Hybrid Genetic Filter for Restoration of Brain MRI Images corrupted with Impulse Noise

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Abstract
Magnetic resonance imaging (MRI) is one of the common and widely used imaging techniques in medical imaging with excellent capability for soft tissues imaging. It is very suitable for brain imaging, muscles and excellent for early diagnosis and detection of brain tumors, treatment monitoring and other brain abnormalities. However, the incorporated noise during MRI image acquisition process makes it difficult for human interpretation as well as computer-aided analysis of the images. The main objective of this paper is to present an effective method for noise removal from brain MRI images which reduce the effect of noise while retaining the structure of the image. In this paper, a hybrid technique has been proposed which ensembles the median and wiener filters through intelligent Machine Learning technique, the Genetic Programming (GP). The GP intelligently correlates and combines the features of the filters with some trigonometric and other functions like sin, cos, and log, mathematical operators and constants with different combinations in an automated manner with the help of fitness function. At the end, GP evolved best mathematical optimal expression which is used to restore the images corrupted with impulse noise. In order to evaluate and show the effectiveness of proposed method, a set of comprehensive experimentation on standard dataset have been performed and validated the performance. Results show that, the performance of the proposed hybrid technique is much better and removes the noise from images both at low as well as at increased noise levels. The results of the proposed method have also been compared with state-of-the-art methods and the performance of the proposed method is also found to be better than previous techniques.
Keywords:
Impulse Noise, Magnetic Resonance Imaging (MRI), Genetic Programming (GP), Median filter, Wiener filter.

1. Introduction

Magnetic resonance imaging (MRI) is a noninvasive and widely used imaging technique in medical imaging. It is one of the most advanced modalities of modern medical imaging due to its capability of providing rich information about soft tissues anatomy of human body [1]. A radiologist or medical expert with the help of these images can diagnose the disease with high precision and accuracy.
MRI technique can also be used when planning for examining patients as well as when to proceed to surgery.

However, the images acquired from MRI scanners sometimes contain unwanted information which is referred to as noise [5]. The noise affects on the quality of the image which hides the desirable and significant information which is necessary to trace the symptoms of the disease. In several situations, it degrades image quality and is especially significant when the objects being imaged are small and have relatively low contrast [2]. The existence of noise gives an image a grainy, mottled, textured, or snowy appearance. So for correct diagnoses, it is necessary that the medical image should be noise free and posses the characteristics of sharp and distinct. The noise in the image occurs from a variety of sources like environment and hardware [3].
There are different kinds of noises such as Gaussian, speckle, random, rician, poison, and salt & pepper [4] [6]. But the most frequent and commonly occurring kind of noise in MR images is impulse noise (also known as salt & pepper noise) which occurs due to several different reasons. It can occur due to different factors such as faulty scanners or coils, bit error due to transmission of imaging data from machine to computer, transferring data from one computer to another, analog to digital converter errors and conversion of images from one format to another format. The salt & pepper noise creates the bright pixels in the dark regions and dark pixels in the bright regions in the image [2] that can be removed by proposing some filtering techniques.
There are two basic categories of image filtering techniques such as spatial domain filtering and transformed or frequency domain filtering [9]. Spatial domain filters perform the operations on the pixels values directly and transformed domain filters transform the image into frequency domain by using some functions [7]. Mean and median filters are the types of spatial filtering which used widely for reducing the effect of impulse noise. Mean filters works by replacing the central pixel with the average value of all pixels in the squared neighborhood window [8]. This filter works better in some cases but most of the time it loses the finer detail of the image. Median filter performs better than the mean filter. It works by replacing the centre pixel value with the median (middle point in sorted order) value in the squared neighborhood window [6]. Median filter is very effective in removing the impulse noise

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sufficiently but it produces some blurriness effect in the image. Wiener filter is a technique of frequency domain filtering which isolates the additive noise from signals. This filter is mostly used for smoothing and deblurring the image [8].

