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Image Denoising Techniques on Medical and Microscopic Images

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I.**ABSTRACT—**Denoising MRI images,denoising is nothing but removing noise from an image.This applies for CT and microscopy images.Equally using deep learning for denoising especially for MRI images, we should say still a new and emerging field so we really do not like to focus a lot on deep learning aspects .In this paper, we have discussed some traditional ways to remove noise from MRI images and validated algorithms such as Gaussian denoising, bilateral filter,anisotropic diffusion, BM3D algorithm along with non-local means filtering. Microscopy is an important part of a biologist's daily work, included in many parameters such as protein sub-cellular localisation , changes microtubule dynamics. A fundamental challenge that is faced even in microscopy is dealing with various noises present in them. To denoise microscope images we are using same algorithms as mentioned in MRI images.

Keywords—denoising,MRI ,BM3D,Gaussian denoising, bilateral filter, anistropic diffusion,non-local means.

II .Introduction

Medical imaging is a method and procedure used to view and create visual picturization of the body for clinical and therapeutic purposes and provides a clear representation of the function of certain internal organs or tissues. Therefore, it plays an essential role in improving public healthcare for various groups of people. Medical images actually helps to reveal the hidden structures of the skin and bones, in order to diagnose diseases. It is part of biological imaging and helps in establishing a database of common body structure of humans and physiology for the discovery of abnormalities. Includes imaging technology X-ray radiography [1], magnetic resonance imaging, medical ultrasonography, elastography,endoscopy, thermography, tactile imaging, medical imaging and positron emission tomography (PET), Single-photon emission computed tomography also known as SPECT which is a technique used in nuclear medicine. Since many repetitive patterns exist in natural and medical imaging, the NLM filter proposed by it has attracted special attention to audio output especially MR images. Traditional MRI denoising techniques were originally designed to remove Gaussian noise from an image. Later new methods were proposed as non-native (NLM) methods, wavelets In this paper, we proposed an overview of different image modes, sound types and their filtering methods and discussed the removal of various sounds in MR images using different filters. .

III.RELATED WORK

The BM3D is generally considered to be the best at removing noise from an image, Burger etal. [1] demonstrated how similar denoising performance can be achieved with a plain multi layer perceptron also known as MLP. Denoising auto-encoders are the latest addition to audio removal books. They are used as a blockchain to build deep networks, which is delivered by Vincent et al, as an prior extension to the classic automatics. It was briefly shown that the default auto encoders can be packed to build a deep neural network.

The output of image produced using convolutional neural networks was a research work done by Jain et al [2]. He has proven that usage of small sample training datasets shows better performance than the usual wave fields and Markov stadiums. Agostenelli et al. [3] works with deep neural networks with many flexible columns to produce an image. With different audio images, this program shows excellent results. In Jain and Seung [4] (2008), a new image was described, describing an algorithm based on a common neural network, equivalent to the Markov Random Field (MRF) model and the multi-layer view used successfully in image extraction.

The algorithm for analyzing the new image with advanced convolutional neural networks with vision loss was largely focused on the research work done by Shan Gai. The image extraction based on the gaussian filter contains clear details of BK Shreyamsha's research work [5].

The use of a two-dimensional filter for image removal has been the main focus of Bonsle's work [6]. More detailed research work can be found in Barash's research work based on the basic relationships within dual filter, flexible, and indirect smoothing

distribution rates [7].

The amount of differential filtering [8] and the filtering of non-native methods [9] [10] in medical imaging have been the field of extensive research competing with emerging algorithms such as BM3D [11].

Small image extraction and effects of [12] Gaussian-Poisson sound in very small images and their removal using a 2D wavelet algorithm [13] and a new sparsity-based approach [14] are well discussed by Meiniel and Williams in their research work .

