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Research Article

BILATERAL MESH FILTERING FOR MR IMAGES

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ABSTRACT

The paper here a innovative graph-based realization of bilateral filtering. Based on the Laplacian mesh smoothing framework, the proposed filter imitate the performance of the conventional mesh filter while preserve in some of the appealing properties of mesh smoothing. The corresponding two filters are benchmarked according to their ability to denoise complex synthetic image transitions. The relevant performance of the filters are then assessed in a multiresolution denoising scheme for grayscale images, combining wavelet decomposition, shrinkage and bilateral filtering. The results obtained are encouraging and shows that the BMF is a viable alternative to classical bilateral filtering. An important issue with the application of the bilateral filter is the selection of the filter parameters, which affect the results significantly. A mesh is crucial for feature-preserving mesh denoising. Our bilateral filter is a additional accepted conservatory of the elegant bilateral filter for image denoising than those used in preceding bilateral mesh denoising methods.

Keywords: Bilateral Filter,BMF,Bilateral Mesh denoising,Graph Implementation.

INTRODUCTION

The bilateral filter (BF) was first introduced in 1998 by Tomasi and Manduchi (1998) and applied to noise removal in images. The bilateral filter is a non-linear filter designed to smooth noisy images whereas preserving the border structure and may be seen as an extension of Gaussian filters. The bilateral filter is the definition of intensity nearness between pixels. In the bilateral circumstance, two spatially close pixels with similar gray levels will interact through the filtering process, while these relations decrease exponentially with a superior difference in pixel intensities. However, the bilateral filter may be approximated by iterative methods which are close to the ideal filter in terms of results and capable in terms of implementation (Pham and van Vliet, 2005). Moving to the confines of the filter, the main drawback of the filter is to create a staircase effect due to its propensity to estimated the image by piece-wise constant regions[1-5].

In recent times, the image processing and analysis gained popularity by using graphs, with successful appliance to image segmentation (Goksel and Salcudean, 2011) and registration (Weibel et al., 2010). In general, a graph is a non-empty set of points (vertices) and the most basic information conserved by any graph arrangement is adjacency relationships (edges) between some pairs of points. The method mimics the behaviour of the pixel-based bilateral filter while applying exponential law. It highlights the challenges to be addressed to improve the performance of the BMF. Mesh denoising is a essential preprocessing tool for improving deficient meshes obtained from scanning devices and digitization processes. Although there already exist a variety of mesh denoising methods, research on attribute preserving denoising remains active due to its challenging nature. In this paper, we propose a fast separable implementation of the bilateral filter. As an application, the separable bilateral filtering is applied to improve image quality & coding efficiency of MRI images[6-10.]
Filtering is perhaps the most fundamental operation of image processing and computer vision. In the broadest sense of the term "filtering", the value of the filtered image at a given location is a function of the values of the input image in a small neighborhood of the same location. For example, Gaussian low-pass filtering computes a weighted average of pixel values in the neighborhood, in which the weights decrease with distance from the neighborhood center. Although formal and quantitative explanations of this weight fall-off can be given, the intuition is that images typically vary slowly over space, so near pixels are likely to have similar which values, and it is therefore appropriate to average them

together. The noise values that corrupt these nearby pixels are mutually less correlated than the signal values,The assumption of slow spatial variations fails at edges, are consequently blurred by linear low-pass filtering. Bilateral filtering is a simple, non-iterative scheme for edge-preserving smoothing.

PIXEL-BASED BILATERAL FILTE

The pixel-based bilateral filter (BF) proposed by Tomasi and Manduchi uses a non-linear kernel to smooth the noise while preserving edge structures. BF is based on the introduction of the concept of intensity proximity between pixels. In this framework,the contribution of the neighbouring pixel to the filtered value of the center pixel will not only depend on a geographic proximity between pixels but also on their respective intensities. As the support of the exponential function is unlimited, the extend of the filtering is limited for computational reasons to a window X, with typical dimensions of 5 _ 5 pixels. It may be observed that the result of the bilateral filter depends on two parameters in addition to the size of the window. These two parameters, rd and rr, respectively control the width of the lobe in the geographic and intensity space. A large value of r leads to a wide lobe and the opposite effect is obtained with a small value of r. When rr is very large, the bilateral filter degenerates to a Gaussian filter[11-12].