The main objective of this paper is to propose an effective hybrid method for impulse noise removal from MR images with capabilities of reducing the effect of noise while retaining the image structure both at low as well as high noise levels. In the proposed method, two filters have been ensemble through the intelligent Machine Learning technique, the Genetic Programming (GP). GP is a biologically inspired operation which creates a pool of working computer programs in an automated manner from a high-level problem statement of the problem. The genetic operations comprise reproduction, crossover, and mutation. At the end, the GP evolve best optimal expression based on some fitness function. A good evaluation function is critical to implement GP properly for any particular problem space.

The remaining of the paper is organized as: Section 2 describes the related work; Section 3 describes the detailed methodology of the proposed work. A validation mechanism of the proposed method is explained in Section 4. Section 5 presents the detailed results and discussion of the experimentations performed to justify and validate the proposed method. Conclusion and future direction is given in Section 6.

2. Related Work

In the last few decades, many algorithms have been proposed to remove the noise from images. Image de-noising still remains a challenging task for research community as noise removal methods introduce several artifacts, causes blurring of the images, and alter the structural information of the image as noise level increases [5].

Wang and Li et al. [10] proposed an impulse noise removal method by the combination of fuzzy gradient values and fuzzy logic theory. This method works by first differentiating noisy and noise free pixels in the image. After this the noisy pixels are adjusted by generating the difference matrix between gray value of pixels and mean of the signal point intensity. This filter generates good results at normal noise levels but produces blur edges as the noise level increases. Kaur et al. [11] proposed an impulse noise reduction technique. This technique works in three steps. First, it detects the noise and then reduces the noise by median filter. In the last step, a histogram is generated and again the noise is suppressed by using soft thresholding method. The results obtained by this method still contain the noisy pixels and also produces blur edges. A method for impulse noise removal is proposed by Mahallati [12]. In this method, two 3×3 neighborhood windows have been established and mean of central pixels of these two windows is replaced at the central position of considered window. This method performs better and preserves the structural information of the image. Jain et al. [13] proposed a technique fuzzy switching median method for the suppression of noise from images. This method works in two stages. In first stage, it detects the noisy pixels by using clustered based approach and in second stage; this method removes the noisy pixels by using fuzzy reasoning based approach. This approach performs better and removes sufficient amount of noise. The edges produced in the final restored images are slightly blurred. Baek et al. [14] proposed impulse noise removal method by using the switching median filter. In this method noise is detected by boundary discriminative noise detection method and then noisy pixel is adjusted by weighted average of uncorrupted values. This method performs better and generates good results by reducing the blurry effect as compared to switching median filter. Devi et al. [15] proposed a hybrid approach for impulse noise reduction by using the Mamdani and Sugeno based fuzzy interference system approach. This method works better at normal noise levels. However, this method is computationally very expensive.

3. Proposed Methodology

The proposed noise removal method hybrid genetic filter (HGF) is divided into three phases, Features Extraction Phase, Genetic Programming Phase and Estimation of Restored Value Phase. The framework of the proposed method is given in Figure 1. The detail of each phase is given one by one in the following subsections.

3.1 Features Extraction Phase

As described earlier, different filters have been combined through Genetic Programming (GP). To train the GP, first features are extracted from the filters to form the feature vector. For this purpose, first features are extracted by proposing the usage of Median and Wiener filters. The Median and Wiener filters are described briefly one by one in the following subsections.

3.1.1 Median Filter

Median filter is a nonlinear widely used technique for the removal of noise from MR images. The performance of this filter is better and considered to be very effective in preserving the edges detail. In this method, a neighborhood window is established around a central pixel which is under consideration. The central pixel is replaced with median value. To select the median value, all pixels values are ordered in a sorted manner and the median is selected. The median filter is defined as:

$$u[m,n] = median\{v[i,j], \qquad i,j \in NBH\} \quad (1)$$

Where *NBH* represents squared neighborhood window centered at pixel position *[m, n]* in the image.