IV. **Types of Noises used** Gaussian

noise:

Gaussian noise also referred as Gaussian distribution. The Gaussian distribution is as shown in fig 1., is added to MR image during image[12] acquisition. This statistical noise is known for having equal normal distribution and probability density function.This noise is further removed with the help of various filters in experimentation held.

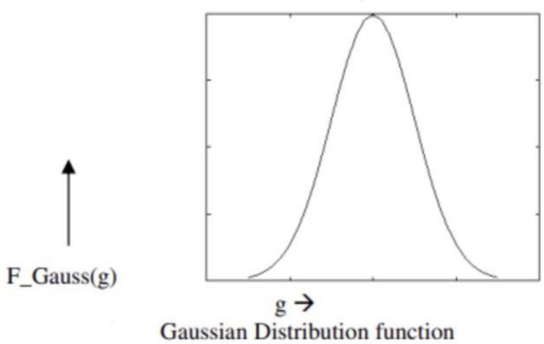


Fig 1. Gaussian distribution

Salt and Pepper noise:

Salt and pepper noise defined by Impulse noise or generally referred as Spike noise, normally occurs due to imperfect or noisy pixels in camera sensors, distorted memory locations present in hardware. Another type of noise is the random-valued noise, which can take grey value level from 0 to 225.

V. Denoising Techniques used:

1. Gaussian Filter:

Two dimensional digital Gaussian filter can be defined as[5] shown in eq(1).

$G(x,y) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(x^2+y^2)/2\sigma^2}$----(1)

G (x y) – Output obtained from Gaussian Kernel formula, that forms part of the Kernel, which represents one object. π - Fixed figures are defined as 22/7.

σ - This symbol simply represents the limit or value of a feature, as specified by input user.
e - Euler's number. Euler's numerical value is defined as a statistical value which is numerically 2.7182818284.
x, y – These two variables denote pixels linking within the image.
y Represents a direct row and x represents a horizontal column.

2. Bilateral Filter:
Bilateral was introduced as a linear filtering method which can combine domain and range filtering[7].
The bilateral filter is defined as shown in eq(2).

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

$$I^{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|), \qquad (2)$$

And the normalisation term Wp is given as

--(3)

Where,

I^{filtered} defines output filtered image;

I is assigned input image to be filtered;
X gives coordinates of current filtered pixels ;
Sigma denotes windows centered in x;
And f_r and g_s are range kernel for smoothening variations in intensities and spatial kernel for smoothening variations in coordinates respectively.

It is edge-preserving, non-linear noise reduction filter for works by replacing the intensity of each pixel with weighted average of intensity values obtained from nearby pixels [6]. Weights are generally based on Gaussian distribution. Bilateral filter takes both spatial and intensity into consideration between a particular point and ints neighbouring points unlike other filters[7]. This helps in preserving sharp boundaries while noise is averaged out.

3.Total variation (TV) :

Commonly known *as total variation regularisation* of total variation filtering, is a noise removal process based on principle that signals with excessive and possibly spurious detail having high total variation.
The rate of change in signal values can be measured accordingly with the usage of TV filter
Specifically, the total variation of an N- po*int*

Signal $f(n)$, $1 \le n \le N$ is as described as below.

$$\mathrm{TV}(\mathbf{x}) = \sum_{n=2}^{N} |x(n) - x(n-1)|.$$

The total variation of $\mathbf{x}$ can also be written as

$$\mathrm{TV}(\mathbf{x}) = \|\mathbf{D}\mathbf{x}\|_1$$

where $\|\cdot\|_1$ is the ℓ_1 norm and

$$\mathbf{D} = \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & & \ddots & \\ & & & -1 & 1 \end{bmatrix}$$

is a matrix of size $(N-1) \times N$.

But the algorithm described here may converge slowly for some problems.The regularization parameter controls how much smoothing is to be performed. Larger the noise, larger the volume of parameter required.[8]

4.Wavelet denoising :

Wavelet filter command allows us to selectively emphasise or de-emphasise image details in a certain spatial frequency. It has a powerful advantage because of its ability to obtain the information like time, location, and frequency of an image simultaneously. Whereas the FT (Fourier transform) provides only the frequency information of the signal.