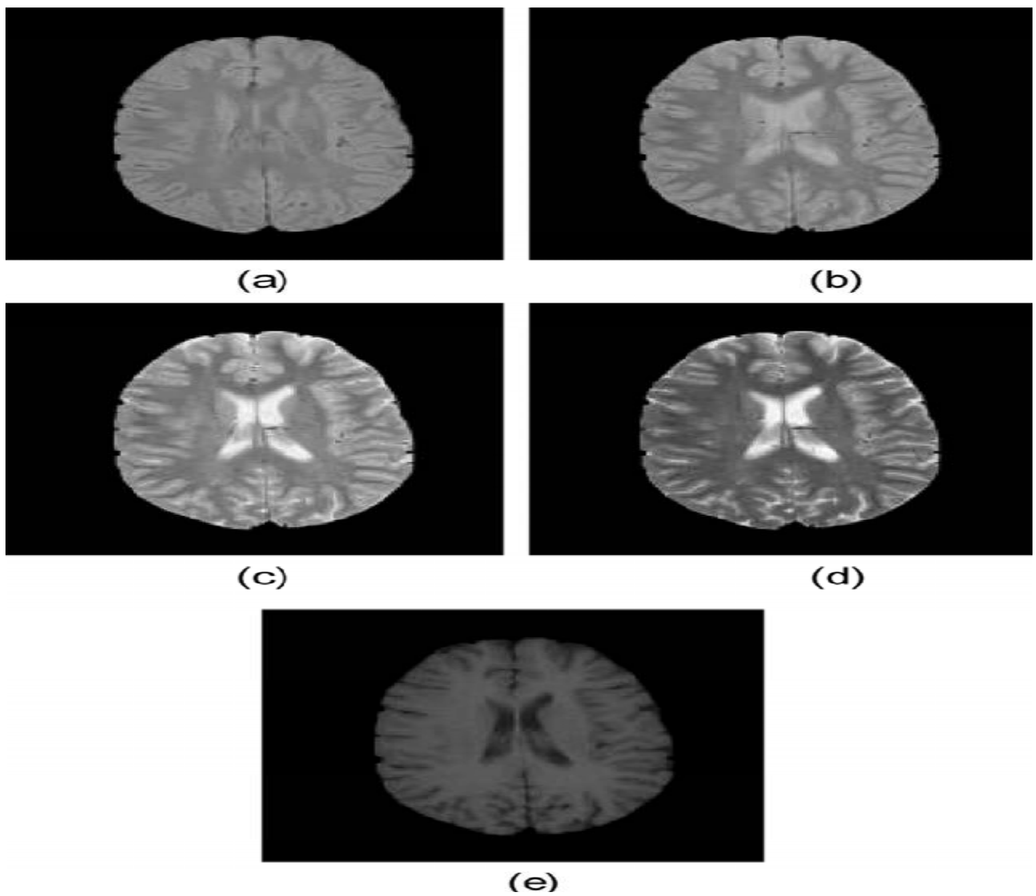

Fig. Five band MR images

BILATERAL FILTER

Bilateral filter is a nonlinear filter which removes Gaussian noise by preserving edges. Each pixel is replaced by a weighted average of the intensities in the window. The weighting function gives high weighting to those pixels that are both near the central pixel and similar to central pixel. Bilateral filter consists of Gaussian filter and range filter. Let $x_{i,j}$ be the current pixel, and let $x_{i+s,j+t}$ is the pixel in a $(2N+1)\times(2N+1)$ window. In the Gaussian filter, the Euclidean distance between centre pixel and other pixels in the window and in the range filter the difference of luminance is computed.

$$y_{i,j} = \frac{\sum_{s,t=-N}^{N} W_G(s,t)\, W_R(s,t) x_i\, x_{i+s,j+t}}{\sum_{s,t=-N}^{N} W_G(s,t)\, W_R(s,t)}$$

Where $W_G(s,t) = \exp - \frac{(\mathrm{i-s})^2 + (i-t)^2}{2\sigma_R^2}$

$$W_R(s,t) = \exp - \frac{x_{i,j}(-x_{i+s,j+t})^2}{2\sigma_R^2}$$

Hence bilateral filter provides a great result in removing Rician noise, but it's difficult to remove impulse noise. To remove both the noise we use switching bilateral filter.

