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Parallel Fuzzy Inference System (PFIS) based Medical Image Denoising

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Abstract

Objective: To remove the noises occurred in the bio medical pictures with less computation time. **Methods:** An innovative technique called Parallel Fuzzy Inference System (PFIS) is introduced for image denoising in the medical images. This method takes input training images, process a dissimilar neighbourhood association between the center pixel and generates the fuzzy inference rules. These rules are distributed to the nodes for simultaneous execution. Then, the type-1 interval fuzzy set is submitted to the resultant defuzzifier module which will decode it into scalar value. If it is impulse pixel, the noise filter is used to reduce the noise. **Results:** The improvement of the PFIS technique is evaluated by using the medical images. PFIS method shows high efficiency when matched with the existing Type-2 Fuzzy Logic (TFL) based impulse detector for impulse noise removal. In the PFIS method, the fuzzy rules are generated analyzing the medical images and these rules are processed simultaneously. If the noise density is 75%, the Mean Squared Error (MSE) in PFIS is 59.48, the False Classification Ratio (FCR) is 3.25 and the computation time is 740 ms. According to the comparison and the results from the experiment shows that the proposed method has high efficiency. **Conclusion:** The findings demonstrate that the PFIS is presented and this method has high efficiency in terms of MSE, FCR and computation time.

Keywords: Fuzzy Logic, Image Processing, Impulse Noise, Noise Filter, Parallel Fuzzy Inference System

1. Introduction

In the image processing field, contamination of medical images is a regular problem. The most frequent noise in the image processing field is impulse noise. Due to the impulse noise, the medical images are contaminated at the time of attainment and transmission process. The impulse noise is additionally referred to as salt & peppers[1]. This impulse noise causes white and black points within the digital pictures that urgently sprinkled on image space. The element worth of the error element is either minimum or most worth in gray scale pictures. Due to the absolute distribution of error pixels, the removal of random valued impulse noise is additional complicated. Primary plan of this work is to revive the initial image from the corrupted image that is happened by impulse noise. This is also called image denoising. Denoising is the operation of eliminating unwanted noise from the images. Image Denoising is used in various applications like astronomy, medical imaging and forensic science.

Various impulse noise removal strategies are recommended to take away the impulse noise. The most likely used filter is normal median filter[2] that could be a class of nonlinear filter. This filter is mostly used as AN impulse noise removal filter due to the simplicity. However, the disadvantage within the median noise filter is that it generally harms the nice pixels. A number of modifications are done and has recommended two strategies known as weighted median filter and center-weighted median filter that provides additional weight for the chosen pixels of the filtering window and scale back the disadvantages of ordinary median filter. However the disadvantage during

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this technique is high costly for impulse noise removal. Another class of non-linear median filter is adaptive median filter that is well-suited if the abstraction density of the salt and pepper noise is not massive. This filter is employed to seek out the noisy pixels and replace with alternative pixels by using median filters. The good thing about this technique is that it seeks to conserve detail whereas smoothing non-impulse noise[3].

Existing research suggested a method called type-2 fuzzy logic[4] based impulse noise detector. This method gives input as the training image to the sub detectors. Each sub detector method the input pixels of the image and method a dissimilar neighbourhood association between the middle pixel of the analysis window and two neighbouring pixels. The higher sub detector computes the vertical neighbourhood and also the lower sub detector computes the horizontal neighbourhood. In this, the logical thinking rules are created. The type-1 interval fuzzy set generated by the sub detectors are given to the corresponding defuzzifier and converts into a scalar worth. The two scalar values given by the defuzzifier is processed and converts to the only scalar value by the post processor. If the resulted pixel worth is zero, the pixel is derived to the output image. If the pixel worth is one, the noise filter is employed to get rid of the noise. However the disadvantage of this technique is high complexness and high logical thinking time for method the logical thinking rules. So, the proposed research Parallel Fuzzy Inference System (PFIS) is introduced for image denoising. In this method, the generated fuzzy inference rules are distributed to the nodes for parallel execution process. The inference rules are processed concurrently to compute the weighted average of the individual rule. So, the time complexity is reduced by using the Parallel Fuzzy Inference System. The work is divided as three phases:

1.1 Generation of Fuzzy Set and Distribution of Fuzzy Rules

Within the initial part the input training pictures are given to the sub detectors and it does a dissimilar neighbourhood association between the middle pixel of the analysis window and two neighbouring pixels. The logical thinking rules are generated to scale back the complexness. The fuzzy logical thinking rules are distributed to the nodes for concurrent execution of the principles. The logical thinking rules are processed at the same time to calculate the weighted average of the individual rule.