In fig 2, An image can be defined withM1 rows and M2 columns, output decomposed results in 4 quartersize images :details (ll,hl,hh) and approximation ll. Approximation figure ll can be defined as product of two low-passband filters and derives an input for upcoming decomposition level. The reformation is performed in the other way around i.e first on columns, then on rows.Three wavelet functions which are given as

$$\psi^1(m,n) = \phi(m)\psi(n) \quad LH wavelet,$$

$$\psi^2(m,n) = \psi(m)\phi(n) \quad HL wavelet,$$

$$\psi^3(m,n) = \psi(m)\psi(n) \quad HH wavelet,$$

and one scale function:

$$\phi^2(m,n) = \phi(m)\phi(n)$$

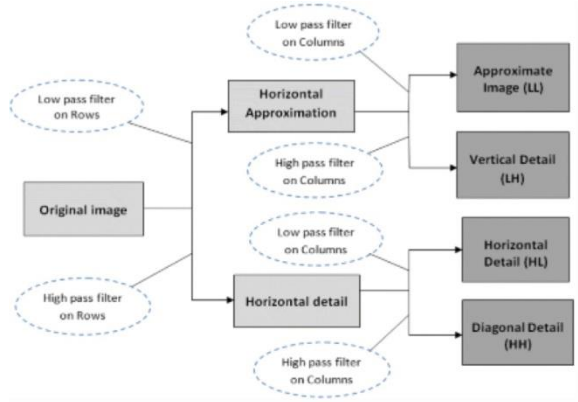


Fig 2. Wavelet denoting algorithm

5.Non Local Means (NLM) :

Other than "local mean" filters which take mean value of grouped pixels around a targeted pixel towards smoothing an image, this filtering takes average value of all pixels in image according to weights relating to how similar these pixels are to target pixels. NLM can normally be classified into 4 different types , which can be used to produce better SNR value and also this is the best method for preserving edges.

Algorithm Non-Local Means
Input 1: Image with Radom value impulsive noise
Output1: NLM (Denoised Image)
For each pixel i, where ii ϵ [1,N],
Do
For each pixel in N_k, where N_k is the square patch around the center pixel k,
Do
Evaluate, normalization constant $Z(i) \sum_j e^{\frac{\|v(N_i)-v(N_j)\|^2}{h^2}}$
Where j refer to the $N_k$patches
Calculate, weight matrix $W(I,j) \frac{1}{z(i)} e^{\frac{\|v(N_i)-v(N_j)\|^2}{h^2}}$
Done
Denoise pixel i; NL[v] (i) $\sum_{j=1} w(i,j) v(j)$
Done

Fig 3. NLM algorithm

The general description of NLM filter can be given as[9] : When input image I is given , the filtered value at a point p which is ,the mean value of all the pixels in the image is calculated using NLM algorithm. Algorithm description is as shown in fig 3.

6.Anisotropic filter:

Filter is known for treating all axes equally. To summarize, when seen at a certain angle filter provides clarity for distant surface textures.

In image processing first anisotropic idea is dated back to Graham in 1962, followed by Newman and Dirlten , Lev , Rosefeld and Zucker , and Matsuyama and Mango. [10] They mainly emphasised on usage of convolutional mask that depends on the underlying image structures. Spatial regularisation strategies are usually applied in anisotropic diffusion filters.

There are two types of representations of anisotropic diffusion processes. First one shows an advantage at noisy edges , whereas second one is efficient in processing one- dimensional features.

Generally, let $\Omega \subset R^2$ denotes a subset of plane and $I(\cdot,t) : \Omega \rightarrow R$

be a group of gray scale images.

I(.,0) is input image.

