

# PREPROCESSING OF MRI IMAGES FOR BRAIN TUMOR DETECTION

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**Abstract:** In today's biomedical research and diagnosing field it is well known that MRI stands still the best option for identifying many internal body problems. Among all those applications this paper concentrates on Brain MRI scanning. Because MRI place very vital role in diagnosing the brain tumor. Since MRI can create more accurate and detailed pictures of body anatomy rather than computerized tomography (CT). But MRI images are normally suspected to some of the noises such as Gaussian noise and Poisson noise. Hence it is very much required to pre-process them before going for clustering.

**Keywords** – MRI, CT, Gaussian noise, Poisson noise.

## 1. INTRODUCTION

MRI scanning stands best solution for detecting various types of tumors as of now. MRI uses magnetic waves in order to get the exact picture of internal body parts by scanning. Also this MRI can be utilized to measure the size of brain tumors. For this purpose, it is necessary to inject special dye to the patient's vein before scanning to produce very clear picture or this can be given in pill form or in liquid form to swallow. MRI produces 3D anatomical view of brain thus it helps the radiologist to analyze and diagnose the problem. Apart from these benefits, some of the pre-processing techniques must be included to MRI images to get rid of some noises like Gaussian noise and Poisson noise upon using appropriate filters after that these MRI brain images are subjected to brain skull extractor process, that means removing the redundant features like skull, scalp, eyes and other unnecessary structures which doesn't contain any useful information but just consumes more processing time and thus reduces the processing speed. For this purpose the BSE technique is included to effectively suppress the unnecessary information from our region of interest.

## 2. GAUSSIAN NOISE

White noise is a term for Gaussian noise. Gaussian noise is also known as Gaussian distribution because it is one of the statistical noises with a probability density function (PDF) that is equivalent to the normal distribution. The uniform distribution of Gaussian noise throughout the signal is a distinguishing feature.

The pixels in these noise-corrupted pixels are frequently a mix of their original pixel values and random Gaussian noise values. As a result, the probability distribution function of this Gaussian noise takes on the shape of a bell.

The Probability distribution function  $\rho$  of a Gaussian variable  $Z$  is given by

$$P_G(Z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(Z-\mu)^2}{2\sigma^2}}$$

Where 'Z' denotes the grey level

' $\mu$ ' denotes the mean grey value

' $\sigma$ ' represents Standard Deviation

Among Gaussian noise, white Gaussian noise is one special case where the values of noise at any pair of time is identically distributed and then they are statistically independent of each other thus it is uncorrelated.

It is possible to reduce Gaussian noise while retaining edges using the wiener filter. The wiener filter is a type of linear digital filter that is used to reduce noise from images or signals. A typical pre-processing procedure to improve the results of later processing is noise reduction (for example, edge detection on an image). Wiener filtering is frequently employed in digital image processing because it keeps edges while reducing noise under certain conditions.

### 3. FILTERING

Image processing is used to eliminate noise, which causes errors in the image. The presence of noise causes the image's information to be disrupted. This noise information can be introduced for a variety of causes, including acquisition process due to camera quality and restoration, acquisition situation, such as lighting level, calibration, and positioning, or scene environment. Image processing includes noise reduction. To reduce noise from the poor image, a digital filter [1][3] is deployed. Because any image noise might cause major problems, any noise in the image should be eliminated. Unwanted information appears as noise, which is an unwanted signal. As a result, the image that is contaminated by noise is damaged, and different filters, such as linear or nonlinear filters, are employed to filter the noise and also to enhance the image [4].

There are three main processes to designing digital filters:

- (i) Specifying the necessary system features,
- (ii) Approximating these requirements with a causal discrete time system, and
- (iii) Realizing the system with finite precision arithmetic [2].

Norbert Wiener proposed the Wiener filter in 1942 as an optimum linear filter. It looks for a linear time-invariant filter whose output is as similar to the original signal as possible. To put it another way, the goal is to reduce the MSE between the expected noise-free signal and the actual output signal. The Wiener filter is based on the assumption that the input consists of the sum of useful signals and noise, both of which are generalized stationary processes with established second-order statistical properties. As a result, it is not adaptable and is always used in the frequency domain.