3.1. SWITCHING SCHEME

In switching scheme, the noise detector searches for noisy pixels in an image and distinguish them from uncorrupted ones and it also decides whether the current pixel should be filtered by using SBF impulse or SBF Gaussian or whether it should bypass the SBF. Also $S1$ and $S2$ denote binary control signals generated by the noise detector. The filtered image is defined as follows:

$$u_{i,j} = \begin{cases} SBF_{im}, & S1 = 1 \ S2 = 1 \\ SBF_{ga}, & S1 = 1 \ S2 = 0 \\ u_{i,j}, & S1 = 0 \ S2 = 0 \end{cases}$$

The switching scheme can be implemented in a recursive manner provides better results.

NOISE DETECTOR DESIGN

Noise detector is used to determine whether current pixel is corrupted or not. This decision can be done on the basis of features of SQMV. Here the decision making mechanisms can be realized by employing a reference median and the two thresholds $(TK_1 and TK_2)$ and the noise detection algorithm is given by:

If $\left(\left|x_{ij} - SQMR\right| \geq TK_1\right)$

$S1 = 1, S2 = 1 \left(x_{i,j} \text{ is impulse noise}\right)$

If If $\left(\left|x_{ij} - SQMR\right| \geq TK_2\right)$

$S1 = 1, S2 = 0 \left(x_{i,j} \text{ is Gaussian noise}\right)$

Else

$S1 = 0, S2 = 0 \left(x_{i,j} \text{ is noise free}\right)$

End

Where $(TK_1 and TK_2)$ are thresholds for identifying impulse noise or Gaussian noise.

DESIGN OF SWITCHING BILATERAL FILTER

Switching bilateral filter (SBF) is a universal noise removal algorithm. Let $x_{i,j}$ be the current pixel, and let $x_{i+s,j+t}$ is the pixel on a $(2N+1) \times (2N+1)$ window surrounding $x_{i,j}$.

$$y_{i,j} = \frac{\sum_{s,t=-N}^{N} W_G(s,t)\, W_{SR}(s,t)\, x_{i+s,j+t}}{\sum_{s,t=-N}^{N} W_G(s,t)\, W_{SR}(s,t)}$$

Where $W_G(s,t) = \exp - \frac{(i-s)^2 + (i-t)^2}{2\sigma_R^2}$

$$W_{SR} = \exp - \frac{\left(I - x_{i+s,j+t}\right)^2}{2\sigma_R^2}$$

$$I = \begin{cases} SQMR, & s_2 = 1 \ for\ SBF_{im} \\ x_{i,j}, & s_2 = 0 \ for\ SBF_{ga} \end{cases}$$

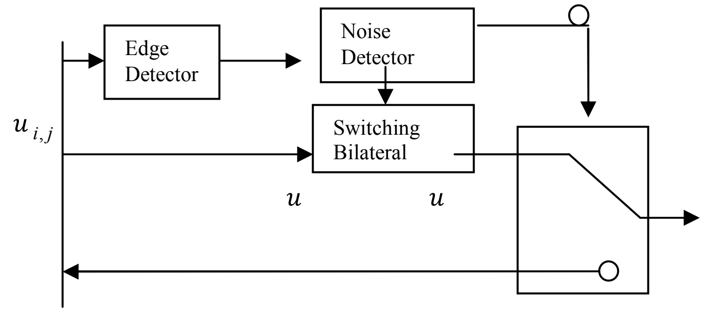

Figure: Switching scheme detection with two detectors

By replacing $x_{i,j}$ with $SQMR$ of the bilateral filter, the impulse noise can be removed. The difference between neighbours and median would not be too large and, thus edges and details can be preserved while removing the noise. The SBF provides sharper image than the median filter. Thus SBF not only removes Gaussian noise but also impulse noise while keeping the details and the edges.