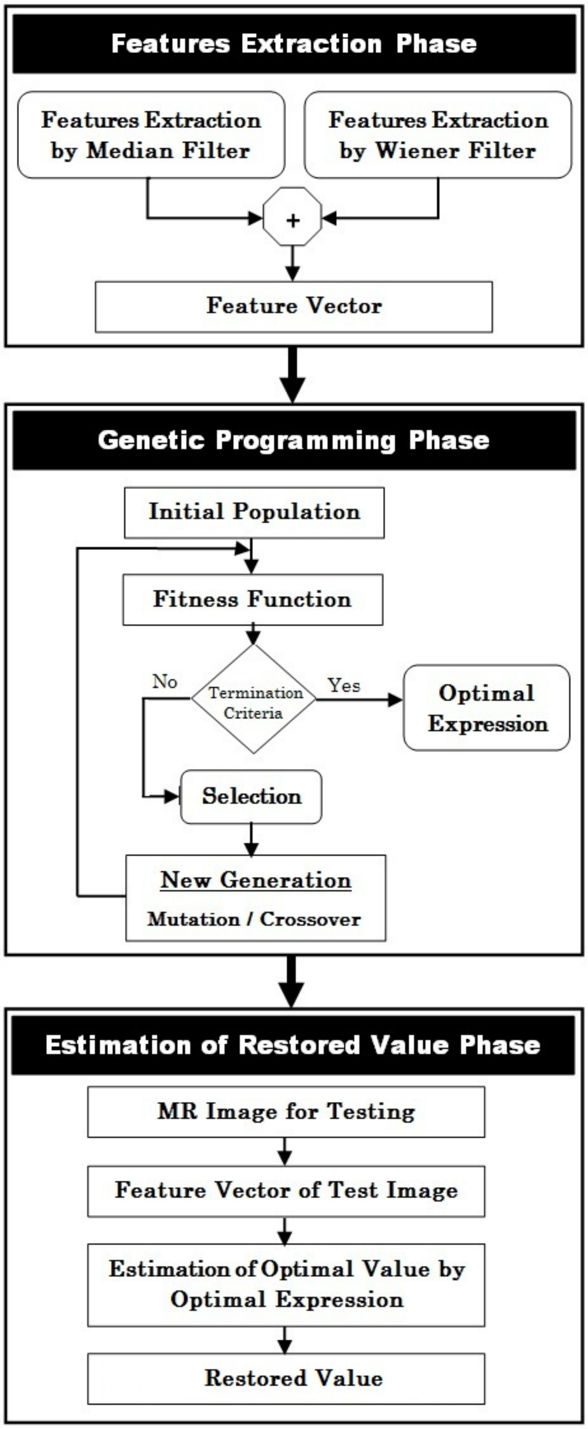

Fig. 1 Framework of Proposed Noise Removal Method.

3.1.2 Wiener Filter

The Wiener filter performs an optimal tradeoff between inverse filtering and noise smoothing and minimizes the overall mean squared error (mse). It eliminates the effect of additive noise and overturns the blurring at the same time. The Wiener filter composed of two separate parts, one is inverse filtering and other one is noise smoothing part. It performs deconvolution by inverse filtering operation by using highpass filter and eliminates noise by a lowpass filter. The Wiener filter in Fourier form is expressed as:

$$W(f_1,f_2) = \frac{H^*(f_1,f_2)\, S_{xx}(f_1,f_2)}{|H(f_1,f_2)|^2\, S_{xx}(f_1,f_2) + S_{nn}(f_1,f_2)} \quad (2)$$

Where $S_{xx}(f_1,f_2)$ and $S_{nn}(f_1,f_2)$ are power spectrum of original image and noise respectively. $H(f_1,f_2)$ represents the blurring filter.

After extracting the features from above filters, the information of these features is combined and a feature vector is formed which contains the features of both filters Median and Wiener. The features are then used for the next phase.

3.2 Genetic Programming Phase

In this phase, the feature vector formed previously is passed to Genetic Programming (GP) module to evolve an optimal expression for the restoration of actual values of noisy pixels. To start the training of GP and evolve the optimal mathematical expression, it is prerequisite to generate an initial population of individuals to serve as the starting point for the GP. So in the proposed method, an initial population consisting of 100 individuals is created randomly by using the *ramped half and half* [10] method. All variables, constants and functions used have been initialized randomly at beginning.