Formally, let  $f(x, y)$  be the input image and  $g(x, y)$  be the degraded image with some point-spread function  $H(x, y)$  and additive noise  $\eta(x, y)$ . So, in the spatial domain, the blurred image is

$$g_{x,y} = H(x, y) * f(x, y) + \eta(x, y) \quad (1)$$

where \* means two-dimensional convolution,

$H(x, y)$  = blurring function

$\eta(x, y)$  = additive noise and it is often refers to Gauss white noise, uniform noise, etc.

The Wiener filter interprets image and noise as random processes, with the goal of finding an estimate  $\hat{f}$  of the original image  $f(x, y)$  with the least amount of MSE.

$$F^{u,v} = H^*(u, v) H(u, v) 2 + \left( \frac{S_\eta(u, v)}{S_f(u, v)} \right) \quad (2)$$

Where  $H^*(u, v)$  = complex conjugate of  $H(u, v)$ ,

$S_\eta(u, v)$  = power spectrum of the noise, and

$S_f(u, v)$  = power spectrum of the original image.

If  $(S_\eta(u, v) / S_f(u, v))$  is larger, then the Wiener filter becomes smaller, hence the frequency will be ignored [5].

#### 3.1 Wavelet Transformation

Wavelet de-noising is a technique for removing noise from a wide range of data, including one-dimensional signals (such as EEG) and two-dimensional signals (such as MRI images). This method is easy to use and it has been shown to be successful in images de-noising [6]. Because typical noises like Gaussian white noise do not correlate with wavelets, the energy recovered by employing the wavelet transform frequently centers on large coefficients, which correspond to the majority of the original signal. As a result, wavelet coefficients with large amplitudes are often necessary signals, whereas wavelet coefficients with modest amplitudes are typically noise. Wavelet thresholding is the most frequent approach for decreasing noise in image because of these above features.

#### 3.2 Evaluation Methods

The performance of different images denoising algorithms examined in two different ways, one is objective and another one is subjective. The original image and the denoised image are visually compared with bare eyes; this method is termed as subjective assessment technique. An indicator is used to measure denoising performance using the objective assessment approach. The mean square error (MSE) and peak signal-to-noise ratio are used as objective assessment metrics (PSNR). The mean square error (MSE) is calculated as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (13)$$