Then the anisotropic diffusion can be defined as

$$\frac{\partial}{\partial' t}=\mathrm{div}(c(x,y,t)\nabla l)=\nabla_c ?\nabla l+c(x,y,t)\Delta l \text{---(4)}$$

Where Δ denotes Laplacian , gradient is denoted by ∇, and divergence operator div(..) and c(x,y,t) is coefficient of diffusion.

Normally the results of anisotropic filters can be generalized to higher dimensions. This can be useful when considering medical image sequences from magnetic resonance imaging (MRI) or computerized tomography (CT) or while applying diffusion filters to post processing of higher dimensional numerical data.

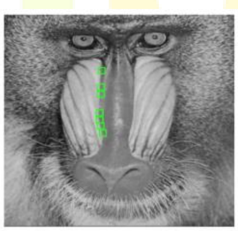
7.BM3D

Recently, fields of interest in image processing research are non-local algorithms . In this algorithm, instead of filtering neighbourhoods, similar image blocks across image are recognised. These likely patch groups form the 3D matrix and then the obtained matrix is subjected to filtering in the transform domain with thresholds selected appropriately.

These patches have smaller equivalence of noise when compared to local neighbourhoods hence provide improved results than many neighborhood based filtering schemes.[11]

Also BM3D is known for smoothening artefacts from outputs of adaptive and median filters which Appear in images with high percentage of impulses. The test image of BM3D algorithm is as shown in fig 4.

The BM3D algorithm is split into coarse and fine algorithm runs. Brief algorithm of BM3D paper can be obtained from reference paper[11].



”“

Fig 4. Similar block recognition in BM3D algorithm.

VI. EXPERIMENTATION:

We took a sample of DICOM format, and later converted them into TIFF format before adding noise to it. Then the Gassian and Salt and Pepper noise area added to same images in two different instance and simulation outputs related to six denoising algorithms and respective run time for every filter is recorded and tabulated.

Spyder was used for implementation of all the 6 described algorithms using python on macbook pro(Intel core i9, 1 TB SSD, no GPU).

Images were compared using Peak Signal to Noise Ratio(PSNR) in every case using different algorithms. The PSNR gives us the peak signal-to-noise ratio, in decibles, between noisy image and output image. This ratio can be used as a quality approximation parameter between the original and filtered image . Higher PSNR results in improvised compression quality or denoised image.

In order to find the PSNR value, we first need to calculate the mean squared error, which can be done using following equation (5)

$$\mathrm{PSNR} = 10 \times \lg\left(\frac{255^2}{\mathrm{MSE}}\right)$$

$$\mathrm{MSE} = \frac{1}{M \times N}\sum_{i=1}^{N}\sum_{j=1}^{M}\left[I(i,j) - I'(i,j)\right]^2 \text{ ----(5)}$$

V. EXPERIMENTAL RESULTS AND OUTPUTS :

PSNR is calculated for input images(MRI) and output images by applying filters.The results are tabulated.

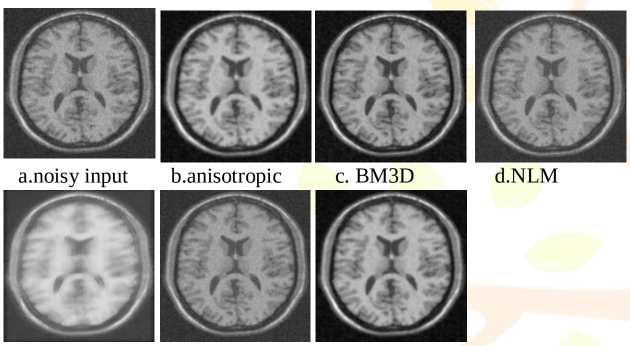
Filters	PSNR of input image with gaussian noise	PSNR of output image after applying filters.
Bilateral	17.037899826242	16.2251970892
Total variation	17.037899826242	17.191619311
Wavelet	17.037899826242	17.05250325
Anisotropi c	17.037899826242	17.1631621540
NLM	17.037899826242	17.037900092742
BM3D	17.037899826242	17.371954134550

Filters	PSNR of input image with salt and pepper noise	PSNR of output image after applying filters.
Bilateral	18.1315911584	19.57473591
Total variation	18.1315911584	26.6029950
Wavelet	18.1315911584	18.49343609
Anisotropic	18.1315911584	22.3694429511
NLM	18.1315911584	18.7318945229
BM3D	18.1315911584	29.3040244722

Table 1:PSNR comparisons before and after filter.