After generating the population, the fitness of each solution has been calculated by using fitness measure. In the proposed method, Mean Squared Error (MSE) is used as fitness function which checks the overall fitness of each individual to serve for the next generations. This fitness of each solution provided fitness of each mathematical expression by calculating MSE. Thus, the fitness of each solution is checked by MSE. Individuals having minimum MSE values show good solution as compared to those solutions which have large MSE values. Minimum MSE also shows the degree to which GP evolved while GP mathematical expression has been initialized randomly. Later on, during the evolution process, it evolved its expression so that MSE may decrease till the limit of finding suitable criteria of problem has been achieved. There are different terminating criterions to stop the GP evolution process. In the proposed method, we set the minimum error rate or number of maximum generation size criteria (which one is achieved first) to stop the GP evolution process.

During evolution process of GP, there are different methods to select best solutions from initial population, but tournament selection has been performed for selection of solution for generation executions as it performs better among other selection criterions. In this case, ten solutions have been selected through tournament and used for generation size. The tournament size plays an important role in the selection of individuals and if it is larger, weak individuals have a smaller chance to be selected. These solutions have been used later during crossover and mutations which increase the evolution process of GP.

In the proposed method, one point crossover with probability 0.7 and point mutation with probability 0.1 have been used. Too high mutation rate reduces the search ability of GP while a too small almost always fails to a local optimum. Crossover tries to converge to a specific point. The proposed method is tested with different combinations of rates between 0 and 1 of crossover and mutation but the above settings are most suitable for restoration of images corrupted with impulse noise. The proposed method is also tested by performing the two point crossover and multipoint crossover but the single point crossover generates good results. Parameters setting for the simulation of GP are given in Table 1.

3.3 Estimation of Restored Value

After evolving GP for number of times, an optimal mathematical expression has been returned by the GP in an automated manner. The best optimal expression returned by GP is given in Figure 2. The best optimal expression has been generated after complete training of the GP by using feature set generated in the feature extraction step. The evolved best mathematical expression is a combination of all those features extracted with median and wiener filters, functions like trigonometric and some constants. This best optimal evolved expression has been generated after more than one thousand generations. Thus, it takes too much time to evolve it completely. This is the one drawback of this proposed method that training of GP takes too much time. But after completing evolved expression to estimate the true value, testing has been performed but, it takes very less time to complete this process. Thus, it can be concluded that testing to estimate the true value takes very less time as compared to training once GP has been completely trained.

Table 1: Settings of parameters of Genetic Programming to develop functions

GP Parameters	Set values
Terminals set	Features of Median and Wiener Filters, Random constants between 0 and 1.
Functions set	+, -, *, /, log, sin, cos, exponent, power.
Fitness criterion	$\mathrm{MSE} = \mathrm{sum}(\mathrm{sum}(\mathrm{originalImage} - \mathrm{noisyImage})^2)/(\mathrm{rows} * \mathrm{columns})$
Size of population and no. of generations	100 &1000 respectively
Initial tree depth	5
Population initialization	Ramped half and half Method
Expected offspring	Rank-85
Operators probabilities	Variable crossover with rate 0.7/mutation ratio 0.1
Population Sampling	Tournament Selection
Survival	Best individuals to survive