1.2 Defuzzification and Detection of Impulse Noise

During this second part, the type-1 interval fuzzy set is given to the corresponding defuzzifier and converts into a scalar worth. The two scalar values from the defuzzifiers are given to the post processor and converts to the singular value. If the component worth is zero, it copies to the output image. If the component worth is one, the noise filter is employed to get rid of the noise and restore the image.

1.3 Classification Process

In the third phase, the test images are given for the experiments and generate the inference rules for the pixels and use the training set for classifying the normal and noisy pixel.

2. Related Work

In this section, various methods are suggested for impulse noise removal in image processing field.

Tzu-Chao lin et al.[5] instructed a replacement noise call filter known as Multiple Thresholds Switch (MTS) filter for reinstate pictures that is contaminated by the salt-pepper impulse noise. This filter relies on detection-estimation approach. This technique uses multiple thresholds with multiple neighbourhood data of the signal within the filter window, is incredibly correct, whereas evading an undue augment in procedure complexness. Ashutosh Pattnaik et al.[6] prompt a changed call primarily based on Median Filter that is employed for the primary stage of method. The second stage includes a integration of a replacement algorithmic rule that computes the mean of distinction in neighbourhood pixels and a changed unsymmetrical cut Mean Filter.

Suresh Babu et al.[7] presented a switching median filter that identifies the noisy pixels by using neighborhood mapping method and the contaminated pixels are removed by using fuzzy function. A. Jourabloo et al.[8] presented a new method for impulse noise removal. This method is used only on the contaminated by the impulse noise. This method has better trade-off between the quality of the image and computation time.

Stefan Schulte et al.[9] prompt a replacement technique Fuzzy Impulse Noise Detection and Reduction Technique (FIDRM) for removing all classes of impulse noise. This technique is used for the mix of impulse noise and different class of noise. Wenbin Luo[10] bestowed a technique referred to as new skilful algorithmic program for the exclusion of impulse noise from corrupted pictures whereas protective image details. The algorithmic program relies on the alpha-trimmed mean, that may be a distinctive case of the order-statistics filter.

M. Emin Yuksel et al.[11] bestowed a technique referred to as hybrid filter nonheritable by befittingly integrating a median filter, a position detector, and a neuro-fuzzy network. By mistreatment the training method, the inner factors of the neuro-fuzzy network are optimized in an adaptational manner.

B. Somayeh Mousavi et al.[12] presented a method for gender categorization which is an important application in commercial domains. In this method, an innovative technique is presented called a Novel Automatic Classifier which applies accurately designed fuzzy inference system. This method has 2-inputs, 1-output Sugeno type one and applies the facial characteristics as inputs and discloses the probability of being male face or not.

3. Fuzzy Inference System based Image Denoising

In this methodology, type-2 fuzzy logic primarily based impulse detector[4] is usually recommended to cut back the impulse noise. The impulse detector includes the detector, defuzzifier and post processor. The detector includes two type-2 fuzzy logic primarily based sub detectors, two defuzzifiers and a postprocessor. The detector processes the pixels within the filtering window and produces the output. Every sub detector method a unique neighbourhood association between the middle pixel of the analysis window and two neighbouring pixels. The vertical neighbourhood is computed by the higher sub detector and horizontal neighbourhood is computed by the lower sub detector. The structures of the two sub detectors are same and also the internal parameters are also similar. However the values of the interior parameters of the sub detectors are varied. Within the impulse detector, the interior factors are optimized by the learning phase. The inside parameters of the impulse detector are optimized by the learning.

