This chapter clearly analyzes the subject of the preprocessing and its methods which are essential during the MRI segmentation. This phase concentrates on the denoising for the purpose of enhancing the image qualities which consecutively increase segmentation accuracy for MRI. At the same time several algorithms have been formulated for the effectiveness of image denoising. The problem of noise image suppression continues to be an open issue, since noise removal initiates artifacts and root for blurring of the images. In this research work, Non Local Means, Anisotropic Diffusion, Bilateral and Total Variation methods are employed to diminish the image artifacts and noise in MRI images. At last, PSO is implemented in order to discover the optimal value of the regularization parameter of total variation method.

4.1. Preprocessing of Noisy MRI brain images

Brain imaging has been extensively utilized in several medical applications that are supportive in the process of detection of brain abnormalities like brain tumour, paralysis, stroke and breathing complications. During the recent years, skull stripping has been one of the most important preprocessing phases in the field of brain imaging applications (Hahn and Peitgen, 2000) and for additional investigation of MRI brain images (Park and Lee, 2009). Earlier investigation relating to MRI brain images and skull stripping employed in clinical applications are brain mapping (Thompson and Toga, 1996), brain tumour volume analysis (Dubey et al., 2009), tissue categorization (Shattuck et al., 2001), epilepsy examination (Jafari-Khouzani et al., 2003; Jafari-Khouzani and Soltanian-Zadeh, 2006) and brain tumour segmentation (Moon et al., 2002). MRI brain images are exploited as the soft tissues are manipulated without any difficulty and provides higher-definition images (Chavhan, 2006), as a result is useful in diagnosing certain brain irregularities (Park and Lee, 2009). Skull stripping is a key part in all the brain imaging applications (Hahn and Peitgen, 2000) and it indicates the elimination of non-cerebral tissues like skull, scalp, vein or meninges (Hahn and Peitgen, 2000).
Several schemes have been formulated in the area of skull stripping investigations like region-based segmentation techniques like watershed (Segonne et al., 2004; Grau et al., 2004), region growing schemes (Adams and Bischof, 1994) and mathematical morphology (Lemieux et al., 1999). Hahn and Peitgen (2000) explained the watershed schemes in accordance with the model of pre-flooding which is to keep away from the over segmentation and to reduce the complication of noise. The benefits of the watershed algorithm are, it is an uncomplicated and quick scheme and normally constructs complete boundaries (Grau et al., 2004). On the other hand, Grau et al. (2004) dealt with watershed scheme which can cause over-segmentation, sensitivity to noise, poor detection of important regions with low contrast boundaries and thin structures. Region growing tasks are done by adding neighbouring pixels of preliminary seed pixel to generate a region based on predefined criteria (Hojjatoleslami and Kittler, 1998). The drawback of this scheme is that user has to choose the seed regions and threshold values.

As a result, Park and Lee, 2009, addressed this complication by launching a 2D region growing algorithm which automatically decides seed regions that signify the brain and non-brain regions. As a result, it is strong against low contrast, intensity inhomogeneities, noise and efficiently handles the connection issue of the brain regions. Gonzales and Woods (2002) found mathematical morphology as a tool for the purpose of extracting image constituents helpful in the representation and depiction of region shape like boundaries, convex hull and skeletons. Earlier investigations of brain segmentation and examination have utilized mathematical morphology (Goldszal et al., 1998). These investigations generally applied morphological opening for the purpose of separating the brain tissues from the neighboring tissues, in addition to morphological dilation and closing are necessary for the segmentation of the brain tissues without holes. Since morphological processes need binary form images, it offers an easy and well-organized method for integrating distance, neighbourhood details in segmentation (Kapur et al., 1996) in addition, it presents a unified and powerful approach to several image processing problems (Gonzales and Woods, 2002). On the other hand, morphology needs a prior binarization of the image into object and background areas (Kapur et al., 1996).