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+(sin(0.731),+(+(sin(F1),+(+(sin(+(sin(0.431),+(+(+(+(F1,F2
),sin(0.731)),sin(F2)),sin(244)))),+(+(+(+(0.431,F2),sin(+(
+(+(+(0.431,F2),sin(F1)),sin(F1)),+(sin(F1),+(+(+(+(+(0.431
,F2),sin(F1)),sin(F1)),+(+(+(+(0.431,F2),sin(F1)),log(0.431
)),sin(F1))),sin(+(+(sin(F2),-(F1,+(+(cos(sin(-(-(0.76983,-
(0.431,-(0.91359,F2))),cos(0.02542)))), *(F2,0.431)),F1)))
,sin(F2)))))))),sin(F1)),sin(F1))),sin(+(+(+(+(0.431,F2),
sin(F1)),sin(F1)),+(sin(F1),+(+(sin(F2),+(+(+(+(0.431,F2),s
in(F1)),sin(sin(F1))),sin(F1))),sin(+(+(sin(F2),+(+(+(+(0.4
31,F2),sin(F1)),sin(F1)),sin(F1))),sin(F1)))))))))),sin(+(+(
sin(+(sin(F2),+(+(+(+(0.431,F2),sin(F1)),sin(F1)),sin(+(+(+
(0.431,F2),sin(F1)),sin(F1)))))),+(+(+(+(0.431,F2),sin(F2))
,sin(F1)),sin(F1))),sin(+(+(+(+(0.431,F2),sin(F1)),sin(F1))
,+(sin(F1),+(+(sin(sin(F1)),+(+(+(+(0.431,F2),sin(F1)),sin(
0.431)),sin(F1))),sin(+(+(sin(F1),+(+(F1,sin(F1)),F1)),sin(
F2)))))))))))
```

Fig. 2 Best evolved optimal expression.

In order to de-noise the image, features have been extracted from testing noisy image and replaced in the optimal evolved expression. After restoring the estimated true values of noisy pixels, these values are replaced in the noisy image at their respective positions. In this way, the image is de-noised.

4. Validation of Proposed Method

4.1 Used Dataset

In order to evaluate and validate the proposed noise removal method, experimentation is performed on simulated dataset which is downloaded from publically available dataset. This dataset is downloaded from BrainWeb [16] and provided by McConnell Brain Imaging Centre at Montreal Neurological Institute and Hospital, McGill University. The volume of the dataset is 181×217×181 axial view with slice thickness 1mm, echo time (TE) 10ms and repetition time (TR) 18ms.

4.2 Performance Parameters

In order to evaluate the performance of the proposed noise removal method, three standard performance measures, Peak Signal-to-Noise-Ratio (PSNR) [17], Root Mean Squared Error (RMSE) [18] and Structured Similarity Index Measure (SSIM) [19] were used and summarized here as:

PSNR: $$PSNR(R,I) = 10 \times log_{10} \frac{S^2}{MSE(R,I)} \quad (3)$$

Where *I*, *R* and *S* are the reference image, restored image and maximum intensity value respectively. For 8-bit grayscale images, maximum value of *S* is 255. The PSNR values greater than 20db indicate the better performance of the denoising method.

RMSE: $$MSE(R,I) = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (I(i,j) - R(i,j))^2 \quad (4)$$

Where *I* and *R* are the reference and restored images respectively. M×N are the image dimensions. The MSE values less than the noisy image values correspond to the better performance of the filtering techniques.

SSIM: $$SSIM(a,b) = \frac{(2\mu_a\mu_b + C1)(2\sigma_{ab} + C2)}{(\mu_a^2 + \mu_b^2 + C1)(\sigma_a^2 + \sigma_b^2 + C2)} \quad (5)$$

Where μ_a, μ_b denote the mean intensity of image blocks *a* and *b*, σ_a and σ_b denote standard deviation of set image blocks *a* and *b*, while σ_{ab} represent their cross correlation. C1, C2 represent constants having low values which are used to control the problem of instability when the denominator factor becomes closer to 0. The SSIM metric generates decimal values between 0 and 1. The SSIM values nearer to 1 indicate the better performance.