MESH SMOOTHING

This paper presents frameworks to extend the mean and median filtering schemes in image processing to smoothing noisy 3D shapes given by triangle meshes. The frameworks consist of the application of the mean and median filters to face normals on triangle meshes and the editing of mesh vertex positions to make them fit the modified normals. We also give a quantitative evaluation of the proposed mesh filtering schemes and compare them with conventional mesh smoothing methods such as Laplacian smoothing flow and mean curvature flow. The quantitative evaluation is performed in error metrics on mesh vertices and normals. Experimental results demonstrate that our mesh mean and median filtering methods are more stable than conventional Laplacian and mean curvature flows. We propose thee new mesh smoothing methods as one possible solution of the oversmoothing problem.

Edge-preserving smoothing is an image processing technique that smoothes away textures whilst retaining sharp edges. When we need to preserve edge information and at the same time preserve the edges. Even when uniform smoothing does not remove the boundaries, it does distort them. This is not acceptable in the context of,medical imaging.An alternative to linear filtering, called anisotropic diffusion, was introduced by Perona and Malik. It is related to earlier work by Grossberg who used a similar nonlinear diffusion processes to model human vision. The motivation for anisotropic diffusion (also called nonuniform or variable conductance diffusion) is that a Gaussian smoothed image is a single time slice of the solution to the heat equation, that has the original image as its initial conditions. Anisotropic diffusion includes a variable conductance term that, in turn, depends on the differential structure of the image. Thus, the variable conductance can be formulated to limit the smoothing at "edges" in images, as measured by high gradient magnitude[13].

FEATURE PRESERVATION

The filtering method we have proposed preserves features through two combined actions. First is the use of a robust weight function,while the second is our use of a predictor for vertex positions based on the tangent planes of the mesh. This predictor does not move vertices located at sharp features separating smooth areas of the mesh, since feature vertices are supported by the prediction from both sides. Neither of these actions is sufficient alone, but together they provide excellent feature-preserving behavior. Note the connection to bilateral filltering for images, which uses a prior of piecewise constant images. This is a special case of our formulation, corresponding to the predictor q(p) = cq. As well, the use of the existing mesh facets helps to simplify our formulation and its implementation, as they provide direct estimates for surface tangents.In a nutshell, they seek to avoid dissipation of shocks the equivalent of sharp features in our geometric setting. They base their local evaluation of differential quantities only on the local neighbors of similar field[14].

BILATERAL MESH DENOISING

We open with a description of our method for filtering a mesh using local neighborhoods. The main idea is to define a local parameter space for every vertex using the tangent plane to the mesh at a vertex. The heights of vertices over the tangent plane are synonymous with the gray-level values of an image, and the closeness components of the filter are the tangential components. The term *offset* is used for the heights. Let *S* denote the noise-free surface,and let M be the input mesh with vertices that sample *S* with some additive noise. Let **v** 2 *M* be a vertex of the input mesh, *d*0 its signed-distance to *S*, and **n0** the normal to *S* at the closest point to **v**. The noise-free surface *S* is unknown and so is *d*0, therefore we estimate the normal to the surface as the normal **n** to the mesh, and *d* estimates *d*0 as the application of the filter, updating **v** as follows:

$$\hat{\mathbf{v}} = \mathbf{v} + d \cdot \mathbf{n}. \quad (1)$$

Note that we do not have to define a coordinate system for the tangential component; as explained below, we apply a onedimensional filter with a spatial distance as a parameter. The filter is applied to one vertex at a time, computing a displacement for the vertex and updating its position.

CONCLUSIONS AND FUTURE WORK

This paper proposes a new bilateral filter based on the Laplacian mesh smoothing framework. The filter is easy to implement and gives promising results for denoising grayscale images. However, several challenges still remain. First of all, the proposed method requires the solution of a very large scale linear system. Several techniques to solve large scale linear systems such as block and domain decomposition as well as multi-grid techniques would be beneficial to decrease the computation time of BMF. On the other hand, further experiments based on the other applications of BF like image fusion are necessary to validate the BMF as a potential alternative to the BF, not only in denoising but also in all other applications making use of the BF. Finally, it would be interesting to analyse the link between the proposed method includes the following:

- Many noise removal algorithms, such as bilateral filtering, tend to treat impulse noise as edge pixels, and hence, end with unsatisfactory results.
- In order to process noise pixels and edge pixels differently, SQMV algorithm is used to obtain edge information present in an image and reference median value for noise detection, which detects impulse,Rician noise and Gaussian noise.
- By incorporating this SQMV algorithm into a new non linear filter called switching bilateral filter, where it switches between the Gaussian and impulse noise based on the control signals and replaces the current pixel with the reference median value in the range filter function.
- This switching bilateral filter shows good performance in identifying mixed noise models.

