An Enhanced Two-Stage Impulse Noise Removal Technique based on Fast ANFIS and Fuzzy Decision

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Abstract

Image enhancement plays a vital role in various applications. There are many techniques to remove the noise from the image and produce the clear visual of the image. Moreover, there are several filters and image smoothing techniques available in the literature. All these available techniques have certain limitations. Recently, neural networks are found to be a very efficient tool for image enhancement. A novel two-stage noise removal technique for image enhancement and noise removal is proposed in this paper. In noise removal stage, Adaptive Neuro-Fuzzy Inference System (ANFIS) with a Modified Levenberg-Marquardt training algorithm was used to eliminate the impulse noise. The usage of Modified Levenberg-Marquardt training algorithm will reduce the execution time. In the image enhancement stage, the fuzzy decision rules inspired by the Human Visual System (HVS) are used to categorize the image pixels into human perception sensitive class and nonsensitive class, and to enhance the quality of the image. The Hyper trapezoidal fuzzy membership function is used in the proposed technique. In order to improve the sensitive regions with higher visual quality, a Neural Network (NN) is proposed. The experiment is conducted with standard image. It is observed from the experimental result that the proposed FANFIS shows significant performance when compared to existing methods.

Keywords--- *Fuzzy Decision, Impulse Noise, Peak Signal to Noise Ratio (PSNR), Modified Levenberg-Marquardt Training Algorithm, Adaptive Neuro-Fuzzy Inference System*

1. Introduction

IMAGES are usually affected by means of impulse noise because of noisy sensors or channel transmission mistakes. The main aim of noise reduction is to smother the noise, and also probably to safeguard the sharpness of edge and feature information. The nonlinear filtering method—standard median (SM) [9], [10] filter—according to order statistic, has been discussed to be usually better than linear filtering in reducing the impulse noise. Conversely, the median filter is inclined to blur fine details and demolish edges while smoothing out the impulse noise. For producing better result, the median filter has been altered in several manners. Those were expected to raise the signal preservation but relatively reduce the noise reduction capability, applying these algorithms altogether.

In the majority of applications, it is very essential to suppress the impulse noise [11] from image because the performances of subsequent image processing techniques are strictly reliable on the accomplishment of image noise removal process [12]. Conversely, this is very difficult in any image processing technique since the restoration filter must not alter the useful data in the image and conserve image data and texture during noise removal. The existing noise removal filters generally have the demerits of inducing unwanted distortions and blurring effects into the resulted image during noise removal phase.

So a novel approach is required for noise removal and image enhancement. Two-stage techniques that integrate noise identification and image enhancement have been proposed to eliminate the noise and keep the detail information well [13].

Since neural networks (NNs) have the ability to learn from examples, and fuzzy systems have the ability to deal with uncertainty, they also have a growing number of applications in image noise removal in the past few years [16]. Moreover, fuzzy techniques are also used to detect impulse noise. These methods exhibit relatively better performance but require more computation and memory cost. It is desired to improve the quality of noise removal and reduce the time consumption at the same time.

A new two-stage noise removal technique to deal with impulse noise is proposed in this paper. An Adaptive Neuro-Fuzzy Inference System is designed for fast and accurate noise detection such that various widespread densities of noisy pixels can be distinguished from the detail edge pixels well. The proposed ANFIS uses Modified Levenberg-Marquardt Training Algorithm for reducing the execution time. After suppressing the impulse noise, the image quality enhancement is applied to compensate the corrupted pixels to enhance the visual quality of the resultant images. It consists of fuzzy decision rules based on the Human Visual System (HVS) for image analysis and an NN for image quality enhancement. If a noise-corrupted pixel is in the perception sensitive region, the proposed NN module is applied to this pixel for further quality compensation.

2. Related Works

Schulte et al., [1] proposed a fuzzy two-step filter for impulse noise reduction from color images. A novel method for suppressing impulse noise [4] from digital images is provided in this paper, in which a fuzzy detection process is followed by an iterative fuzzy filtering method [7]. The filter proposed by author is called as fuzzy two-step color filter.

Sun et al., [2] provided an impulse noise image filter using fuzzy sets. The successful use of fuzzy set theory performance on many domains, together with the increasing requirement for processing digital images, have been the main intentions following the efforts concentrated on fuzzy sets [5, 6]. Ibrahim et al., [3] given a simple adaptive median filter for the removal of impulse noise from highly corrupted images.

A novel impulse noise removal approach based on wavelet neural network is applied to restore digital images corrupted by impulse noise. Initially, wavelet neural network is applied to identify the noise-pixels and differentiate it from noise-free pixels. Then, the noise-pixels are categorized further by equivalent threshold and assigned the coefficient. Ultimately, the median filter is combined with the coefficient for the output. The proposed approach effectively eliminates the impulse noise while preserving more fine details. Visual evaluation and detailed statistical analysis show that the proposed technique is very significant than the conventional filters.

3. System Architecture

Optimal noise removal should delete the visible noise as cleanly as possible and maintain the detail information and natural appearance to obtain a natural-looking image. In order to remove the impulse noise cleanly from input images without blurring the edge, the proposed system is divided into two stages.

1. Impulse Noise Removal

2. Image Enhancement

In impulse noise removal stage, the impulse noise is removed without affecting too much detail information, and then, the image quality enhancement is applied to compensate the edge sharpness in the second stage. The two-level NN noise removal process is shown in Figure 1. Inside the first level, only the noisy pixels identified by the NN detection are processed with the 3 × 3 median filter. The second-level noise removal process is used to detect and remove the misclassified and the detected but un-removed noise pixels in the first-level noise removal process with an adaptive median filter.

The 3X3 window is used in this stage to get the features equivalent to the pixel P (O, O) for noise detection.