Where MSE is Mean squared error

N = number of data points

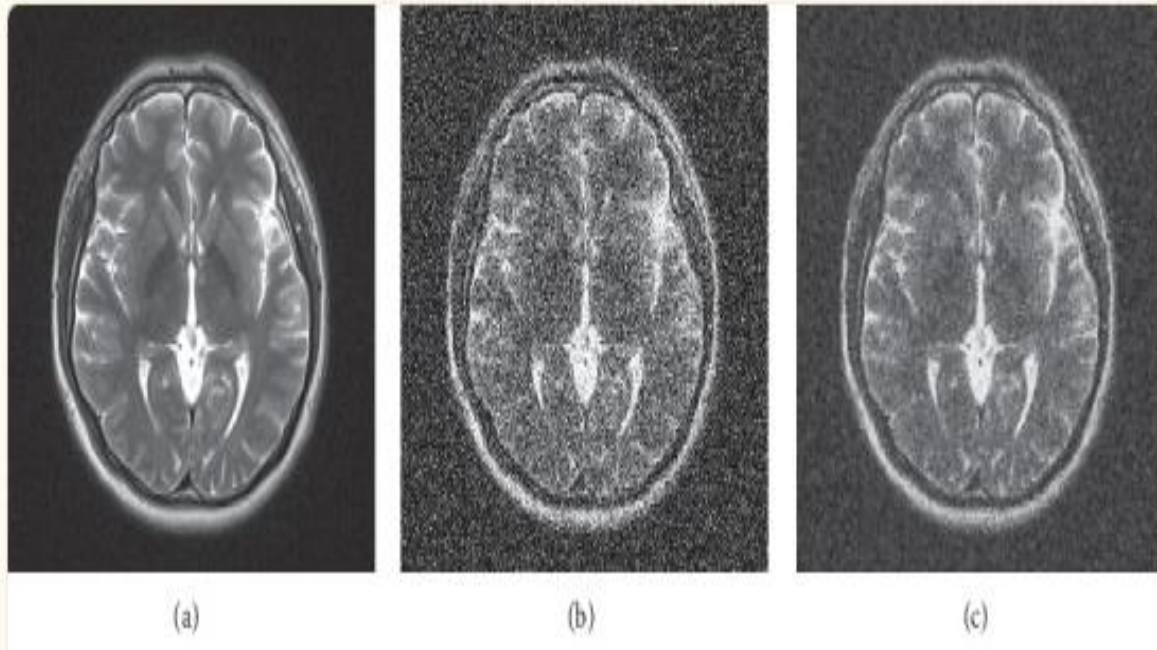
$Y_i$  = Observed values

$\hat{Y}_i$  = Predicted value

The peak signal-to-noise ratio (PSNR) is computed as follows:

$$PSNR = 10 * \log \left( \frac{L^2}{MSE} \right) \quad (14)$$

where  $L$  denotes the maximum gray-scale value of the pixels in an image. Here,  $L = 255$ .



(a) Original image (b) noisy image (c) Wiener filter

#### 4. MORPHOLOGICAL OPERATIONS

Image processing including noise suppression, feature extraction, edge detection, image segmentation, shape recognition, texture analysis, image restoration and reconstruction, image compression etc. uses mathematical morphology which is a method of nonlinear filters [7]. Morphological operators have been employed in image processing and are well-known for their ability to preserve the contour of a signal while reducing noise. Image morphology allows algorithms to include information about the surrounding area and distance. In mathematical morphology, the basic notion is to convolve a picture with a specific mask called as the structural element and then binarize the result using a defined function. The convolution mask and binarization function to utilise are determined by the morphological operator. Shrink or enlarge a binary picture using repeated neighbourhood modifications or "mathematical morphology," as developed by G. Matheron and J. Serra [8] enables image processing according to its form. Morphological operations can be thought of as shape filters that eliminate information from a picture depending on the shape of the image's objects and how they relate to the shape of the filter, leaving just the information of interest in the image. Erosion and dilation are the two basic morphological operators; opening and closure are two derived operations in terms of erosion and dilation [9].

Morphology refers to a group of image processing methods that work with pictures depending on their forms. Morphological operations apply a structuring element to an input picture and produce a similar-sized output image. The value of each pixel in the output picture is determined by comparing the matching pixel in the input image with its neighbours in a morphological process. Dilation and erosion are the most fundamental morphological activities. In a picture, dilation adds pixels to object borders, whereas erosion removes pixels from object boundaries. The size and shape of the structuring element used to process the picture determines the amount of pixels added or deleted from the objects in the image. The state of every given pixel in the output picture is defined by applying a rule to the relevant pixel and its neighbours in the input image in the morphological dilation and erosion procedures. The rule used to process the pixels defines the operation as dilation or erosion.

##### 4.1 Erosion

The erosion process is as same as dilation, but the pixels are converted to 'white', not 'black' [10]. The counterpart of dilation is erosion. If dilatation enlarges a picture, erosion contracts it. The structural element determines how the image is downsized. With a  $3 \times 3$  size, the structural element is usually smaller than the picture. When compared to bigger structuring-element sizes, this will result in quicker computing time. The erosion process, which is comparable to dilatation, will shift the structural element from left to right and top to bottom.

The algorithm will seek for a complete overlap with the structuring element at the centre location, which is represented by the centre of the structuring element. If there is no complete overlap, the centre pixel specified by the structural element's centre will be set to white or 0. The minimum value of all pixels in the vicinity is the value of the output pixel. A pixel in a binary picture is set to 0 if any of its neighbours contain the value 0. Only substantial items remain after morphological erosion eliminates floating pixels and thin lines. The remaining lines get thinner, and the forms become smaller.