The higher sub detector is trained to figure the vertical pixel neighbourhood association and lower sub detector is trained to figure the horizontal pixel neighbourhood association. The sub detector analyse the input data by exploiting the type-2 fuzzy logical thinking and also the output is made that is of type-1 interval fuzzy set. The output of the sub detectors are given to the corresponding defuzzifier. The two defuzzifiers convert the type-1 interval fuzzy set into one scalar worth. The two singular values are combined into single value by exploiting the postprocessor. The postprocessor output value is that of the impulse detector output worth. The complexity during this methodology is high logical thinking time because of raised range of rules needed for the inferencing.

4. Parallel Fuzzy Inference System based Image Denoising

In this section, an innovative technique is introduced called PFIS based impulse detector for impulse noise removal in the image processing field. There are three phases in this technique:

- Generation of fuzzy set based on distribution of fuzzy rules.
- Defuzzification.
- Detection of impulse noise and Classification process.

In this methodology, the input learning pictures are given to the sub detector. The 3-by-3 pixel filtering window is employed in each color band of the noisy input image one pixel at a time. In each filtering window, the acceptable pixels of the filtering window denote the acceptable neighbourhoods of the middle pixel and are given to each of the sub detectors and conjointly noise filter. The sub detectors method the input and therefore the reasoning rules are generated. The generated fuzzy reasoning rules are distributed to the nodes for concurrent execution of the principles. The reasoning rules are processed in parallel manner and turn out the kind one fuzzy sets with less time interval. The output of the sub detectors are given to the two defuzzifiers. The defuzzifiers convert the type-1 interval fuzzy set into scalar values. The two scalar prices from the defuzifiers are integrated into single value by victimization of the postprocessor and it finds whether or not the pixel is vociferous or traditional. If the pixel is traditional, center pixel of the filtering window is directly traced to the output image. If the pixel is vociferous, the noise filter output is traced to the output image. Within the classification method, the check pictures are given for the experiments and generate the reasoning rules for the pixels and use the learning set for classifying the conventional and vociferous pixel.

4.1 Generation of Fuzzy Set based on Distribution of Fuzzy Rules

4.1.1 Fuzzy Rule Generation Process

The input training images are given to the impulse detector and noise filter. Every sub detector processes the central pixel and neighborhood pixels in the filtering window. The sub detectors input is X_1, X_2, X_3 (vertical and horizontal) and D represents the output. The translation of scalar input values into fuzzy numbers is completed by computing the membership degree of each input to the connected fuzzy sets. The membership degrees are set by exploiting the membership functions of the input fuzzy sets to the scalar input values. The rule set includes a selected range of fuzzy rules concerning to the amount of fuzzy sets assigned to the inputs. The rule set is as follows:

- *if* $(X_1 \in M_{11})$ & $(X_2 \in M_{12})$ & $(X_3 \in M_{13})$ *then* $R_1 = c_{11} X_1 + c_{12} X_2 + c_{13} X_3 + c_{14}$
- *if* $(X_1 \in M_{21})$ & $(X_2 \in M_{22})$ & $(X_3 \in M_{23})$ *then* $R_2 = c_{21} X_1 + c_{22} X_2 + c_{23} X_3 + c_{24}$
- *if* $(X_1 \in M_{i1})$ & $(X_2 \in M_{i2})$ & $(X_3 \in M_{i3})$ *then* $R_i = c_{i1} X_1 + c_{i2} X_2 + c_{i3} X_3 + c_{i4}$
- *if* $(X_1 \in M_{N1})$ & $(X_2 \in M_{N2})$ & $(X_3 \in M_{N3})$ *then* $R_i = c_{N1} X_1 + c_{N2} X_2 + c_{N3} X_3 + c_{N4}$ (1)

In this rule set, N represents the fuzzy rules within the rule set, M_{ij} denotes an interval type-2 fuzzy membership function that represents i^{th} membership function of the j^{th} input and run represents the output of the i^{th} rule. within the rule set, the left hand aspect denotes the fuzzy variety and right hand aspect denotes the crisp variety. The type-2 interval gaussian membership functions with unsure mean are selected as the antecedent membership functions:

$$M_{ij}(x) = \exp\left[-\frac{1}{2}\left(\frac{x - m_{ij}}{\sigma_{ij}}\right)^2\right] m_{ij} \in \left[\underline{m}_{ij}, \bar{m}_{ij}\right] \quad (2)$$

In the equation (2), $i = 1,..N$ and j = 1, 2, 3. The mean and standard value for the membership function is represented as m_{ij} and σ_{ij}. Subsequently, the sub and super bound of the indecision of the suggest is denoted as $\underline{m}_{ij}$ and $\bar{m}_{ij}$.

