Dynamic Block Coding for Image Enhancement for MRI Image Analysis

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***Abstract*:- In the process of image coding, external noises impact a lot in processing efficiency. In the application of medical image processing, this effect is more important due to its finer content details. It is required to minimize the noise effect with preserving the image content information, without loosing the image generality. Towards the objective of image denoising, in this work, a dynamic block coding approach for noise minimization in medical image processing is presented. The filtration approach is an enhancement to the objective of noise elimination using median filtration. The suggested approach, improves the retrieval accuracy more effectively under variant noise condition in consideration to conventional filtration approach.**

Keyword: Denoising, medical image processing, dynamic block coding, MRI images.

I. INTRODUCTION

Current developments have led to attaining higher coding efficiency in image processing applications and its utilization. At various stages of applications, medical image processing has its own significance. In the area of medial image coding, finer details coding and preservation is of most important factor. Towards enhanceing the accuracy in image coding, different methods were developed in past, to attain the objective of image quality enhancement. Different well-established methods, such as median filtration are successfully applied in gray scale imaging. Median filtration technique is particularly applied for impulsive noise elimination. It has been revealed that median filtration have the advantage of removing noise without blurring edges since they are nonlinear operators of the class of rank filters and their output is one of the original gray values [1][2]. The development of the idea of median filtering to color images is not trivial. The major problem in stating a rank filter in color image is that there is no "natural" and unambiguous array in the data [3][4]. During recent past, Various approaches were projected to employ median filters in color medical image techniques [5][6]. Whatsoever the vector filtration technique, the major task is to identify and restore noisy pixels while the related information is conserved. But it is acknowledged that in some MRI image areas the majority of vector filters blur thin fine points and image edges [7][8][9]. Normally impulse noise pollutes medical images during data acquisition through camera sensors and transmission in the communication channel. [10] Proposed a two-stage algorithm. In the first stage of this algorithm, an adaptive median filter (AMF) is applied to categorize degraded and unspoiled pixels; in the second stage, specific regularization technique is applied to the noisy pixels to conserve the edges and noise suppression. The major disadvantage of this technique is that the processing time is very high since it uses a large window dimension of 39 x 39 in both stages to attain the best output; in addition, more complicated circuitry is required for their realization.

[11] Proposed a sorting based algorithm in which the corrupted pixels are substituted by either the median pixel or neighborhood pixel in contrast to AMF and other presented algorithms that employ simply median values for substitution of corrupted pixels. At higher noise densities this algorithm does not conserve edge and fine information adequately. In this paper a novel robust evaluation based filtration technique is proposed to eliminate fixed value impulse noise efficiently. The proposed filter eliminates low to high density fixed value impulse noise with edge and detail conservation up to a noise density of 90%. Recently, nonlinear estimation approaches are attaining recognition for the problem of image denoising. The familiar Wiener filter for minimum mean-square error (MMSE) assessment is considered under the assumption of wide-sense stationary signal and noise a random approach is said to be stationary when its statistical features are time domain invariant [12]. For the majority of the natural MRI images, the stationary condition is not satisfied. In the precedent, numerous noise eliminating filters were designed with the stationary assumption. These filters eliminate noise although they are liable to blur edges and fine details. This algorithm fails to eliminate impulse noise in high frequency regions such as edges in the MRI image. To conquer the above mentioned problems a nonlinear estimation method for the difficulty of medical image denoising has been designed based on robust statistics. Robust statistics addresses the difficulty of estimation when the idealized assumptions about a structure are seldom desecrated. The contaminating noise in an image is considered as a violation of the assumption of time domain coherence of the medical image intensities and is considered as an outlier random variable [12]. [13] Proposed a robust parameter estimation algorithm for the medical image representation that contains a combination of Gaussian and impulsive noise. In [12] a robust estimation based filter is developed to remove low to medium density Gaussian noise with feature preservation. Though these methods were designed for filtration of Gussain or impulsive noise they are been designed for gray level images and are not appropriate for color images. In this paper an adapted approach to time domain median

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filter is projected for the noise elimination in digital medical images. The paper is further presented in six sections. Where conventional time domain filtration techniques and their restrictions were presented in Section 2. Section 3 outlines the proposed modified median filtration approach for MRI images. The simulation observations were presented in section 4.