#### 4.2 Dilation

Dilation is the process of expanding a binary picture from its initial geometry. The structural element determines how the binary image is enlarged. This structuring element is smaller than the picture itself, and the standard size for the structuring element is  $3 \times 3$ .

The structuring element is mirrored and moved from left to right and from top to bottom, and the process will seek for any overlapping comparable pixels between the structuring element and the binary picture at each shift, similar to the convolution process. If there exists an overlapping then the pixels under the center position of the structuring element will be turned to 1 or black. The maximum value of all pixels in the vicinity is the value of the output pixel. A pixel in a binary picture is set to 1 if any of its neighbors contain the value 1. Morphological dilatation increases the visibility of things and fills in tiny gaps. Fill forms seem bigger and lines appear thicker. The dilated picture then merges with the reduced-intensity input image (0.03 of its original intensity value).

#### CONCLUSION

MRI is very convenient for brain tumor detection as it can be visualized in 4 different modalities. Apart from these advantages MRI usually suffers from additional noises like Gaussian noise and Poisson noise. Hence it is very much necessary to remove all those additional noises to extract our region of interest without losing any of the crucial parameters. Because of this reason, preprocessing (i.e., denoising and morphological operations) place major role in MRI imaging before clustering and segmentation.

#### REFERENCES

- [1] A.K.Jain, "Fundamentals of Digital Image Processing", Engelwood Cliff, N. J.: Print ice Hall, 2006.
- [2] S. K. Satpathy, S. Panda, K. K. Nagwanshi and C. Ardil, "Image Restoration in Non-Linear Filtering Domain using MDB approach", International Journal of Information and Communication Engineering, Vol. 6, No. 1, 2010.
- [3] J.S.Lee, "Digital Image Enhancement and Noise Filtering by use of Local Statistics", IEEE Trans. On Pattern Analysis and Machine Intelligence, Vol.PAMI-29, March,1980.
- [4] H.Taub, D.L. Schilling, "Principles of Communication Systems", TMH,1991.
- [5] Vaseghi S. V. *Advanced Digital Signal Processing and Noise Reduction*. Hoboken, NJ, USA: John Wiley & Sons; 2000. [[Google Scholar](#)]
- [6] Kazubek M. Wavelet domain image denoising by thresholding and Wiener filtering. *IEEE Signal Processing Letters*. 2003;10(11):324–326. doi: 10.1109/lsp.2003.818225. [[CrossRef](#)] [[Google Scholar](#)]
- [7] A.M.Raid, IMAGE RESTORATION BASED ON MORPHOLOGICAL OPERATIONS, 10.5281/zenodo.2602520, 2019.
- [8]. Serra J., (1982), "Image Analysis and Mathematical Morphology," London Academic Press .
- [9]. Asma'a Abbas Ajwad Al-Tamimy , (2005), "Artificial Intelligence for Magnetic Resonance Image (MRI) Recognition ", M.Sc. Thesis in Medical Engineering
- [10] Mohamed A El-dosuky, Image Restoration Based on Morphological Operations, Research gate 2014; 10.5121/ijcseit.2014.4302
- [11] V. J. Nagalkar and S. S. Asole, "Brain tumor detection using digital image processing based on soft computing," Journal of Signal and Image Processing, vol. 3, no. 3, pp. 102–105, 2012.
- [12] T. Wang, N. Manohar, Y. Lei et al., "MRI-based treatment planning for brain stereotactic radiosurgery: dosimetric validation of a learning-based pseudo-CT generation method," Medical Dosimetry, 2018.
- [13] Chong Zhang, Xuanjing Shen, Hang Cheng, Qingji Qian, "Brain Tumour Segmentation Based on Hybrid Clustering and Morphological Operations", International Journal of Biomedical Imaging, vol. 2019.
- [14] Dr. Ramasamy Velmani, Dr. Arun Prasath Raveendran, "Brain Tumour Detection using Hybrid Clustering with Estimate Arguing", TURCOMAT, 2020.
- [15] Wilson B, Dhas JPM, An experimental analysis of Fuzzy C-means and K-means segmentation algorithm for iron detection in brain SWI using Matlab. Int J Comput Appl 2014;104(15):36–8.