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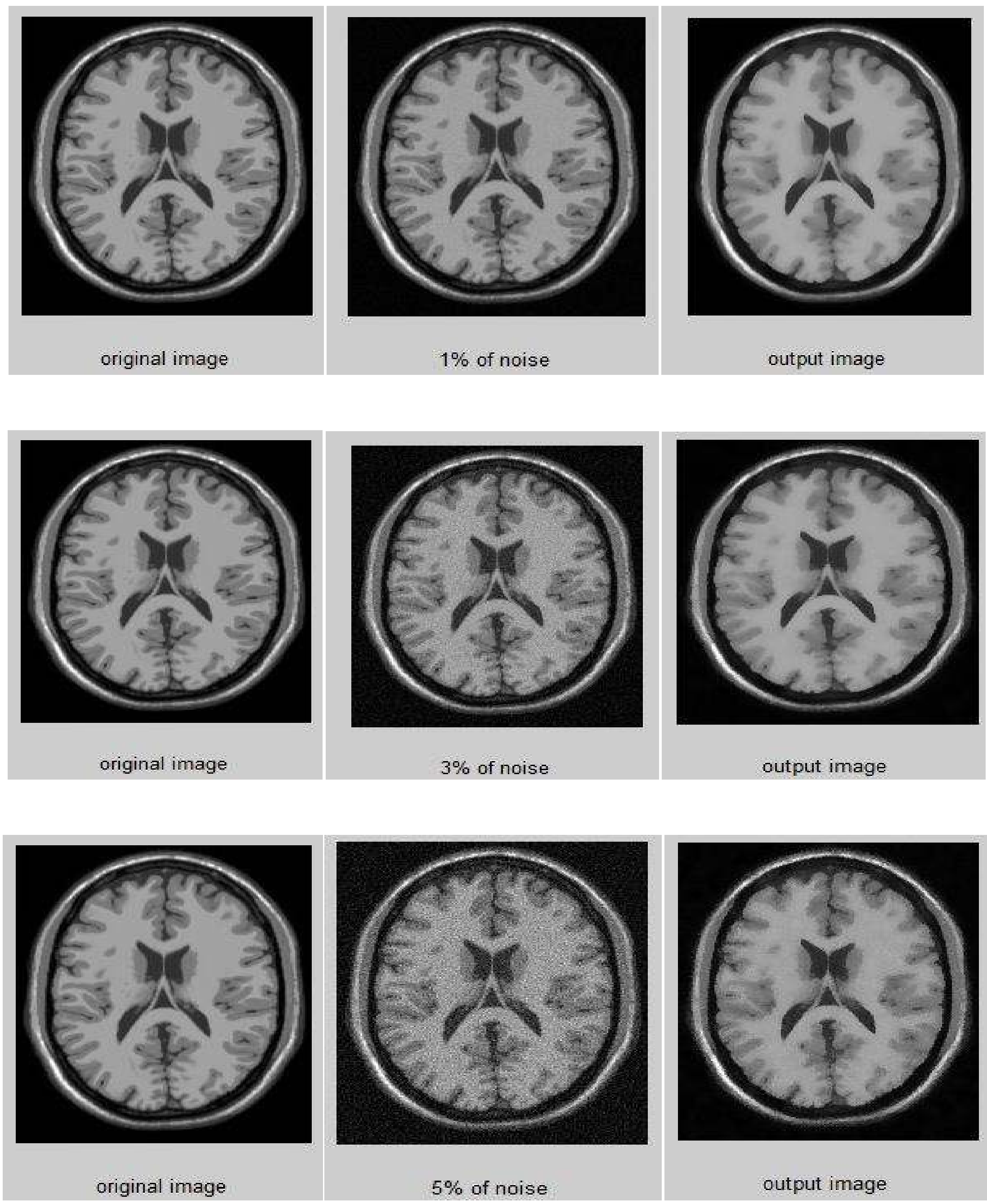