II. MEDICAL IMAGE CODING – PREPROCESSING APPROACH

In the approach of medical image processing, automated image recognition for tumor detection has its own significance and automated system can provide an early stage analysis and decision based on the image data passed with more effective way. An approach of automated processing medical image data analysis system is presented in figure 1. The system basically consists of a preprocessing stage, feature extraction and classification stage. The primary requirement of any image coding system is to process the image to an extent of maximum accuracy retaining the image integrity.

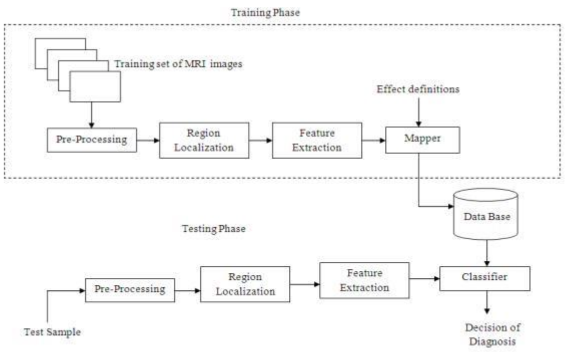

Figure 1: Proposed system architecture for the automated Diagnosis system

In the pre-processing unit the given sample is processed for a standard processing size, extracting the pixel values and applying filtration to eliminate noise effects. The process of denoising was observed in different literatures to eliminate noise effects at preprocessing level. In existing technique towards denoising of MRI sample at preprocessing median filtration was recommended [3]. Wherein median filters are effectual under a discrete level of noise effect, under dynamic noise variations the immunity is condensed. In the operation of median filtration, the values of the pixel in the window are stored and the median, the middle value in the sorted list (or average of the middle two if the list has an even number of elements) is the one plotted into the output image. The median filtered image g(x, y) can be obtained from the median pixel values in a neighborhood of (x, y) in the input image f(x, y), as defined by the equation given below,

2

$$MdF\,(x_i) = Median(x_i \qquad \| \;\; \| \qquad)$$

Where, i = 1…. N

These filtration approaches were observed to be efficient in gray scale images. When processed over color images these filtration approaches give less significant performance. To attain accurate reconstruction of medical image the median filtration approach is adapted to time domain median filtration. The time domain Median Filter is a uniform smoothing algorithm with the principle of removing noise and fine points of medical image data at the same time maintaining edges around better shapes.

III. DYNAMIC BLOCK CODING

In a Time domain Median Filter the vectors are ranked by some criteria and the top ranking point is used to the replace the center point. No deliberation is made to determine if that center point is original data or not. The adverse drawback to using these filters is the smoothing that occurs uniformly across the image. Across areas where there is no noise, original medical image data is eliminated needlessly. In the modified time domain median filter, after the time domain depths among every point inside the mask are computed, an effort is made to employ this information to first choose if the mask's center point is an uncorrupted point or not. If the determination is made that a point is not corrupted, then the point will not be modified and if the point is corrupted then it will be modified.

The proposed modified filtration approach performs as explained below,

1) Compute the time domain depth of each point inside the mask selected.

2) Arrange these time domain depths in descending order.

3) The point with the maximum time domain depth represents the Time domain median of the set. In cases where noise is determined to exist, this representative point is used to restore the point presently located under the center of the mask.

4) The point with the minimum time domain depth will be considered the least similar point of the set.

5) By ranking these time domain depths in the set in descending order, a time domain rank statistic of depth levels is formed.

6) The maximum depth measures, which represent the collection of uncorrupted points, are pushed to the front of the ordered set.

7) The minimum depth measures, representing points with the maximum time domain difference among others in the

mask and possibly the most corrupted points, and they are pushed to the end of the list. This prevents the smoothing by looking for the position of the center point in the time domain order statistic list. The image inter relation error is then reduced using a least mean error (LMSE) computation. The Least Mean Square (LMS) algorithm is an adaptive algorithm, which employs a gradient-based approach of steepest decent. LMS algorithm makes use of the estimates of the gradient vector from the existing data. LMS integrates an iterative approach that makes successive modifications to the weight vector in the direction of the negative of the gradient vector, which ultimately leads to the least mean square error. Compared to other algorithms LMS algorithm is comparatively simple; it does not need correlation function computation nor does it require matrix inversions. From the approach of steepest descent, the weight vector equation is given by;