4.3 Experimental Setup

The performance of the proposed noise removal method has been tested and validated on simulated MRI dataset, for which we have performed a comprehensive set of experiments under the following setup.

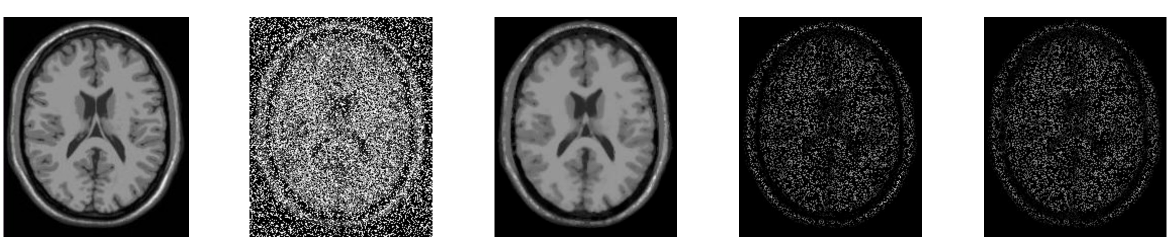
- In the first experiment, we have calculated and showed the accuracy of the proposed noise removal method.
- In the second experiment, the performance of the proposed method was compared with some state-of-the-art methods available at the moment. For this purpose, we borrowed the implementations for some of the techniques, whereas for other approaches, we have implemented their respective methods for fair comparison.

5. Results and Discussion

5.1 First Experiment: Accuracy of Proposed Method

In order to assess and evaluate the performance of the proposed noise removal method, experiments have been performed on simulated dataset. The performance of the proposed method is assessed both qualitatively and quantitatively.

Figure 3 shows the qualitative results of the proposed method on image corrupted with 50% impulse noise. Figure 3(c) shows the restored image with proposed technique. Figure 3(d) and 3(e) show the amount of noise added in the original image and amount of noise removed from noisy image respectively. It can be observed from Figure 3 that the proposed noise removal method reduces sufficient amount of noise and retains the maximum structural information. The edges are preserved and restored image does not contain the noise. The further qualitative results of the proposed method at different noise levels are shown in Figure 3.



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

Fig. 3 Visual Performance of Proposed Method (a) Original Image (Slice 90), (b) Noisy image corrupted with 50% impulse noise, (c) Restored image with proposed method, (d) Amount of noise added, (e) Amount of noise removed with proposed method.

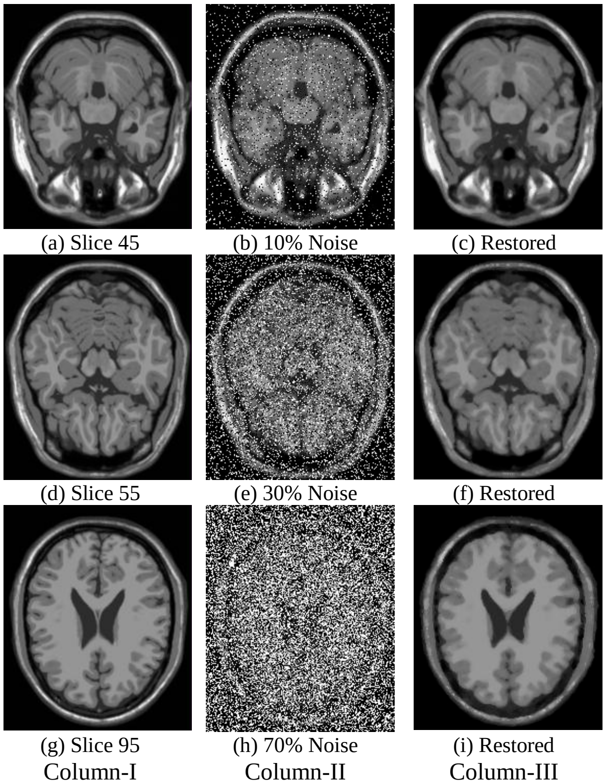


Fig. 4 Qualitative results of the Proposed Method at different noise levels, Column-I: Original images, Column-II: Noisy images corrupted with impulse noise at different noise levels, Column-III: Restored images with proposed method.

Table 2 shows the quantitative results of the proposed method in terms of PSNR, RMSE and SSIM. From Table 2, it can be observed that the proposed method performs better at low as well as at high level of noise. As SSIM quantify the structural information, so it can also be observed from Table 2 that better values of SSIM of proposed method are the indications to preserve the significant structural information.

Based on both qualitative and quantitative results, it can be concluded that the performance of the proposed noise removal method is better. The proposed method sustains its performance and retains the structure of the image at low and increases noise levels.

5.2 Second Experiment: Comparison with Existing Methods