Figure 2 shows the schematic block diagram of the second stage image quality enhancement system. The proposed approach contains a fuzzy decision module, an angle evaluation module, and an adaptive compensation module. A fuzzy decision module based on the HVS categories each reference pixel O (0, 0) as sensible delineated edge or not. Depending on this category, the proposed adaptive NN compensation module is applied to the sensible delineated edge region. When the adaptive NN compensation is activated, the angle evaluation section will estimate the dominant orientation of the original image present in the sliding block as the input data of the proposed NN. The 4 × 4 window is applied at this stage to get the features equivalent to the pixel O(0, 0) for HVS-based image compensation.

The weighted compensation of O (0, 0) is applied to the noise-corrupted pixel F(m, n) at the position (m, n) in the sensible delineated edge region and can be presented as

$$F(m,n) = \sum_{i=-1}^{2}\sum_{j=-1}^{2} O(i,j)W_\theta\,(i,j) \qquad (1)$$

where W_θ is derived from an NN after offline training. The NN is trained according to the edge angle of the reference image pixel to obtain the corresponding weights.

4. Proposed Impulse Noise Removal

4.1. Impulse Noise Model

Impulse noise is when the pixels are randomly failed and replaced by other values in an image. The image model containing impulse noise can be described as follows:

$$X_{ij} = \begin{cases} N_{ij}, & with\ probability\ p \\ S_{ij}, & with\ probability\ 1-p \end{cases} \qquad (2)$$

where S_{ij} represents the noiseless image pixel and N_{ij} represents the noise substituting for the Original Pixel (OP).With the noise ratio *p*, only *p* percent of the pixels in the image are replaced and others keep noise uncorrupted. In a variety of impulse noise models for images, fixed- and random-valued impulse noises are mostly discussed. 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]. In this paper, both fixed and random-valued impulse noises are adopted as the noise model to test the system robustness.

4.2. NN for Noise Detection

As the residual noise greatly affects human perception, exact noise detection is an important factor for the noise removal.

A NN with high accuracy and ability of dealing with various noisy images is proposed for noise detection. It is a 3-layer NN with one hidden layer. The input layer contains three nodes equivalent to the Gray-level Difference (GD), Average Background Difference (ABD), and Accumulation Complexity Difference (ACD) in the 3 × 3 sliding window. The second layer is the hidden layer that contains six nodes, and the bipolar sigmoid function is applied as the activation function. The weighting vectors between the first and second layers, and between the second and third layers, are denoted as S and R, respectively. The output layer contains one node that denotes the identified attribution of the pixel: “noise” or “non-noise,” and moreover the bipolar sigmoid function is also used as the activation function. The three features in the input layer are discussed as follows.