4.1.2 Parallel Processing by Distribution of Fuzzy Rules

The sub detector output is obtained by calculating the weighted mean of the entity rule outputs:

$$D = \frac{\sum_{i=1}^{N} w_i R_i}{\sum_{i=1}^{N} w_i} \quad (3)$$

In this equation (3), the interval weighted mean is computed that's a vital case of the standard weighted mean. During this equation, wei denotes the weight value of the i^{th} rule and it's computed by the membership expressions within the predecessor of the rule that belongs to the translation of the scalar input values to fuzzy membership values by the employment of the predecessor membership functions M_{ij} and so application of the and operator to the fuzzy membership principles. The foundations are processed at the same time in a very distributed pc. this will be obtained by multiprocessing of the fuzzy rules.

The generated fuzzy rules are evaluated in parallel manner by scattered the principles to many nodes for reducing the time interval. The generated rules ought to be accumulated in each node of the parallel pc. The principles are scattered for every node and is accomplished by the modulo operate. the quantity of nodes is denoted as N_0 toN_(m-1). The principles have particular addresses in every node. The native memory of each node is named as memory bank that's pictured as 〖MB〗_i. 〖MB〗_i indicates the memory for the i^{-th} node. Within the distribution method, the fuzzy input values are return to N_0(input node) denoted as an input vector X is given to input node to all or any alternative nodes. The scattering from one node to all or any alternative nodes is completed by One-to-All algorithmic rule. Within the scattering method, an address of each node is indicated as bit string which has n bits. This One-to-All algorithmic rule masks the bit string by exlpoiting AND operation. To decide on succeeding destination node, XOR operation is employed. The results are accumulated at an intermediate result vector Y. The vector Y in each node is mapped to the output node by exploiting All-to-One algorithmic rule.

The and operator is used by evaluating the product between predecessor membership values of different modulators:

$$w_i = M_{i1}(X_1).\ M_{i2}(X_2).\ M_{i3}(X_3) \quad (4)$$

The coefficient issue w_i could be a type-1 interval set, i.e. $w_i = \left[\underline{w}_i, \overline{w}_i\right]$ as the membership functions M_{ij} within the predecessor of the ith rule are type-2 interval membership functions. $\underline{w}_i$ and $\overline{w}_i$ denotes the sub and higher limitations of the coefficient issue. The output D of the sub detector is recognized by calculating the weighted mean of the single rule outputs. The output D is calculated $D = \underline{D}, \overline{D}$ that's sub and higher limitations of the coefficient issue.

4.2 Defuzzification Process

In this part, the type-1 interval fuzzy set got from the sub detector is sent to the consequent defuzzifier. Each defuzzifier translates the fuzzy set into scalar values. The translation is completed by doing centroid defuzzification. The input set of the type-1 interval fuzzy set $D = \underline{D}, \overline{D}$ its centroid is similar to the center of the individual.

$$d = \frac{\underline{D} + \overline{D}}{2} \tag{5}$$

4.3 Detection of Impulse Noise and Classification Process

The two scalar metric values non heritable from the two defuzzifiers are submitted as input for postprocessor. The two scalar metrics are translated into individual scalar metric value which is the output for the impulse detector. The postprocessor calculates the typical metric value for the two defuzzifier outputs and link with the metric value as either zero or one by changing it with the threshold similar to the half of the dynamic light vary.

The outputs of the defuzzifier is denoted as d_V and d_H. The input-output association is computed as,

$$p = \begin{cases} 0 & if \quad \dfrac{d_V + d_H}{2} < 128 \\ 1 & otherwise \end{cases} \tag{6}$$

In the equation (6), p is the output of the postprocessor. After performing this process, testing images are given to the experiments. The testing images are analyzed by using the training process and classify the pixel whether it is noisy or normal. If the element is traditional, the middle element of the filtering window is directly traced to the output picture. If the element is noisy, the noise filter is employed to revive the image. For noise filtering, median filter is employed. For this picture that is noisy, the median filter could be a descending square window of strange size that moves over the entire image, and replaces the actual element of the picture by the median of every pixels of the window.