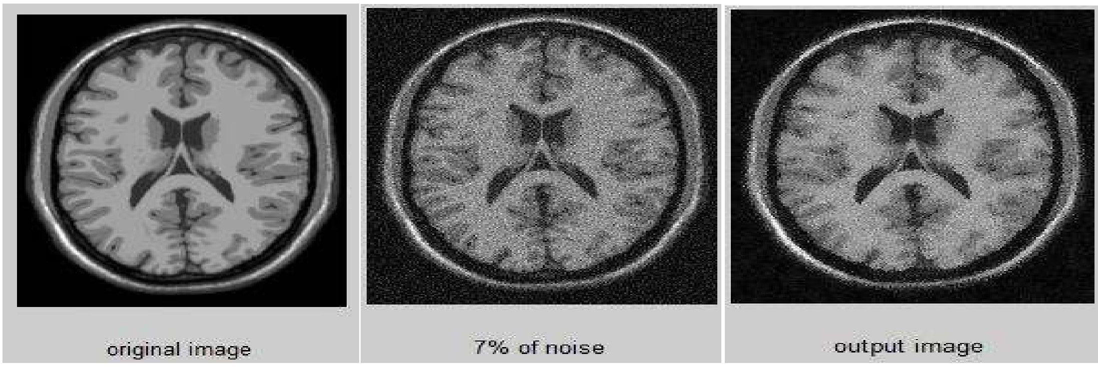
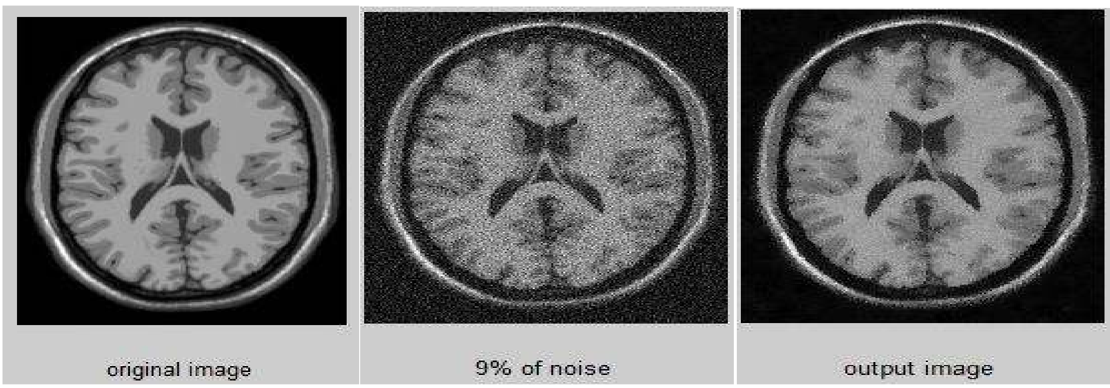
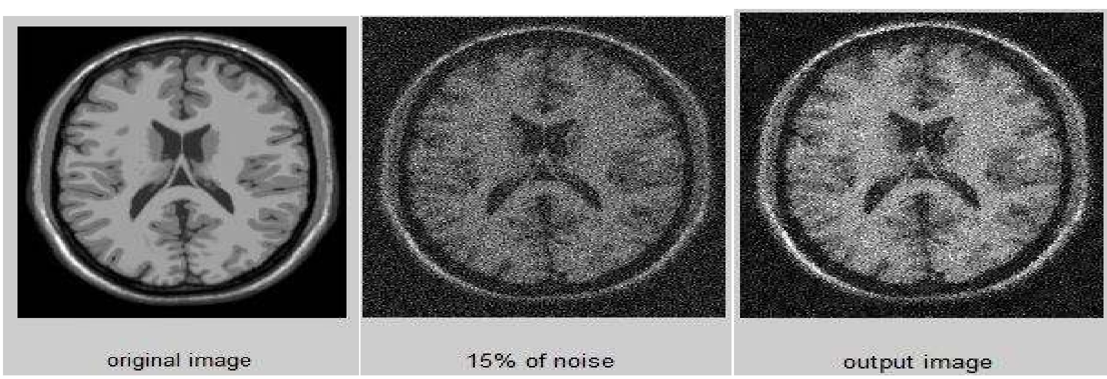