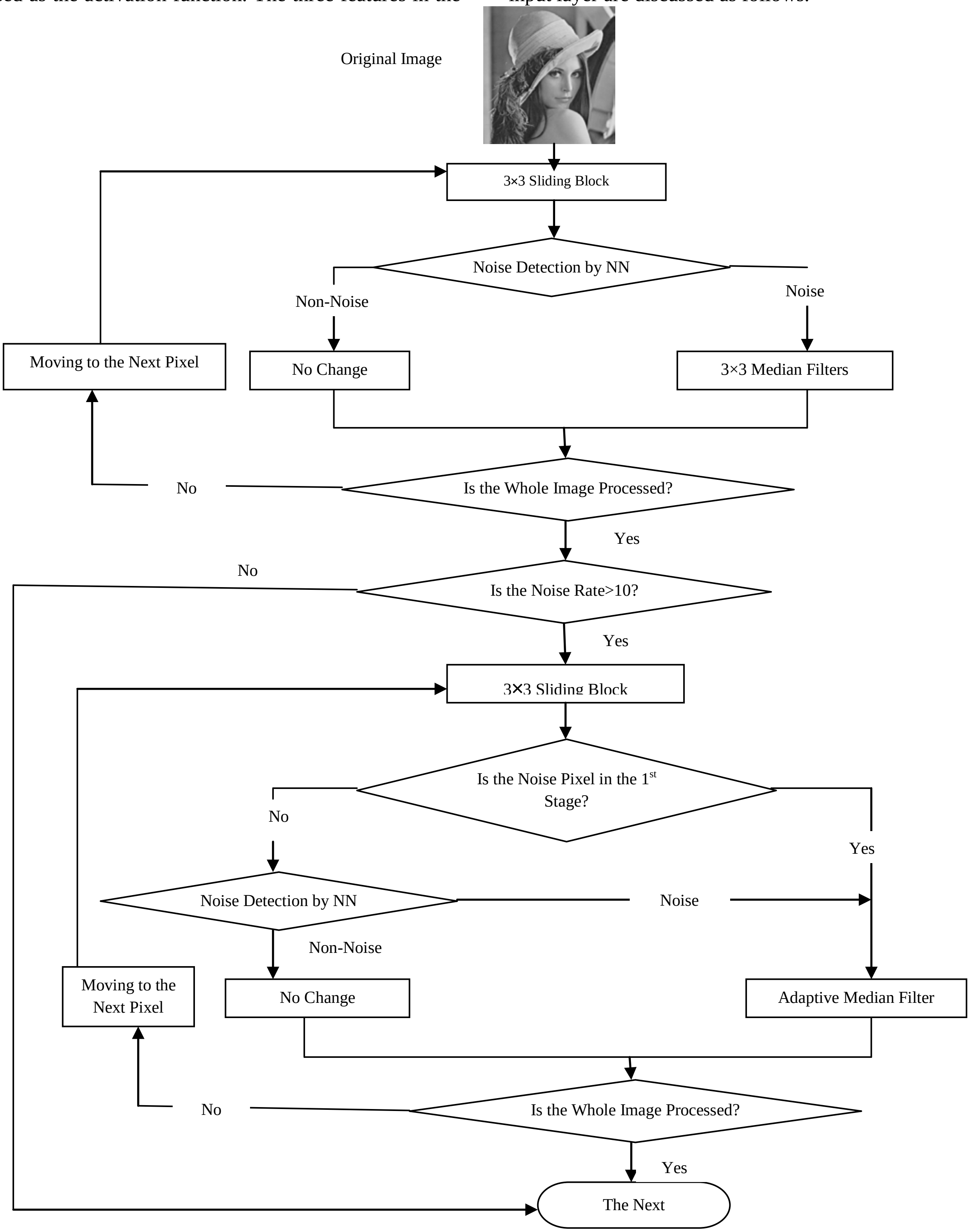

Figure 1: Procedure diagram of the two-level impulse noise removal

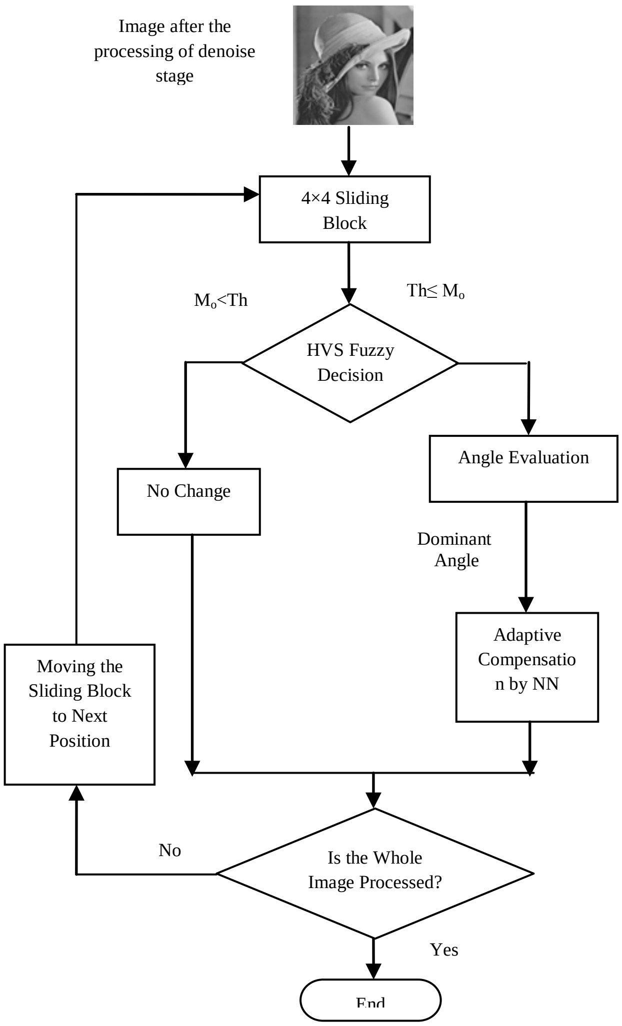

Figure 2: Procedure diagram of the image quality enhancement

1) Gray-Level Difference (GD): The GD represents the accumulated variations between the central pixel for identification and each surrounding local pixel. It is defined by

$$GD = \sum_{i=-1}^{1} \sum_{\substack{j=-1 \\ (i,j)\neq(0,0)}}^{1} |P(0,0) - P(i,j)| \qquad (3)$$

where P(0, 0) is the reference pixel and P(i, j) is the surrounding local pixel.

The GD feature is considered to identify the noise over a flat area. It is expected that the corrupted pixels would yield much bigger differences as compared with the uncorrupted pixels.

2) Average Background Difference (ABD): The surrounding pixels averaged as the Background Luminance (BL) of the sliding block which is then compared with the central pixel. This is an assistant feature to detect the noise. This feature, called the ABD, denoting the overall average variation with the central pixel in the block, is defined by

$$ABD = \left| P(0,0) - \frac{\sum_{i=-1}^{1} \sum_{\substack{j=-1 \\ (i,j)\neq(0,0)}}^{1} P(i,j)}{8} \right| \qquad (4)$$

The corrupted pixels provide bigger differences as compared with the clean ones. For the pixels in the texture area, the GD value is large but the ABD feature will be small.

3) Accumulation Complexity Difference (ACD): Accumulating the difference between each pixel in the 3 × 3 sliding block and its four neighboring pixels as defined next shows the structure information of the block

$$ACD = \sum_{i=-1}^{1} \sum_{j=-1}^{1} |4 \times P(i,j) - P(i-1,j) - P(i+1,j) - P(i,j-1) - P(i,j+1)| \qquad (5)$$

In the edge area, the summation is lower than that in the noise-pixel area, though the GD difference might be similar. So, it provides an assistant feature between the edge and noise pixels.

The neural network can be replaced by Adaptive Neuro-Fuzzy Inference System for better detection of noise. ANFIS is explained as below:

Architecture of ANFIS

The ANFIS is a framework of adaptive technique to assist learning and adaptation. This kind of framework formulates the ANFIS modeling highly organized and not as much of dependent on specialist involvement. To illustrate the ANFIS architecture, two fuzzy if-then rules according to first order Sugeno model are considered:

$$Rule\ 1: If\ (x\ is\ A_1) and\ (y\ is\ B_1) then\ (f_1 = p_1 x + q_1 y + r_1)$$

$$Rule\ 2: If\ (x\ is\ A_2) and\ (y\ is\ B_2) then\ (f_2 = p_2 x + q_2 y + r_2)$$

where x and y are nothing but the inputs, Ai and Bi represents the fuzzy sets, fi represents the outputs inside the fuzzy region represented by the fuzzy rule, pi, qi and ri indicates the design parameters that are identified while performing training process. The ANFIS architecture to execute these two rules is represented in figure 2, in which a circle represents a fixed node and a square represents an adaptive node.