Algorithm 1: Algorithm for Parallel Fuzzy Inference System (PFIS) based Image Denoising.

Input: Training Images.

Output: Classification of noisy and normal pixel.

Step 1: Nearest pixels of the middle pixel are sent to both the sub detectors and also noise filter.
Step 2: Translate scalar input values into fuzzy numbers by calculating the membership degree and create the fuzzy rules.
Step 3: Fuzzy rules are scattered to the nodes for parallel processing and calculates the type-1 interval fuzzy set.
Step 4: Type-1 interval fuzzy set is sent to consequent defuzzifier and translated into scalar value.
Step 5: The two scalar values are given to the post processor to find if the pixel is noisy or normal.
Step 6: If the pixel is usual the middle pixel of the filtering window is copied.
Step 7: Otherwise, median filter is used as noise filter for filtering the noise.
Step 8: The testing images are processed to evaluate the false classification ratio.

5. Performance Evaluation

In the numerical results, the Type-2 Fuzzy Logic (TFL) based impulse detector and Parallel Fuzzy Inference System (PFIS) based Impulse detector are compared in terms of mean squared error, false classification ratio and processing time. The existing method presents a method called Type-2 Fuzzy Logic based impulse detector for medical image denoising. In the proposed method, Parallel Fuzzy Inference System (PFIS) based impulse detector is presented for medical image denoising. By using the PFIS based impulse detector the processing time is reduced.

In the experiments, the noisy analysis medical pictures are non inheritable by contaminating a given testing picture with an impulse noise of given noise density. Numerous noise density values are used. Those are 25^{th}, 500^{th} and 75^{th} which indicates the low, medium and high noise densities, correspondingly.

5.1 Mean Squared Error

The mean squared error is defined as,

$$MSE = \frac{1}{LC}\sum_{l=1}^{L}\sum_{c=1}^{C}\left(s[l,c]-\gamma[l,c]\right)^2 \quad (7)$$

Where s [l,c] and γ [l,c] represents the light worth of the component at line l and column c of one of the three color bands of the initial and therefore there built versions of a ruined testing image correspondingly. The Meas Squared Error (MSE) is valid for the gray-scale pictures. However the testing pictures are color pictures. So, the MSE calculation is evaluated for three times, one for every color bands and also the three leading MSE values are averaged to accumulate the actual MSE value for the medical picture.

Figure 1. shows the Mean squared comparison for the existing and proposed system. In the existing system, Type-2 Fuzzy Logic (TFL) based impulse detector is exploited and in the proposed system Parallel Fuzzy Inference System (PFIS) based Impulse detector is used. In the X-axis the noise densities are given. In the Y-axis Mean squared error is taken. When compared to the existing method, there is less mean squared error in the proposed method.

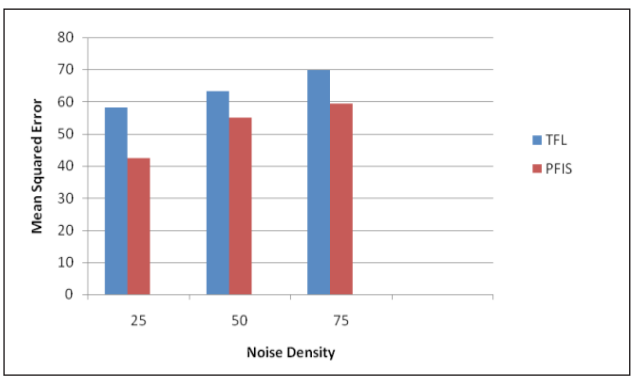

Figure 1. Mean Squared Error.