$w(n+1)=w(n)+1/2\mu[-\Delta(E\{e^2(n)\}]$ ……….(1)

Where μ is the step-size parameter and controls the convergence characteristics of the LMS algorithm;

$e^2(n)$ is the mean square error between the output y(n) and the reference signal which is given by,

$e^2(n)=[d^*(n)-w^h x(n)]^2$ ……….(2)

The gradient vector in the above weight update equation can be computed as

$\Delta_w(E\{e^2(n)\})= -2r+2Rw(n)$ ………..(3)

In the method of steepest descent the biggest problem is the computation involved in finding the values r and R matrices in real time. The LMS algorithm on the other hand simplifies this by using the instantaneous values of covariance matrices r and R instead of their actual values i.e.

$R(n)=x(n)x^h(n)$
$R(n)=d^*(n)x(n)$ ………..(4)

Therefore the weight update can be given by the following equation,

$W(n+1)=w(n)+\mu x(n)[d^*(n) – x^h(n)w(n)]$
$= w(n)+\mu x(n)e^*(n)$ …………….(5)

The LMS algorithm is initiated with an arbitrary value w(0) for the weight vector at n=0. The successive corrections of the weight vector eventually leads to the minimum value of the mean squared error. Therefore the LMS algorithm can be summarized in following equations;

Output, $(n)=w^h x(n)$ ……….(6)

Error, $e(n)=d^*(n)-y(n)$………..(7)

Weight, $w(n+1)=w(n)+\mu x(n)e^*(n)$ ………..(8)

This computed weight provides an optimal value for noise elimination. Using this noise limit, the images are denoised and passed for higher grid interpolation. The experimental result obtained for the developed system is as illustrated in the following section.

IV. EXPERIMENTAL RESULTS

To evaluate the accuracy of the adapted time domain median filter, a medical image with noise is applied through some means. To evaluate the quality of a reconstructed MRI image, first compute the Root-Mean-Squared Error among the original and the reconstructed image. The Root-Mean-Squared Error (RMSE) for an original image I and reconstructed MRI image R is defined by,

$$RMSE(I,R)=\sqrt{\frac{1}{I_w \times I_h}\sum_{i=0}^{Iw}\sum_{j=0}^{Ih}\|I(i,j)-R(i,j)\|^2}$$

The algorithm for the Modified Time domain Median Filter (MSMF) requires two parameters. The first parameter considered is the size of the mask to use for each filtering operation. The second parameter, threshold ζ, represents the estimated number of

original points for any given sample under a mask. A collection of ten MRI images of various sizes was used in these tests. These images are a variety of textures and subject matter. The texture of these MRI images impact on the threshold chosen than the window mask size.

The tests to conclude the best mask size were conducted in this manner:

1. Each of the ten MRI images in the collection was artificially distorted with ρ =0.01, ρ =0.05, ρ =0.10, and ρ =0.20 noise composition, resulting in 40

images.

2. Each of the forty medical noisy images was then reconstructed using the SMF with mask sizes of N=3, N=5, and N=7 (the second argument, threshold ζ, is

set to 1), resulting in 120 reconstructed medical images.

3. The RMSE was calculated between all 120 reconstructed MRI images and the originals. The RMSE is a simple estimation score of the variation between two MRI images. An ideal RMSE would be zero, which means that the algorithm acceptably identified each noisy point and also correctly derived the original data at that location in the signal. For the assessment of the work a performance

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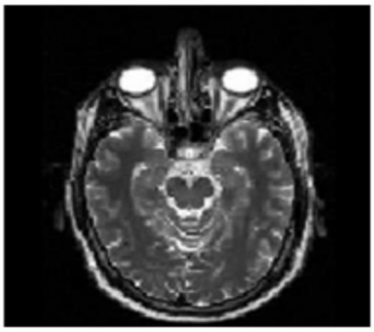
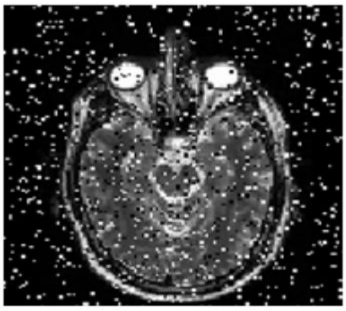
evaluation is conducted on different samples and the results obtained are shown below.