In the first layer, every node are adaptive nodes. The outputs of first layer are the fuzzy membership grade of the inputs that are represented by:

$$O_i^1 = \mu_{A_i}(x) \quad i = 1,2 \qquad (6)$$

$$O_i^1 = \mu_{B_{i-2}}(y) \quad i = 3,4 \qquad (7)$$

where $\mu_{A_i}(x), \beta_{B_{i-2}}(y)$, can accept any fuzzy membership function. For example, if the bell shaped membership function is employed, $\mu_{A_i}(x)$ is represented by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left(\frac{x - c_i}{a_i} \right) \right\}^{b_i}} \qquad (8)$$

where ai, bi and ci represents the parameters of the membership function, controlling the bell shaped functions consequently.

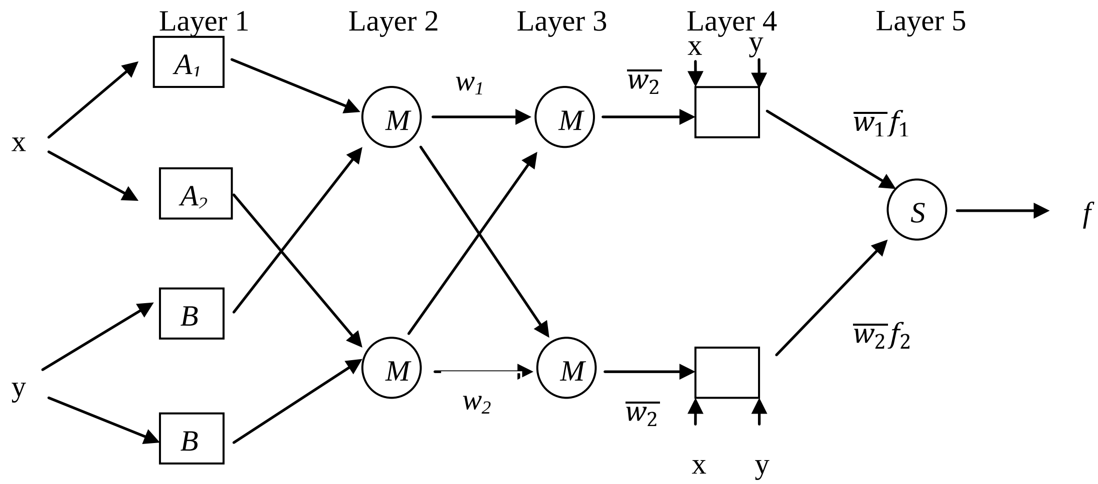

Figure 2: ANFIS Architecture

In layer 2, the nodes are fixed nodes. These nodes are labeled with M, representing that they carry out as a simple multiplier. The outputs of this layer can be indicated by:

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \qquad (9)$$

which are called as firing strengths of the rules.

The nodes are fixed in layer 3 as well. They are labeled with N, representing that they are engaged in a normalization function to the firing strengths from the earlier layer.

The outputs of this layer can be indicated as:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \qquad (10)$$

which are called as normalized firing strengths.

In layer 4, all the nodes are adaptive nodes. The output of the every node in this layer is merely the product of the normalized firing strength and a first order polynomial. Therefore, the outputs of this layer are provided by:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad i = 1,2 \qquad (11)$$

In layer 5, there exists only one single fixed node labeled with S. This node carries out the operation like summation of every incoming signal. Therefore, the overall output of the model is provided by:

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \qquad (12)$$

It can be noted that layer 1 and the layer 4 are adaptive layers. Layer 1contains three modifiable parameters such as ai, bi, ci that is associated with the input membership functions.

These parameters are called as premise parameters. In layer 4, there exists three modifiable parameters as well such as {pi, qi, ri}, related to the first order polynomial. These parameters are called consequent parameters.

Learning algorithm of ANFIS

The intention of the learning algorithm is to adjust all the modifiable parameters such as{ai, bi, ci} and {pi, qi, ri}, for the purpose of matching the ANFIS output with the training data.

If the parameters such as ai, bi and ci of the membership function are unchanging, the outcome of the ANFIS model can be given by:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \qquad (13)$$

Substituting Eq. (5) into Eq. (8) yields:

$$f = \overline{w}_1 f_1 + \overline{w}_2 f_2 \qquad (14)$$

Substituting the fuzzy if-then rules into Eq. (15), it becomes:

$$f = \overline{w}_1(p_1 x + q_1 y + r_1) + \overline{w}_2(p_2 x + q_2 y + r_2) \qquad (15)$$

After rearrangement, the output can be expressed as:

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2 \qquad (16)$$

which is a linear arrangement of the adjustable resulting parameters such as p1, q1, r1, p2, q2 and r2. The least squares technique can be utilized to detect the optimal values of these parameters without difficulty. If the basis parameters are not adjustable, the search space becomes larger and leads to considering more time for convergence. A hybrid algorithm merging the least squares technique and the gradient descent technique is utilized in order to solve this difficulty. The hybrid algorithm consists of a forward pass and a backward pass. The least squares technique which acts as a forward pass is utilized in order to determine the resulting parameters with the premise parameters not changed. Once the optimal consequent parameters are determined, the backward pass begins straight away. The gradient descent technique which acts as a backward pass is utilized to fine-tune the premise parameters equivalent to the fuzzy sets in the input domain. The outcome of the ANFIS is determined by using the resulting parameters identified in the forward pass. The output error is utilized to alter the premise parameters with the help of standard backpropagation method. It has been confirmed that this hybrid technique is very proficient in training the ANFIS. Learning can be fast up in ANFIS using Modified Levenberg-Marquardt algorithm

Modified Levenberg-Marquardt algorithm

A Modified Levenberg-Marquardt algorithm is used for training the neural network.