Thresholding produces binary images from gray-level ones by processing the entire pixels below of the threshold value to zero and the entire pixels above the threshold value to one.
value to one (Morse, 2000). The choice of a satisfactory threshold of gray-level for extracting objects from their background is extremely vital (Otsu, 1979) and thresholding scheme is an intuitive properties and ease of execution of the application of image segmentation (Gonzales and Woods, 2002). On the other hand, it is extremely complicated to discover the robust threshold values which generate a high-quality output for some of the images. Consequently, skull stripping technique is formulated which uses the mathematical morphology experimenting on using the double and Otsu threshold values with the intention of addressing the disadvantage of selecting the incorrect threshold values.

4.1.1. Preprocessing using Skull Stripping

Mathematical Morphology Segmentation

The objective of this proposed scheme is to get rid of the non-brain tissues of the 2D MRI axial brain images by means of mathematical morphology functions. The intention of this experimentation is to recognize the robust threshold values, to get rid of the non-cerebral tissue from MRI brain images. Figure 4.1 demonstrates the non-cerebral tissues (skull, meninges, cerebrospinal fluid,) to be extracted.

![Figure 4.1: Anatomical of Cerebral and Non-cerebral Tissues](image)

Subsequently, mathematical morphology processes (i.e. erosion, region filling and dilation) are executed on the binary image in order to take away the non-cerebral tissue. The major idea is to convolve the binary image with a structuring component to construct the skull stripped image. In view of the fact that the brain comes under the
category of an oval-shape image, a disk shape structuring element as shown in Figure 4.2 is preferred during the convolution process.

![Structuring Element](image)

**Figure 4.2: Structuring Element of Morphological Erosion and Dilation**

Erosion is utilized for the purpose of taking away the pixels on the MRI brain image’s boundaries, as a result eliminating the non-brain regions like skull, cerebrospinal fluid and meninges. As given (Gonzales and Woods, 2002), erosion of binary image, \( A \) with structuring element, \( B \) can be given as:

\[
A \ominus B = \{ z | (B)_z \subseteq A \} \tag{4.1}
\]

This equation points out that the erosion of \( A \) by \( B \) is the collection of the entire points \( z \) such that \( B \), translated by \( z \), is enclosed in \( A \). In the proposed scheme, the morphological dilation is applied with the intention of enhancing and connecting the entire intracranial tissues inside the image. Mathematical morphology dilation of binary image, \( A \) by means of the structuring component, \( B \) in Figure 4, however with different size, can be given as:

\[
A \oplus B = \{ z | (\hat{B})_z \cap A \neq \phi \} \tag{4.2}
\]

where \( \phi \) indicates the empty set. This equation depends on getting hold of \( z \) the reflection of \( B \) with reference to its origin and changing this reflection by \( z \). The dilation of \( A \) by \( B \) subsequently is the collection of all displacements, \( z \) such that \( \hat{B} \) and \( A \) overlap by at any rate by one element. The eroded image is provided in Figure 4.3.
Two pieces of data are taken as inputs by the dilation operator. The initial one is the image which undergoes dilation. The second one is a collection of coordinate points recognized as a structuring component. It includes a matrix of 0s and 1s. The structural component might be a disk, diamond and square shape. The dilation progression is almost close to the convolution process, to be precise, the structuring component is reflected and changed from the left to right and from top to bottom, at every shift; the course of action will search for any overlapping related pixels among the structuring component and that of the binary image. In case when there is an overlapping, then the pixels under the centre spot of the structuring component will be changed to 1 or black. Consider A as the opening through reconstructed image and B as the structuring component. Dilated image is given as,

\[ D = A \Theta B = \{Z[(\bar{B})_z \cap B] \subseteq B \} \quad (4.3) \]

The dilated image is shown in Figure 4.4.
Region filling is utilized for the purpose of filling in the holes within the brain region. Provided a brain region, $A$ and a preliminary point $p$ of the holes region, region filling is done by means of the following equation,

$$X_k = (X_{k-1} \oplus B) \cap A^c; \quad k = 1,2,3 \ldots$$

(4.4)

and $B$ indicates a structuring component.