In order to evaluate the effectiveness of the proposed method, the results have also been compared with existing methods in this domain. The results are compared with Mean filter, Median filter, Wiener filter, Decision based Algorithm (DBA) [20], and Noise Adaptive Fuzzy Switching Median (NAFSM) [21] filter. For Mean, Median and Wiener filters, inbuilt Matlab functions with 3×3 window size have been used. The experimental setup for DBA and NAFSM algorithms is set same as recommended by the authors.

Table 2: Performance of proposed method in terms of PSNR, RMSE and SSIM

Noise Ratio	PSNR	RMSE	SSIM
10%	40.4015	16.7120	0.9922
20%	38.0945	29.0963	0.9833
30%	35.4275	38.0684	0.9748
40%	32.1756	64.3690	0.9461
50%	29.5730	104.3534	0.9105
60%	26.7210	142.1671	0.8756
70%	26.3139	179.7536	0.8417
80%	25.5390	214.4598	0.8009

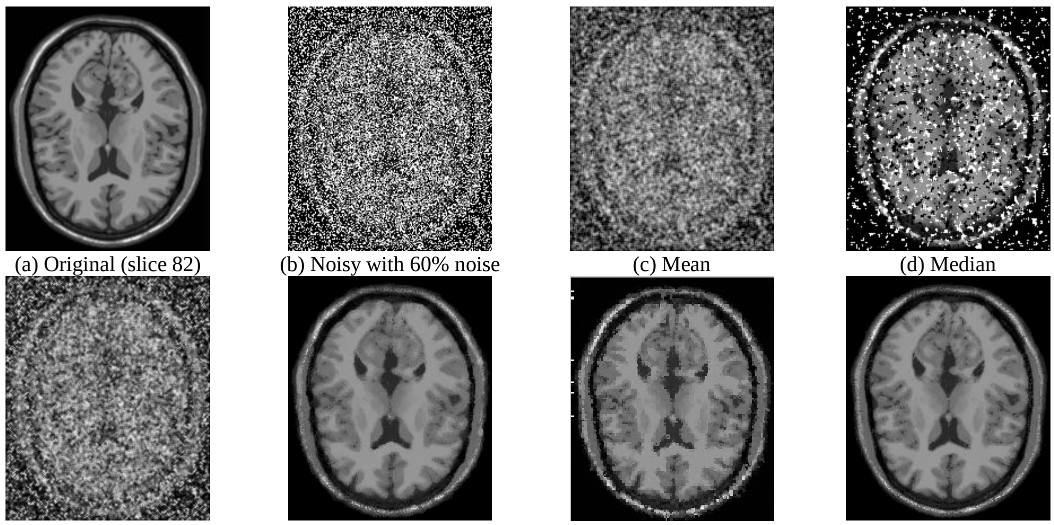
Figure 4 shows the qualitative comparison of proposed method with existing methods with 50% noise level. From Figure 4, it can be observed that the Mean, Median and Wiener filters fail in reducing the noise and restoring the structure of the image and are not superior with respect to edge preserving.

On the other hand, DBA and NAFSM filters perform better and suppress more noise than Mean, Median and Wiener filters. But the proposed technique can efficiently suppress more noise, preserves edges detail, and provide good quality images than these existing methods.

Table 3 compares the quantitative results of the proposed method with existing methods in terms of PSNR and RMSE. From Table 2, it can be clearly observed that the proposed method improves much more PSNR and RMSE and provides superior results as compared to existing methods both at low as well as at high noise levels. The PSNR and RMSE are global metrics for quantitative measures and do not quantify the significant structural information about the preservation of the image features.

In order to measure the structural information about the preservation of important features in the image in detail, the SSIM is used which quantify the structural information. Figure 6 shows the SSIM based comparison of the proposed method with previous methods in maintaining and retaining the significant features. From Figure 6, it is obvious that the proposed method preserves more structural information and sustains its performance at all noise levels as compared to existing methods. This is one of the drawback of existing methods that as the noise levels increases, the performance of methods becomes limited and do not maintain the image structure. Mean, Median and Wiener filters completely fail in retaining the structural information as level of noise increases. However, the DBA and NAFSM techniques maintains and preserves image features at increased noise levels, but the proposed method preserves more information than these methods. This significant performance of the proposed method indicates that the method is very effective and outperforms. This all is achieved due to GP which in an automated and intelligent manner combines and correlates the features of filters with other functions with different combinations and evolve the best optimal value.