Considering performance index is $F(w) = e^T e$ using the Newton method we have as:

$$W_{K+1} = W_K - A_K^{-1}.g_K$$

$$A_k = \nabla^2 F(w)|_{w=w_k}$$

$$g_k = \nabla F(w)|_{w=w_k}$$

$$[\nabla F(w)]_j = \frac{\partial F(w)}{\partial w_j} = 2\sum_{i=1}^{N} e_i(w).\frac{\partial e_i(w)}{\partial w_j}$$

The gradient can write as:

$$\nabla F(x) = 2J^T e(w)$$

Where

$$J(w) = \begin{bmatrix} \frac{\partial e_{11}}{\partial w_1} & \frac{\partial e_{11}}{\partial w_2} & \cdots & \frac{\partial e_{11}}{\partial w_N} \\ \frac{\partial e_{21}}{\partial w_1} & \frac{\partial e_{21}}{\partial w_2} & \cdots & \frac{\partial e_{21}}{\partial w_N} \\ & \vdots & & \\ \frac{\partial e_{KP}}{\partial w_1} & \frac{\partial e_{KP}}{\partial w_2} & \cdots & \frac{\partial e_{KP}}{\partial w_N} \end{bmatrix}$$

$J(w)$ is called the Jacobian matrix.

Next we want to find the Hessian matrix. The k, j elements of Hessian matrix yields as

$$[\nabla^2 F(w)]_{k,j} = \frac{\partial^2 F(w)}{\partial w_k \partial w_j}$$

$$= 2\sum_{i=1}^{N} \left\{ \frac{\partial e_i(w)}{\partial w_k}\frac{\partial e_i(w)}{\partial w_j} + e_i(w).\frac{\partial^2 e_i(w)}{\partial w_k \partial w_j} \right\}$$

The Hessian matrix can then be expressed as follows

$$\nabla^2 F(w) = 2J^T(W).J(W) + S(W)$$

$$S(w) = \sum_{i=1}^{N} e_i(w).\nabla^2 e_i(w)$$

If $S(w)$ is small assumed, the Hessian matrix can be approximated as

$$\nabla^2 F(w) \cong 2J^T(w)J(w)$$

$$W_{k+1} = W_k - [2J^T(w_k)\cdot J(w_k)]^{-1} 2J^T(w_k)e(w_k)$$

$$\cong W_k - [J^T(w_k)\cdot J(w_k)]^{-1} J^T(w_k)e(w_k)$$

The advantage of Gauss-Newton is that it does not require calculation of second derivatives.
There is a problem the Gauss-Newton method is the matrix $H = J^T J$ may not be invertible. This can be overcome by using the following modification.
Hessian matrix can be written as

$$G = H + \mu I$$

Suppose that the eigenvalues and eigenvectors of H are $\{\lambda_1, \lambda_2, \dots\dots, \lambda_n\}$ and $\{z_1, z_2, \dots\dots, z_n\}$.Then:

$$Gz_i = [H + \mu I]z_i$$

$$= Hz_i + \mu z_i$$

$$= \lambda_i z_i + \mu z_i$$

$$= (\lambda_i + \mu)z_i$$

Therefore the eigenvectors of G are the same as the eigenvectors of H, and the eigen values of G are $(\lambda_i + \mu)$. The matrix G is positive definite by increasing μ until $(\lambda_i + \mu) > 0$ for all i therefore the matrix will be invertible.
This leads to Levenberg-Marquardt algorithm:

$$w_{k+1} = w_k - [J^T(w_k)J(w_k) + \mu I]^{-1} J^T(w_k)e(w_k)$$

$$\Delta w_k = [J^T(w_k)J(w_k) + \mu I]^{-1} J^T(w_k)e(w_k)$$

As known, learning parameter, μ is illustrator of steps of actual output movement to desired output. In the standard LM method, μ is a constant number. This paper modifies LM method using μ as

$$\mu = 0.01e^T e$$

Where e is a $k \times 1$ matrix therefore $e^T e$ is a 1×1 therefore $[J^T J + \mu I]$ is invertible.
Therefore, if actual output is far than desired output or similarly, errors are large so, it converges to desired output with large steps.
Likewise, when measurement of error is small then, actual output approaches to desired output with soft steps. Therefore error oscillation reduces greatly.

4.3. Noise Removal Algorithm

After the first level, the image noise density is calculated to decide whether the second level is necessary or not by the precise detection procedure. By the experiments, it is observed that when the noise density is below 10%, only a one-level noise removal process is enough. More residual noises will occur when the noise density increases. In this case, the second-level noise removal process is essential to detect and remove the residual noises.
As the local features may influence the correctness of the detection part and the median filter may still retain certain noises, the residual noise pixels are detected and removed

with an adaptive median filter in the second level. If there are more than 30% noisy pixels in this image, it is identified as a highly corrupted region and the 5 × 5 median filter is applied for processing. Otherwise, the 3 × 3 median filter is used to process the noisy pixel. The proposed adaptive two-level noise removal technique is very efficient to suppress the impulse noise as well as to preserve the sharpness of edges and detail information.

5. Proposed Image Quality Enhancement

The conventional median filtering techniques have the limitation of blurring details and cause artifacts around edges. In order to compensate the edge sharpness, image quality enhancement is applied to the modified pixels. As the first stage has eliminated the visible noise, the second stage focuses the image enhancement on the edge region. For image analysis, the properties of the HVS are used to acquire the features of images. Thus, region which would worth quality enhancement is realized, since human eyes would be usually more sensitive to this region. For sensitive regions, an adaptive NN is used to enhance the visual quality to match the characteristics of human visual perception.