Filters	Run time after applying filter with gaussian noise	Run time after applying filter with salt and pepper noise
Bilateral	58.56	43.27
Total variation	3.16	2.11
Wavelet	2.06	0.91
Anisotropic	1.40	2.30
NLM	1.42	1.80
BM3D	21.97	15.67

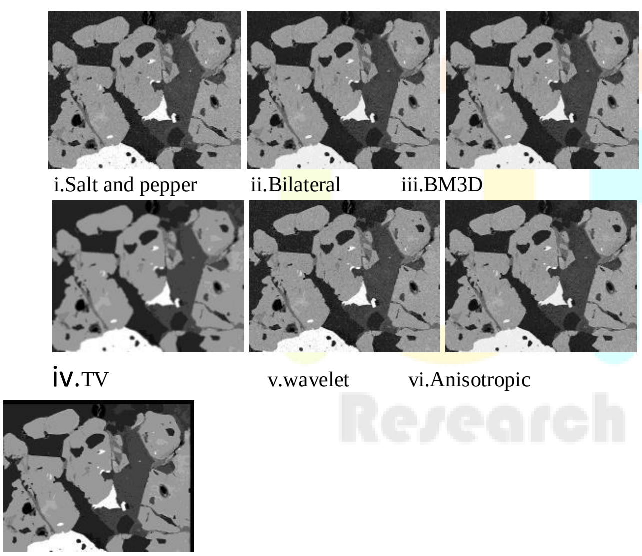
Table 2:Run time is calculated for gaussian and salt and pepper noisein(secs).



a.noisy input b.anisotropic c. BM3D d.NLM

e.Bilateral f.wavelet g. TV

Fig.(a,b,c,d,e,f,g) are obtained after applying filters for gaussian noise.



i.Salt and pepper ii.Bilateral iii.BM3D

iv.TV v.wavelet vi.Anisotropic

vii.NLM

fig(i to vii) are are obtained after applying filters for salt and pepper noise

BM3D variations in sigma value:

Noisy image psnr : 17.03789982624248

sigma_psd	Output psnr
0.2	17.3719541345509
0.25	17.3809080146289
0.3	17.3893919860866
0.35	17.3999750883808
0.4	17.4131062153245
0.45	17.4282624825621

Table 3 : BM3D variations in sigma value

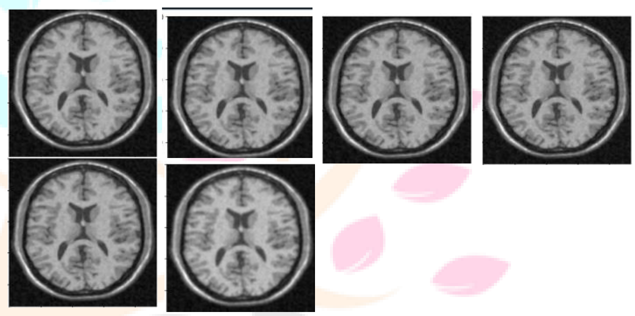


fig 5 : BM3D output images

Anisotropic variations:
Noisy image psnr : 17.03789982624248

Kappa	Gamma	Output psnr
50	0.1	17.2610057306631
50	0.15	17.2145627662508
50	0.2	17.1631621154055
50	0.25	17.1113842854208