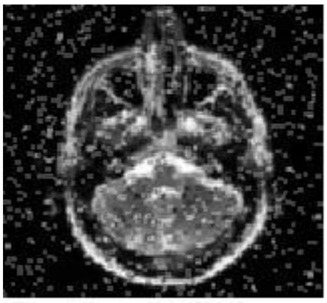
As seen in figure 2, a mask size of 3 clearly outperformed the other tested sizes of 5 and 7. Neither the quantity of noise, the size of the MRI image, nor the subject matter of the image effects on the mask size which performed the best. Less thorough tests were run on higher mask sizes such as 9 and 11. With each increase in mask size, the RMSE of each test increased.



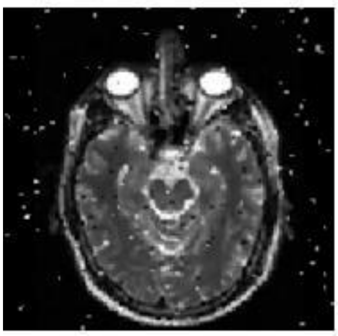
(a) Original Image



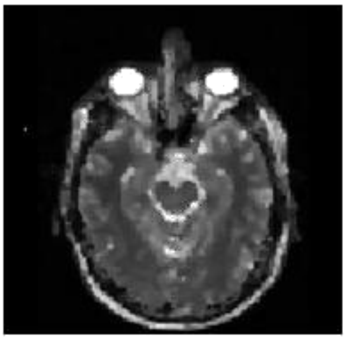
(b) Noised Image



(c) Mean Filtered Image



(d) Median Filtered Image



(e) Adapted median filtered Image

Fig 2 (a) Original MRI sample for processing (b) noised image sample at variance of ρ = 0.1

(c) mean filter output of noise image sample (d) median filter output for the same noised sample

(e) obtained filtered output using proposed AMF filtration

Fig 2 illustrates the obtained result observation for given MRI sample, affected by salt pepper noise at a variance of 0.1. The estimation using Adaptive mask filter is observed to be more effective in estimation in comparison to the conventional filtration approaches. Due to the usage of block mask processing, the surrounding pixels were processed with low region noise distribution in comparison to the existing filtration approach.

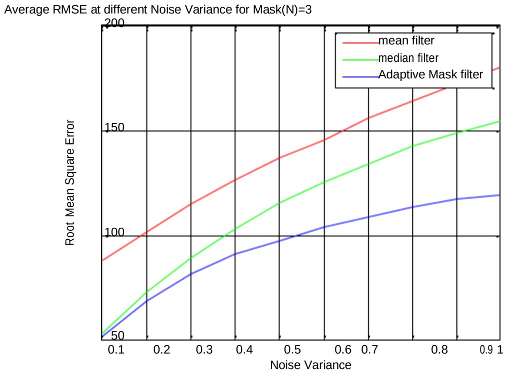


Fig. 3 comparative variation of obtained RMSE value over noise variation for the masking length of 3 for the three filters

As shown in fig.3 the obtained RMSE estimation from the proposed technique shows that with the increase in noise variance, the obtained RMSE for the proposed AMF filtration is relatively lower than the other two conventional techniques. With increase in noise variance to the input signal, it is observed that RMSE effectively drops down almost to 1/2 for median filter and twice for mean filter. Table1 shows the observations for obtained RMSE value over different noise variance for the given sample.

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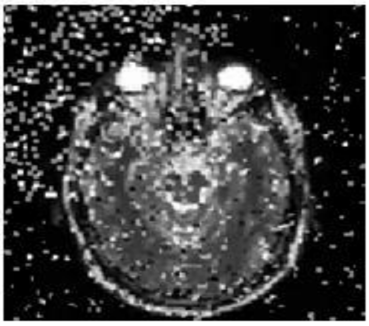
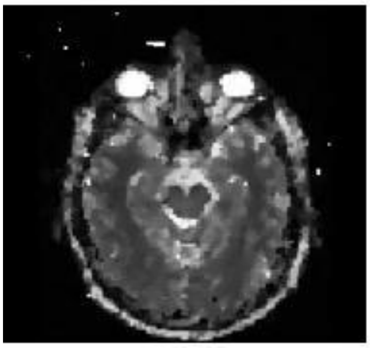
Table 1: Observations for obtained RMSE value over different noise variance for the given sample