5.1. HVS-Directed Image Analysis

A novel fuzzy decision system motivated by the HVS is proposed to categorize the image into human perception sensitive and nonsensitive regions. There are three input variables: Visibility Degree (VD); Structural Degree (SD); and Complexity Degree (CD), and one Output Variable (Mo) in the proposed fuzzy decision system.

Visibility Degree (VD): The capability of human eyes to identify the magnitude difference between an object and its background depends on the BL. Figure 3 shows the actual visibility thresholds called JND corresponding to different BLs, and they were verified by a subjective experiment [15]. The experiments were conducted in a dark room and a square area was located in the center of a flat field of constant gray level. Through varying the amplitude of the object, the visibility threshold for each gray level was determined when the object was just noticeable.

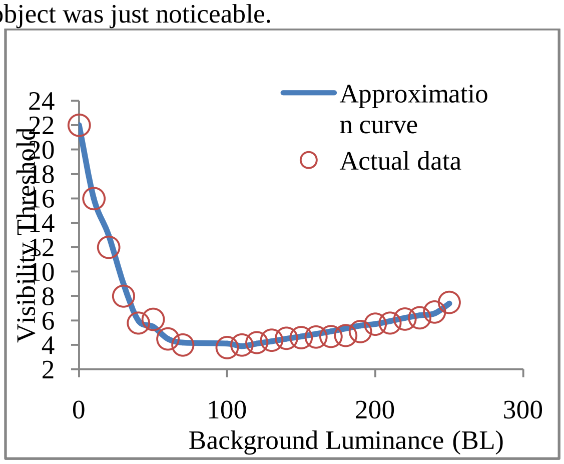

Figure 3: Visibility thresholds corresponding to different BLs

It is observed from figure 3 that the visibility threshold is lower when the BL is within the interval from 70 to 150, and the visibility threshold will increase if the BL becomes darker or brighter away from this interval. In addition, a high visibility threshold will occur when the BL is in a very dark region.

BL is the average luminance of the sliding block proposed to approximate the actual BL and can be calculated by

$$BL = \frac{1}{23}\sum_{i=-1}^{2}\sum_{j=-1}^{2} O(i,j) \times B(i,j) \qquad (22)$$

$$B(i,j) = \begin{bmatrix} 2 & 2 & 2 & 1 \\ 2 & 0 & 2 & 1 \\ 2 & 2 & 2 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \qquad (23)$$

and the denominator 23 in (22) is the weighted sum of all elements in (23) for normalization. The weighting coefficients of B decrease as the corresponding distance away from the reference pixel increases to estimate the average BL. Feature D is the difference between the maximum and minimum pixel values in the sliding block and can be calculated by

$$D = \max\big(o(i,j)\big) - \min\big(o(i,j)\big) \qquad (24)$$

A nonlinear function V (BL) is also designed to approximate the relation between the visibility threshold and BL (as figure. 3), and can be represented as

$$V(BL) = 20.66e^{-0.03BL} + e^{0.008BL} \qquad (25)$$

The parameter of 20.66 is obtained by substituting 0 for BL in the nonlinear approximation equation by setting the coefficient of e0.008 BL to be 1.

The first input variable of the fuzzy decision system, VD, is defined as the difference between D and V (BL) and can be represented as

$$VD = D - V(BL) \qquad (26)$$

If VD > 0, it means the magnitude difference between the object and its background exceeds the visibility threshold and the object is sensible. Otherwise, this object is not sensible.

The other two input variables, SD and CD, are used to indicate whether the pixels in the sliding block own the edge structure.

Structural Degree (SD): SD shows if the sliding block is a high contrast region, and the pixels in the block can be evidently partitioned into two clusters. It is calculated by

$$SD = \frac{\big|\max\big(O(i,j)\big) - \text{mean}\big(O(i,j)\big) - \big[\text{mean}\big(O(i,j)\big) - \min\big(o(i,j)\big)\big]\big|}{\max\big(O(i,j)\big) - \min\big(O(i,j)\big)} \qquad (27)$$

Where

$$\text{mean}\big(O(i,j)\big) = \frac{1}{16}\sum_{i=-1}^{2}\sum_{j=-1}^{2} O(i,j) \qquad (28)$$

Equation (11) can be expressed as $|\sigma 1 - \sigma 2|/(\sigma 1 + \sigma 2)$. So, the SD has been normalized to [0, 1] and this rule can also be applied to images with a different intensity range. If SD is small and σ2 and σ1 are close, it means the pixels in the block can be partitioned into two even clusters. The block may contain edge or texture structure. On the contrary, if SD is a large value, $0 < |\sigma_1 - \sigma_2|$, it means the pixel number of one cluster and that of the other cluster are not even; thus, the block may contain noise.

Complexity Degree (CD):

In these two plots, pixel numbers of the two clusters are the same. Hence, the SD values equivalent to these two structures are close. As the proposed NN is used to compensate the sensitive regions, a CD input variable based on the differential process is used to tell the delineated edge structure from the texture structure. It is calculated by

$$CD = \sum_{i=-1}^{2}\sum_{j=-1}^{2}\left|4O'(i,j) - [O'(i+1,j) + O'(i-1,j) + O'(i,j-1) + O'(i,j+1)]\right| \quad (29)$$

Where $O'(i,j)$ is the binarized version of $O(i,j)$. Assuming mean (O) is the mean gray value of the sliding block, $O'(i,j)$ is defined as

$$O'(i,j) = \begin{cases} 1, & if\ O(i,j) \geq mean(O) \\ 0, & otherwise \end{cases} \quad (30)$$

In (29), each pixel in the 4 × 4 sliding block takes the 4-directional local gradient operation and the CD is the summation of the 16 local gradient values. If the CD is a large value, it means the block may contain texture structure. On the contrary, if the CD is a small value, the block may contain delineated edge structure.