This method comes to an end at iteration step $k$ if $X_k = X_{k-1}$. The region filling result $s_i$ is shown in Figure 4.5.
By means of setting the threshold condition together with region filled image and input brain image, anywhere the pixel in the image consists 1, then place intensity level of input image and wherever the pixel in the image consists 0, then place the intensity level of output image. The output image includes only the brain tissues. The concluding output image named as $G$, binarized image as $F$ and input image as $A$,

$$G = \begin{cases} 0, & F < 0 \\ A, & F \geq 0 \end{cases}$$

(4.5)

The final noisy skull stripped end result is illustrated in Figure 4.6.

![Figure 4.6: (a) Original Noisy MRI Brain Images (b) Skull Stripped Images](image)

4.2. Preprocessing of denoised MRI brain images

This phase takes care of preprocessing technique with denoising schemes in MRI. MRI is a commanding diagnostic technique. On the other hand, the integrated noise at some stage during image acquisition corrupts the human interpretation or computer-aided examination of the images. Time averaging of image sequences, intended at enhancing the SNR, would end in extra acquisition time and considerably lessen the temporal resolution. As a result, denoising should be carried out for the purpose of
enhancing the image quality for more precise diagnosis. Sensors and amplifiers of the image capturing devices are the source for a fraction of this unwanted additive signals. With the entire denoising filters, it is a challenge not to produce too much inevitable blurring of finer features carried in high frequency modes.

4.2.1. Noise in MRI brain Images

Noise modeling in images is influenced by means of capturing instrument, data transmission media, image quantization and discrete source of radiation. Gaussian noise, also known as random additive, is found in normal images (Yan and Guo, 2006). Speckle noise is found in ultrasound images (Stippel et al., 2002) whereas rician noise (Nowak, 1999) have an effect on the MRI. The feature of noise is based on its source, as does the operator which trims down its effects.

Rician noise

MR images are distorted as a result of Rician noise, which happens from complex Gaussian noise in the original frequency domain dimensions. The Rician Probability Density Function (PDF) for the distorted image intensity $x$ is given as follows:

$$p(x) = \frac{x}{\sigma^2} \exp \left( -\frac{x^2 + A^2}{2\sigma^2} \right) I_0 \left( \frac{xA}{\sigma^2} \right)$$  \hspace{1cm} (4.6)

where $A$ indicates the underlying true intensity, $\sigma$ indicates the standard deviation of the noise, and $I_0$ represents the modified zeroth order Bessel function of the first kind.

Speckle noise

A different category of noise in the coherent imaging of objects is known as speckle noise. This noise is, actually, produced through errors in data transmission (Gagnon and Smaili, 1996). This category of noise has an effect on the ultrasound images (Guo et al., 1994). Speckle noise follows a gamma distribution and is provided as follows:

$$F(g) = \frac{g^{\chi-1}}{(\chi-1)!} a^\chi e^{-\frac{g}{\chi a}}$$  \hspace{1cm} (4.7)
where $\alpha^2$ indicates the variance, $\times$ indicates the shape parameter of gamma distribution and $g$ represents the gray level.

**Amplifier Noise (Gaussian Noise)**

The benchmark model of amplifier noise is additive, Gaussian, independent at each pixel and free of signal intensity. In case of color cameras where more amplification is employed in the blue color channel than in the green or red channel, there can be additional noise in the blue channel. Amplifier noise is the foremost ingredient of the "read noise" of an image sensor, specifically, of the steady noise intensity in dark regions of the image (Zhong and Cherkassky, 2000). Gaussian noise is a kind of statistical noise that has its pdf equal to that of the typical distribution, which is also well-known as the Gaussian distribution. It means, the values that the noise can obtain are Gaussian-distributed. An exceptional case is white Gaussian noise, where the values at any pair of times are statistically independent (and uncorrelated). In certain applications, Gaussian noise is predominantly utilized as additive white noise to yield AWGN. When the white noise sequence is a Gaussian sequence, subsequently it is called a White Gaussian Noise (WGN) sequence (Kumar et al., 2010).