Based on qualitative and quantitative comparisons of the proposed method with existing methods, it is concluded that the proposed method outperforms, retains and preserves the significant image information and sustains its performance at low as well as at high noise levels. GP being an optimization technique gives best solution in the form of a combination of all combined filters based features as well as different functions.



(a) Original (slice 82) (b) Noisy with 60% noise (c) Mean (d) Median

(e) Wiener (f) NAFSM (g) DBA (h) Proposed Method

Fig. 5 Qualitative comparison of proposed method with existing methods.

Table 3: Quantitative comparison of proposed method with existing methods in terms of PSNR and RMSE

Noise Level	Mean		Median		Wiener		DBA		NAFSM		Proposed	
	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE	PSNR	RMSE
10%	21.0594	351.05	33.0773	34.760	17.4709	1000.6	37.4178	17.540	33.8305	21.85	39.8053	16.629
20%	18.0387	748.05	28.9046	83.680	15.5950	1043.3	32.7359	34.630	31.4372	42.76	37.9158	29.620
30%	15.9334	1296.4	22.6546	352.87	14.1529	1945.7	31.7058	43.900	29.0967	72.10	34.4287	39.600
40%	14.4700	1895.5	18.3784	980.56	13.5900	2520	28.9026	83.710	27.8769	97.07	31.8691	65.501
50%	13.0437	2745.3	14.6968	2392.8	12.2561	3284.9	26.6683	140.04	27.0774	116.69	29.4281	109.12
60%	12.4453	3371.9	11.6794	4417.2	11.9408	3776.9	23.3827	298.41	25.7026	160.15	27.1850	146.40
70%	11.6983	4398.0	9.2258	7771.4	11.4311	4677.0	21.3453	477.04	25.0509	203.23	26.6653	183.36
80%	10.9606	5212.1	7.5214	10141	10.7795	5434.1	19.3005	763.88	23.4100	296.54	25.8365	235.33

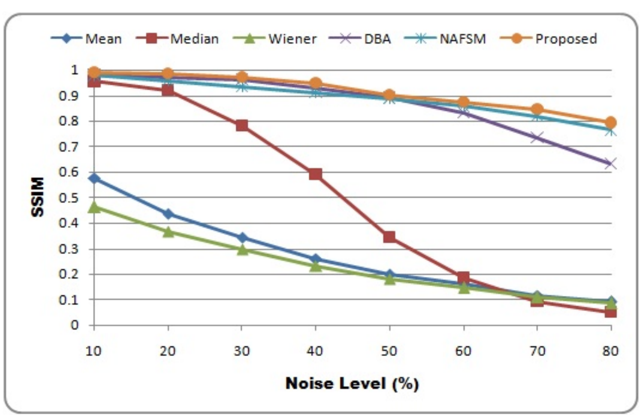


Fig. 6: SSIM based comparison of proposed method with existing methods at different noise levels.

6. Conclusions and Future Direction

In this paper, a novel hybrid technique is presented for the removal of impulse noise from brain MR images. The proposed technique combines the features of median and wiener filters through Genetic Programming (GP). GP evolved an optimal expression which is supported in restoring the noisy pixels in the image. The experiments showed excellent and promising results for the proposed methodology. The main advantage of the proposed technique is its effectiveness in reducing the more noise effect and retaining and preserving the structure of the image. The difference between proposed technique and previous method is that proposed method sustains its performance at low as well as at high noise levels while others fail. The previous methods do not perform better and produce blur edges as the level of noise increases. The other advantage of the proposed technique is that it provides a template and just by changing the combination of filters, it can be used for the reduction of other types of noises other than impulse noise.

There are various exciting areas of application that this work aims to open for future researchers. One major application in future can be to detect the brain tumor. The system can be combined with a segmentation model to become a complete facilitator in treatment, surgery and subsequent pre-surgery procedures for brain cancer patients.

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