Hyper Trapezoidal Fuzzy Membership Function

The proposed system uses the Hyper Trapezoidal fuzzy Membership function.

Hyper trapezoidal membership functions are defined by prototype points and a crispness factor. In a fuzzy partitioning of an N-dimensional space, let each fuzzy set, S_i be defined by a prototype point, λ_i. Furthermore, let the partitioning of the space also be parameterized by a crispness factor, σ . The prototype point, λ_i has a degree of membership in set, S_i , of $\mu_i(\lambda_i) = 1$ and a degree of membership in set S_j, of $\mu_j(\lambda_j) = 1$ where $j \neq i$.

The crispness factor, 0≤σ≤1, determines how much ambiguity exists between the sets of the partitioning. For σ =1, no fuzziness exists between the sets and the partitioning is equivalent to a minimum distance classifier. For fuzzy sets σ <1. One way to define the crispness factor is using Figure 4 and equation (31).

$$\sigma = \frac{2\alpha}{d} \quad (31)$$

The crispness factor establishes fuzzy space between the prototype points. The prototype points are selected as ideal representatives of each fuzzy set. Then, the designer's selection of σ specifies the ratio of α and d.

The next step in the derivation is the definition of a suitable distance measure relating the distance from the crisp input to two prototype points. This distance measure is a ratio of the distance between two prototype points, and the difference in the distances from the crisp input to the two prototype points. For fuzzy sets S_i and S_j, with prototype points λ_i and λ_j, and a crisp input □Λ , that distance measure is

$$\rho_{i|j}(\Lambda) = \frac{|\vec{v}_i|^2 - |\vec{v}_j|^2}{|\vec{v}_{ji}|^2} \quad (32)$$

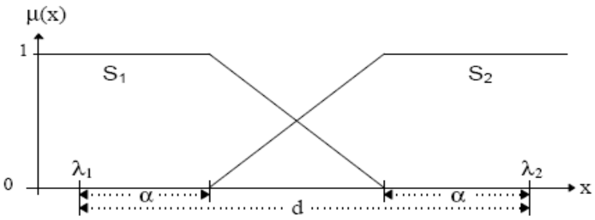

Figure 4: Defining Crispness of a partitioning

Where $\vec{v}_{ji}$ is a vector from λ_i to λ_j; $\vec{v}_i$ is a vector from λ_i to Λ. This distance measure is used to determine if the crisp input Λ lies completely in fuzzy set i, or completely in fuzzy set j, or in the fuzzy region between the two sets.

The third step in the derivation of hyper trapezoidal membership functions is determining the degree of membership that L has in set i, given that set j is the only other set in the partition. Suppose fuzzy sets i and j are the only two sets defined in an N-dimensional space. Using the distance measure of equation (32), that degree of membership is

$$\mu_{i|j}(\Lambda) = \begin{cases} 0; & \rho_{i|j}(\Lambda) \geq 1 - \sigma \\ 1; & \rho_{i|j}(\Lambda) \leq \sigma - 1 \\ \dfrac{\vec{v}_{ji} \cdot \vec{v}_j - \frac{\sigma}{2}|\vec{v}_{ji}|^2}{(1-\sigma)|\vec{v}_{ji}|^2}; & otherwise \end{cases} \quad (33)$$

For the first case in equation (33), Λ lies completely in fuzzy set j. For the second case, Λ lies completely in fuzzy set i. The third case is the case of Λ being in the transition from set i to set j.

The numerical value of Mo after defuzzification is compared with a threshold value, Th, where Th is preferably set as the value 5 by experiments. When Mo ≥ Th, the adaptive NN compensation module with angle evaluation would be chosen; otherwise, the OP value would be used.

5.2. Angle Evaluation

As Mo ≥ Th, the fuzzy system identifies the reference pixel as sensible delineated edge and the trained adaptive NN model is chosen for quality enhancement according to its corresponding edge angle. The angle evaluation is performed to determine the dominant orientation of the sliding block. When the orientation angle of O (i, j) denoted as A (i, j) is computed, the luminance values of the OPs nearby O (i, j) are used for the following computations:

$$Dx(i,j) = O(i-1,j-1) + 2O(i-1,j) + O(i-1,j+1) - (O(i+1,j-1) + 2O(i,j+1) + O(i+1,j+1)) \quad (34)$$

$$Dy(i,j) = O(i-1,j-1) + 2O(i,j-1) + O(i+1,j-1) - (O(i-1,j+1) + 2O(i,j+1) + O(i+1,j+1)) \quad (35)$$

$$A(i,j) = -\frac{180}{\pi}\left[\tan^{-1}\left(\frac{Dy(i,j)}{Dx(i,j)}\right)\right] \quad (36)$$

Where $-1 \leq i \leq 2$ and $-1 \leq j \leq 2$.

The obtained angle of each pixel in the sliding window is quantized into eight quantization sectors such as $\theta = 22.5 \times k$ (in degrees), where k = 0, 1, . . . , 7. Assuming θ is the quantized angle for most pixels in the window; it is regarded as the dominant orientation of the reference edge pixel. The corresponding weighting coefficient Wθ derived from the offline training NN is adopted for compensation filtering.

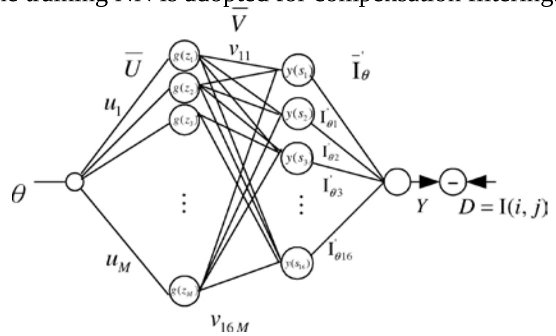

Figure 5: Proposed feed forward NN for image quality enhancement

5.3. NN-Based Image Compensation

The function of the proposed NN is to obtain the weights Wθ defined in (1), where θ represents the quantized dominant orientation of the reference pixel. Thus, the proposed NN is used to obtain eight sets of weighting matrices through training.