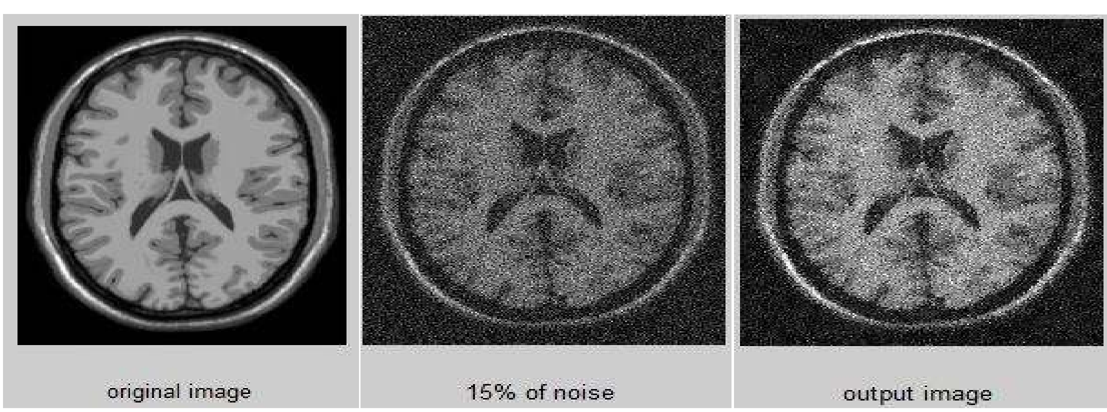
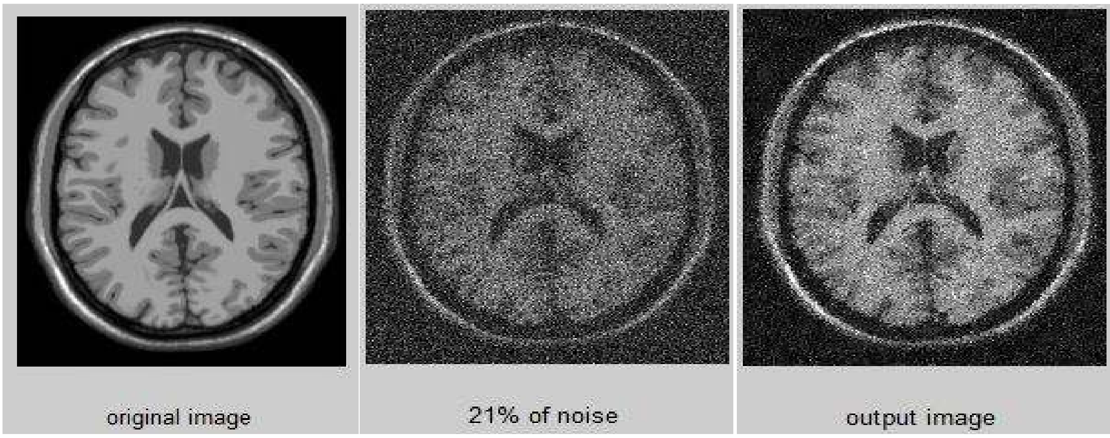