Table 1. MSE Vs Noise density

Sl. No.	Noise Density	TFL	PFIS
1	25%	58.12	42.36
2	50%	63.25	54.96
3	75%	69.87	59.48

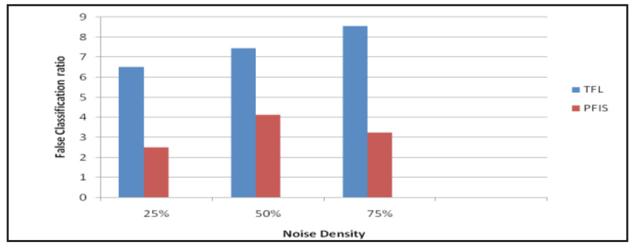

Figure 2. False classification ratio.

Table 2. FCR Vs Noise Density

Sl. No.	Noise Density	TFL	PFIS
1	25%	250	120
2	50%	320	250
3	75%	790	740

5.2 False Classification Ratio

False classification ratio is defined as,

$$FCR = \frac{N_F}{N_T}\times 100 \quad (8)$$

Where N_F indicates the incorrectly classified pixels of the input picture and N_T indicates the total number of pixels.

Figure 2. shows the false classification ratio for the existing and proposed system. In the existing system, Type-2 Fuzzy Logic based impulse detector (TFL) is exploited and in the proposed system Parallel Fuzzy Inference System (PFIS) based Impulse detector is used. In the X-axis the noise densities are given. In the Y-axis false classification ratio is taken. When compared to the existing method, there is less false classification ratio in the proposed method.

Table 2. shows the false classification ratio comparison for the existing and proposed system. If the noise density is 75%, the false classification ratio is 8.56 in the existing TFL method and 3.25 in the proposed PFIS.

5.3 Computation Time

Computation time is defined as the time taken for processing the images and filters the noise.

Figure 3. presents the processing time for the existing and the proposed system. In the existing system, Type-2 Fuzzy Logic (TFL) based impulse detector is exploited and in the proposed system Parallel Fuzzy Inference

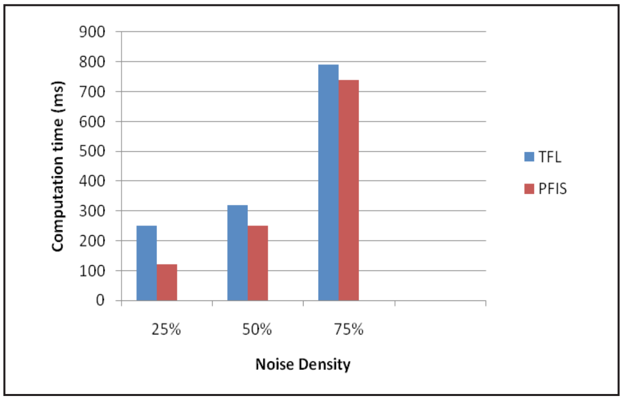

Figure 3. Computation time.

Table 3. Computation time Vs Noise Density

Sl. No.	Noise Density	TFL	PFIS
1	25%	6.52	2.52
2	50%	7.45	4.12
3	75%	8.56	3.25

System (PFIS) based Impulse detector is exploited. In the X-axis the noise densities are given. In the Y-axis computation time in ms is taken. When compared to the existing method, there is less computation time in the proposed method.

Table 3. presents the processing time comparison for the existing and proposed system. If the noise density is 75%, the compuatation time is 790 ms in the existing TFL method and 740 ms in the proposed PFIS.

6. Conclusion

Removal of impulse noise is a serious problem in the image processing field. In the presented work, Parallel Fuzzy Inference System (PFIS) is introduced for impulse noise removal. In this method, input training images are given as for detector and noise filter. Two sub detectors are accustomed to analyse a dissimilar neighbourhood association among the middle pixel of the examination window and two neighbouring pixels. Then, the fuzzy rule set is created and it's scattered to many nodes. Owing to the distributed process the abstract thought time is decreased. Then, the type-1 interval fuzzy set is created. Then, the defuzzifier is employed to translate the type-1 interval fuzzy set to scalar metric values. These two scalar values are translated into single scalar value by the postprocessor and seek out whether or not the pixel is noisy or usual. The testing images are given to the experiments and analyze the false classification ratio.

In order to obtain the better result, optimized selection of fuzzy parameter is very important. This can be considering in future work.

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