Each weighting matrix W_θ can be represented as

$$W_\theta(i,j) = \begin{bmatrix} w_{-1-1} & w_{-10} & w_{-11} & w_{-12} \\ w_{0-1} & w_{00} & w_{01} & w_{02} \\ w_{1-1} & w_{10} & w_{11} & w_{12} \\ w_{2-1} & w_{20} & w_{21} & w_{22} \end{bmatrix} \quad (37)$$

In order to use supervised learning algorithms to train the proposed NN, several clean image portions with dominant orientation are used as training patterns. Assuming a clean image portion is denoted as I, the noise-corrupted version of I has been processed by the proposed noise removal method in the first stage and the filtered result is denoted as I'. According to figure 5, let $I'(i,j)$ be the reference pixel, where $O(0,0) = I'(i,j)$, and it is classified as an edge pixel with dominant orientation θ after angle evaluation. The input of the NN can be defined as IP = θ and the network output is the compensated pixel value of $I'(i,j)$. The pixel value of I (i, j) obtained from the clean original image is used as the desired output of the NN for training.

6. Experimental Results

For experimenting the proposed filtering technique, several 512 X 512 grayscale images affected by the noise with noise occurrence of 1% to 50% is considered. The result of the proposed filter is compared with several existing filters such as median filter and two stage filter with different window size. The quantitative measures used for comparison is the Peak Signal-to-Noise Ratio (PSNR) between the original and restored images and average execution time. PSNR value is evaluated by using the following equation:

$$PSNR = 10log_{10}\left(\frac{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}255^2}{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}[I(i,j) - Y(i,j)]^2}\right) \quad (38)$$

Where {I(i, j)} and {Y (i, j)} are the original and restored images, respectively.

Table 1 provides the comparison of the proposed filter with median filter (3X3 window size), median filter (5X5 window size) and two stage filter. The experimentation is performed at different noise level such as 1%, 5%, 10%, 20%, 40% and 50%.

From the table 1, it can be observed that the PSNR value resulted in 5% noise affected image is 29.6 for the median filter of window size 3 X 3, 30.2 for the median filter of window size 5 X 5, 34.7 for the two stage filter whereas it is higher for the Two Stage filter with hyper trapezoidal fuzzy membership function and Modified LM i.e., 38.2 and for the proposed ANFIS technique the resulted PSNR value is 41.2 .

When the image is affected by higher noise i.e., 50%, other filters results only less PSNR value i.e., 13.6 for the median filter of window size 3 X 3, 14.3 for the median filter of window size 5 X 5, 28.5 for the two stage filter whereas it is higher for the Two Stage filter with hyper trapezoidal fuzzy membership function and Modified LM i.e., 33.9 and for the proposed ANFIS technique the resulted PSNR value is 36.7. When the overall PSNR is considered, the proposed filter shows better PSNR values when compared to the conventional filters.

Table 1: Comparative results in PSNR of different filtering methods for various percentages of noise (Lena image)

Noise Ratio / Filter	1%	5%	10%	20%	40%	50%
Median Filter (3X3)	31.3	29.6	25.9	23.2	20.9	13.6
Median Filter (5X5)	32.5	30.2	27.1	25.1	21.3	14.3
Two Stage filter	36.8	34.7	33.2	32.4	31.2	28.5
Two Stage filter with hyper trapezoidal fuzzy membership function and Modified LM	39.7	38.2	37.6	35.2	34.8	33.9
Proposed Two Stage Noise Removal using FANFIS	41.2	40.5	40.1	39.4	37.5	36.7

Table 2 shows the execution time taken for the proposed filter and the different existing image filters with the noise rate as 80%. From the table, it can be observed that execution time required for the median filter with 3 X 3 window size is 14 seconds, median filter with 5 X 5 window size is 16 seconds, two stage filter is 13 seconds, whereas, the execution time required by the two stage technique is 9 seconds and finally for the proposed FANFIS, only 6 seconds are needed. This clearly indicates that the overall execution time required by the proposed filter is lesser when compared to the existing filters.

Table 2: Comparative results in average execution time of different filtering methods for Lena image corrupted image by 80% salt and pepper noise

Filters	Median Filter (3X3)	Median Filter (5X5)	Two Stage filter with LM training Algorithm	Two Stage filter with hyper trapezoidal fuzzy membership function and Modified LM	Proposed Two Stage Noise Removal using FANFIS
Time (seconds)	14	16	13	9	6

7. Conclusion

A novel two-stage noise removal technique is proposed in this paper. In the first stage, a two level noise removal procedure with NN-based noise detection was applied to remove the noise. In the second stage, a fuzzy decision rule inspired by the HVS was proposed to categorize pixels of the image into human perception sensitive and nonsensitive classes. A Fast Adaptive Neuro-Fuzzy Inference System is proposed to enhance the sensitive regions to perform better visual quality. Moreover, the hyper trapezoidal member function is used which provides significance performance. The proposed technique is experimented with 512 X 512 grayscale image with the noise occurrence of 1% to 50%. The PSNR value obtained for the proposed technique is higher when compared to the existing filtering techniques. Moreover, the execution time taken by the proposed approach is very significant when compared with the existing approaches. Thus the proposed technique is very efficient when compared with the conventional methods in perceptual image quality, and it can provide a quite a stable performance over a wide variety of images with various noise densities.

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