original image
7% of noise
output image

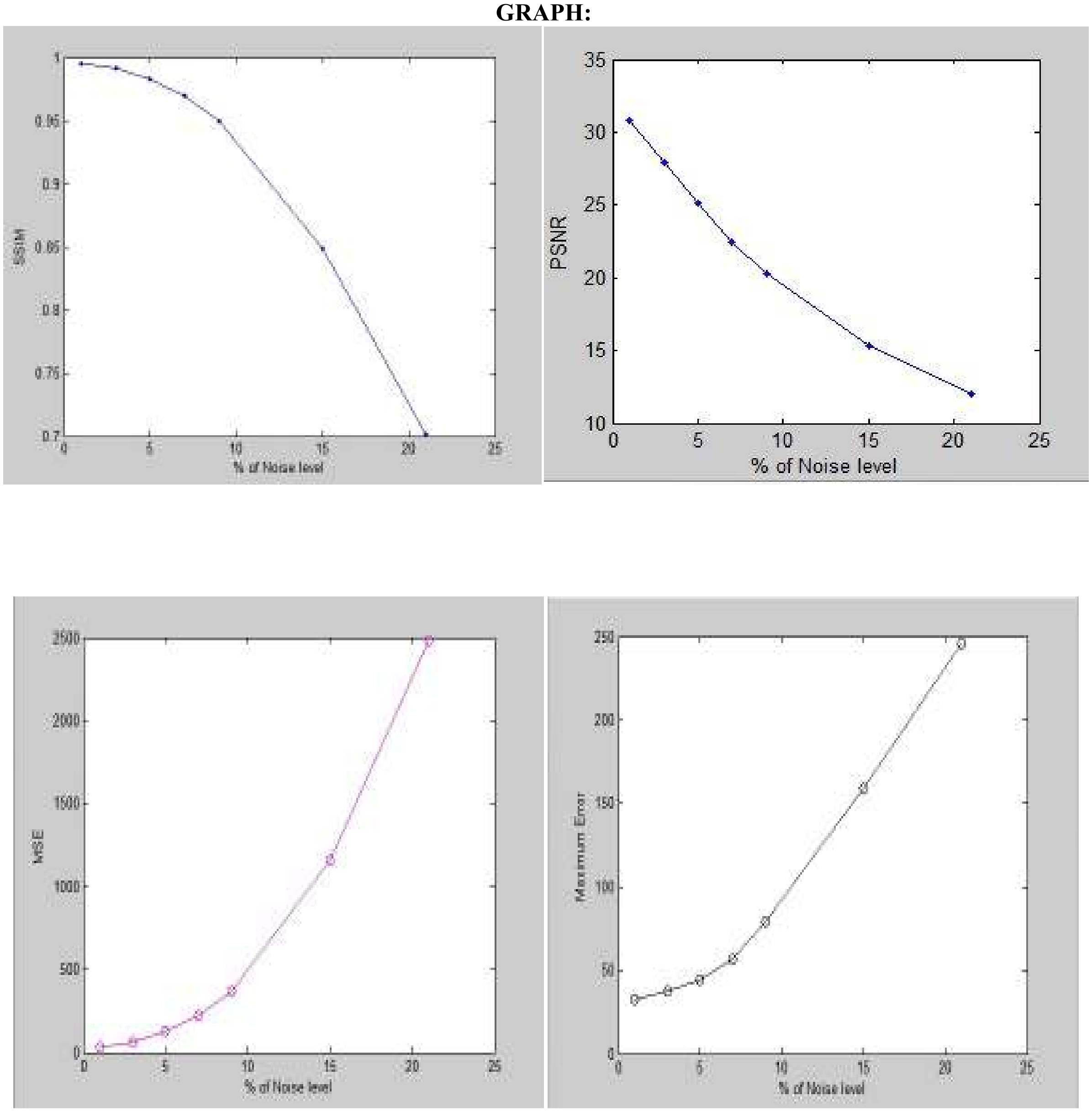

original image
9% of noise
output image


original image
15% of noise
output image


original image
15% of noise
output image


original image
21% of noise
output image

GRAPH:


SSIM
% of Noise level
PSNR
% of Noise level
MSE
% of Noise level
Maximum Error
% of Noise level

TABULATION:

```
SSIMBF =

    0.9954    0.9914    0.9831    0.9696    0.9504    0.8467    0.6969


PSNR =

   32.9536   30.2246   27.2489   24.6402   22.5271   17.4852   14.1193


MSE =

  1.0e+003 *

    0.0329    0.0617    0.1225    0.2234    0.3634    1.1603    2.5186


MAXERR =

   31.7627   38.1192   46.2235   65.2730   76.9155  144.0733  213.0983


noise =

     1     3     5     7     9    15    21
```

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