Table 4: for anisotropic variations in gamma value

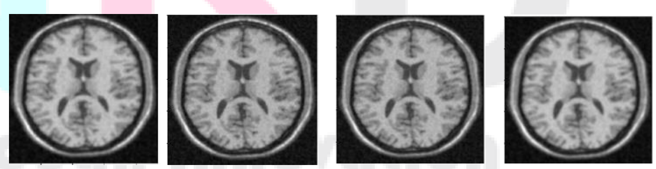


Fig 6: Anisotropic output images

TV algorithm variations:
Noisy image psnr :17.03789982624248

Weight	Output psnr
0.5	17.105390486211
0.4	17.1445354025841
0.3	17.1916193139443
0.2	17.2509800391594
0.1	17.2934450550678

Table 5 : TV algorithm variation in weights assigned

Experimentation results of microscopic images:

Anisotropic variations:

Noisy image psnr : 18.131591158400838

Kappa	Gamma	Output psnr
50	0.1	24.1236570457907
50	0.15	23.3512071425853
50	0.2	22.8151141580984
50	0.25	22.3694429511908

Table 5: Anisotropic variations in gamma value

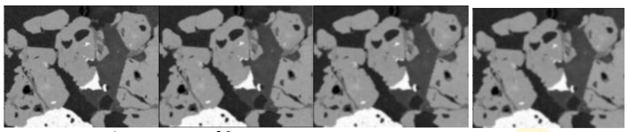


Fig 7 : Anisotropic filter output images

TV algorithm variations: Noisy image

psnr : 18.131591158400838

Weight	Output psnr
0.5	25.1036145943892
0.4	25.7430673972652
0.3	26.6029950225852
0.2	26.8262513991163
0.1	23.1435960885303

Table 6 : Tv algorithm variations in assigned weights

Total variation algorithm when applied with assigned weight is 0.2 gives the better output when compared with all the performed variations.

BM3D variations in sigma value:

Noisy image psnr : 18.131591158400838

sigma_psd	Output psnr
0.2	29.3040244722563
0.25	29.3560448525839
0.3	28.8721200056142
0.35	28.3512753616977
0.4	27.8993707051037
0.45	27.5258578216077

Table 7 : For BM3D variationsin sigma value

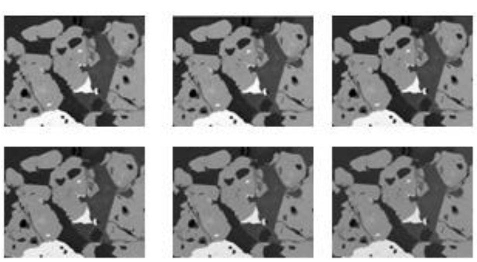


Fig 8 : BM3D output images

The BM3D filter when applied with 0.25 sigma_psd provides the better output out of all the variations performed.

VII.CONCLUSION

Denoising techniques on medical images such as MRI and CT images are essential and hence the strive for the more accurate and precise results. In this paper, we have shown the performance of few very common and traditional denoising algorithms on the MRI samples when applied withtwo types of noises. Deep learning algorithms in the field of medical images in still emerging and availability of large datasets of clean MRI images is not a luxury at hand for many. Hence usage of traditional methods can be fast and relatively effective.

Later part of the paper shows the application of same algorithms on microscopic images and efficiency of each filter in denoising microscopic images added with salt and pepper noise are shown and tabulated.

VIII. FUTURE SCOPE

It is clear from the above experimental results that BM3D algorithm application on taken sample MRI and microscopic image are relatively better when compared with all the other denoising algorithms applied. However BM3D algorithm hasits own draw back taking relatively larger run time. Hence it is inconvenient when this algorithm is applied on larger datasets. This provides us the future scope to explore variations in the algorithm to reduce the run time.

It is clearly visible that single image noise reduction algorithm is not able to cover all advantages with respect to relevance, robustness,denoise and edge protection. This also gives the future scope in research towards developing a universal denoising algorithm.

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