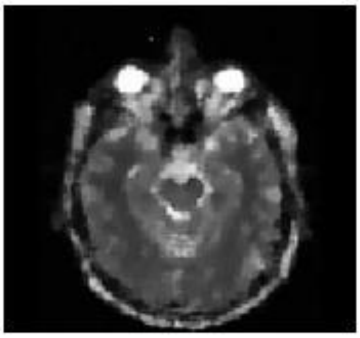
Noise variance(ρ)	RMSE (mean filter)	RMSE (median filter)	RMSE (adaptive filter)
0.1	90	55	55
0.2	101	65	60
0.3	115	90	80
0.4	125	102	90
0.5	137	115	99
0.6	147	125	105
0.7	155	137	110
0.8	160	145	115
0.9	170	150	120
1.0	173	153	123



(a) AM Filtered at N=2



(b) AM Filtered at N=3



(c) AM Filtered at N=4

Fig 4 (a) filtered output at N=2 for the proposed AMF filter (b) Result at N=3 (c) Result at N=4

Figure4 illustrates the obtained result observations with the variation in block size (N) for the Adaptive mask filters. The result at N=3, 4 is observed to be more accurate than and N=2 and get saturated at N=5.

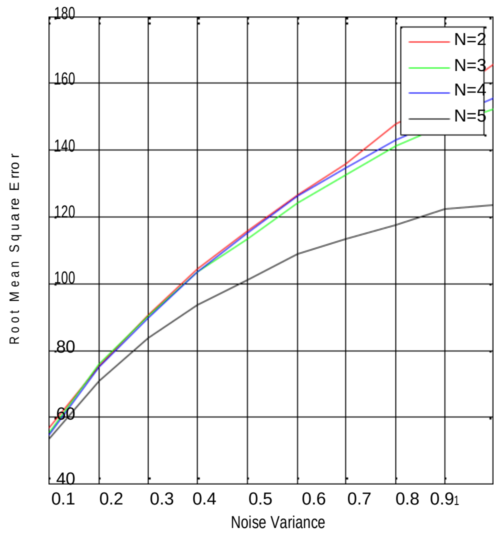


Fig.5 RMSE observed for the AMF filter at different block lengths for Noise variance of 0.1 to 1.

The observation made for the RMSE value at different noise variance with the change in block size

(N) is presented in figure 5. The RMSE value for the test MRI sample is observed comparatively very low for mask size of N=5 for high noise variance in the given test sample. Table 2 shows the observation of RMSE at different noise variance for different mask size.

Table 2: Observation of RMSE at different noise variance for different mask size.

Noise variance (ρ)	RMSE (N=2)	RMSE (N=3)	RMSE (N=4)	RMSE (N=5)
0.1	55	55	55	55
0.2	70	70	70	65
0.3	90	90	90	85
0.4	105	105	105	90
0.5	115	114	115	101
0.6	125	124	125	110
0.7	138	136	137	115
0.8	144	142	143	119
0.9	158	155	156	122
1.0	162	157	158	122

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V. CONCLUSION

In this paper an adaptive filter for the elimination of impulse noise from images is evolved and shown how it perform better than other well-known techniques for noise elimination. Firstly, common noise filtering algorithms were discussed. Next, a Spatial Median Filter was proposed based on a combination of work on the Median Filter and the Spatial Median quantile order statistic. Looking that the order statistic could be employed in order to formulate a decision as to whether a point in the signal is selected is noise or not, a Modified Spatial Median Statistic is projected. The Modified Spatial Median Filter needs two parameters: A window size and a threshold T of the estimated non-noisy pixels under a mask. In the results, the best threshold T to use in the Modified Spatial Median Filter and determined that the best threshold is 4 when using a 3×3 window mask size. Using these as parameters, this filter performance was improved in a comparison to the Mean, Median, and Spatial Median Noise Filters. In the broad comparison of noise elimination filters, it was concluded that for images containing noise variance of ρ = 0.15, the Modified Spatial

Median Filter performed the best and that the Adapted Median Filter performed the best over all noise models tested.

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