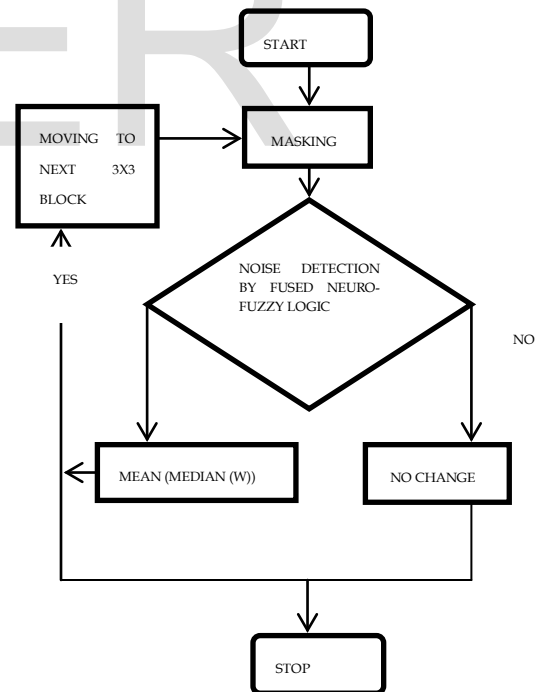Where, i(x, y) is representing image pixel of recovered image and n(x, y) is the pixel value of noisy image.

Fig.4 Flowchart for Proposed Model

In the above flowchart 'w' is representing a window size of 3x3 with center pixel corrupted by impulse noise.

4 EXPERIMENTAL RESULTS

The experiment has been performed on various test images on software MATLAB. Results are shown in Table I and Table II in terms of PSNR and MSE value at different noise densities respectively. Table III shows the comparison of the PSNR value with the traditional mean and median fiter. Fig. 5, Fig. 6 and Fig. 7 show the graphical representation of the measured parameters.

TABLE I. PSNR VALUE AT DIFFERENT NOISE DENSITIES

Image	10%	20%	30%	40%	50%
Lena	27.35	24.48	22.02	20.08	18.19
Coin	27.96	24.38	21.96	19.71	17.36
Cameraman	26.62	23.84	21.44	19.31	17.62
Pirate	30.03	26.41	23.83	21.43	19.25
Moon	29.09	25.78	22.73	19.99	17.28
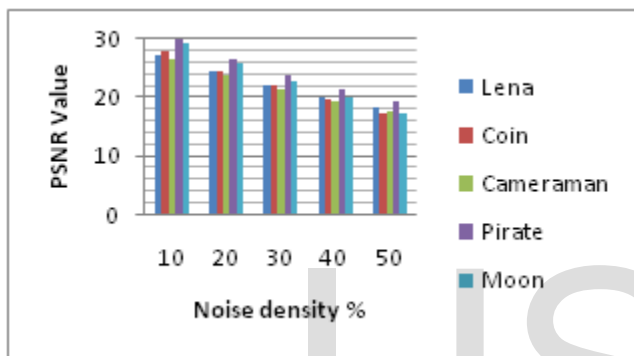
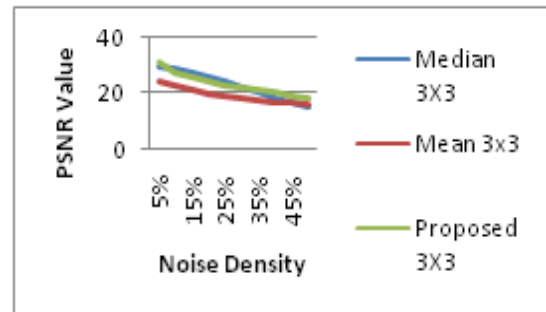Fig.5 Graphical representation of PSNR value at different noise density

TABLE.II. MSE VALUE AT DIFFERENT NOISE DENSITIES

Image	10%	20%	30%	40%	50%
Lena	119.74	231.60	408.70	638.86	986.49
Coin	103.10	237.26	413.81	694.65	1.1934e+003
Cameraman	141.54	268.84	466.65	762.40	1.1236e+003
Pirate	64.55	148.77	269.30	467.75	773.5779
Moon	80.18	171.70	346.59	652.40	1.2151e+003
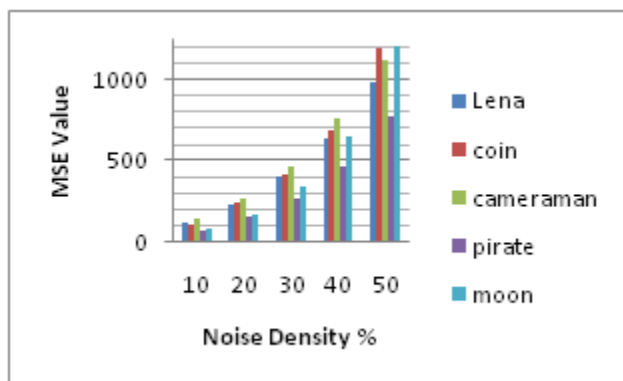
Fig.6 Graphical representation of comparative value of MSE value and Noise density for different images.

TABLE III.PSNR COMPARISON WITH OTHER FILTERS

Noise	Median 3X3	Mean 3x3	Proposed 3X3
5%	29.2921	24.6228	30.94
10%	28.1922	22.7690	27.35
15%	27.0002	21.3020	25.67
20%	25.5888	20.2529	24.48
25%	24.2394	19.2282	22.89
30%	22.1343	18.4887	22.02
35%	20.3280	17.7586	20.88
40%	18.3492	17.0810	20.08
45%	16.3081	16.6367	19.06
50%	14.9836	15.9330	18.19

Fig.7 Comparitive representation of PSNR values of 3 filters.

At 50% noise density proposed model filter is showing recognizable better PSNR value than median & mean filters. This proposed filter is tested at different noise densities on standard Lena Gray image. The original, noisy and recovered images are shown in Fig.8.

Original Images   Noisy Images   Recovered Images
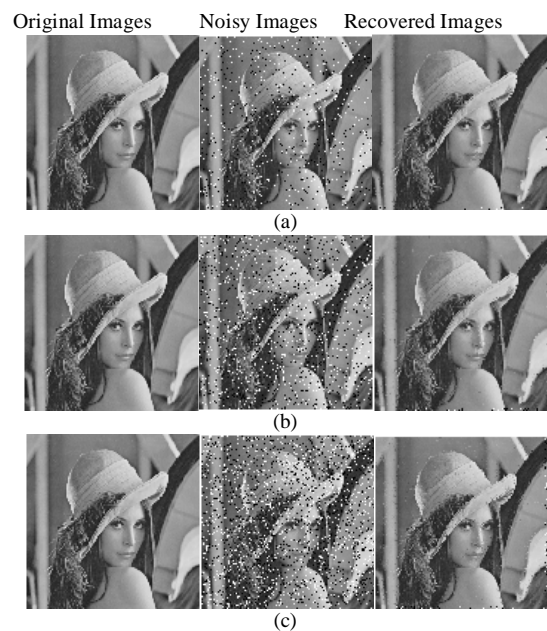

(a)

(b)

(c)

Fig.8 Proposed noise removal filter output for Lena image corrupted by (a)5% (b)10% (c)15% (d)20% (e)25% (f)30% (g)35% (h)40% (i)45% (j)50% noise densities.

5 CONCLUSION

In this proposed model a novel two step process is involved where ANFIS is providing the information about the corrupt pixel while preserving the edge details. A combinational mean of median filter is applied to those corrupted pixels and the results obtained are better for grayscale images as compared to traditional method over high density noise.

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