**Salt-and-pepper Noise**

An image having salt-and-pepper noise will comprise dark pixels in the area of bright regions and bright pixels in dark regions (Zhong and Cherkassky, 2000). This category of noise can be produced by means of dead pixels, analog-to-digital converter errors, bit errors in transmission, etc. This can be removed in large part by using dark frame subtraction and through interpolating in the region of dark/bright pixels. This noise is named for the salt- and-pepper appearance an image takes on after being corrupted by this category of noise (Kumar et al., 2010).

**4.2.2. Preprocessing using denoising techniques**

Several schemes used for image denoising are discussed in Motwani et al., 2004. The denoising of MRIs by means of wave atom shrinkage (Rajeesh et al., 2010) is demonstrated to be achieving a better SNR when compared against wavelet and curvelet shrinkages. A NL denoising scheme for Rician noise reduction is proposed by
Milindkumar et al., 2011. Kruggel et al. (1999) implemented a test bed for baseline correction and noise filtering scheme and compared with other schemes. Suyash and Ross (2005) formulated a non-parametric neighborhood statistics scheme for the purpose of MRI denoising. An adaptive wavelet-based MRI denoising scheme by means of wavelet shrinkage and mixture model concept is initiated by Jiang and Yang, 2003. A scheme to enhance image quality in accordance with the determination of the significant pulse sequence parameters with timing constraints from the entire gradients, more willingly than a single gradient of the image has been given (Zhou and Ma, 2000). A new filter is formulated to diminish random noise in multi-component MR images, by means of spatially averaging similar pixels and a local PCA decomposition, with information from every available image elements, to carry out the denoising process is proposed by José et al., 2009. A new signal estimator depending on the technique of “noise cancellation”, which is normally employed in signal processing is utilized to recover signals distorted by means of additive noise in MRI is proposed by Jorge, 2009.

An estimator with a priori details for the purpose of devising a single dimensional noise cancellation for the variance of the thermal noise in MRI systems known as ML estimator has been formulated by Miguel et al, 2011. Non Local Means (NLM) filtering is an effective scheme for the purpose of reducing artifacts caused in MRI because of under sampling of k-space (to lessen the scan time) is formulated by Adluru et al., 2010. A maximum a posteriori estimation scheme that works openly on the diffusion weighted images and reports for the biases initiated by Rician noise is introduced by Basu et al., 2006 for the purpose of filtering the diffusion tensor MRI’s. A novel scheme for the purpose of evaluating the reconstructions for low-SNR MRI’s is provided in Tisdall and Atkins, 2006. A filtering process in accordance with the anisotropic diffusion is given in Gerig et al., 1992.

A spatially adaptive TV model has been implemented to Partially Parallel MRI (PP-MRI) image reconstructed by means of GeneRalized Approach to Partially Parallel Magnetic Resonance Imaging (GRAPP-MRI) and SENSitivity Encoding (SENSE) MR Imaging is formulated by Guo and Huang, 2009. The novel filtering scheme known as Trilateral Filtering (TF) is formulated by Wong and Chung, 2004; Wong and Chung, 2004.
work similar as bilateral filtering and captures the photometric, geometric and local structural similarities to even the MR images. A noise removal scheme by means of 4th order PDE is initiated by Lysaker et al., 2003 for the purpose of reducing noise in MRI’s. A phase error estimation approach in accordance with iteratively applying a series of non-linear filters each utilized to adjust the estimate into better agreement with one piece of information, until the output converges to a steady estimate is formulated by Tisdall and Atkins, 2005.

A wavelet-based multiscale products thresholding approach with the help of dyadic wavelet transform for the purpose of detecting multiscale edge is initiated by Bao and Zhang, 2003 for the use of noise suppression in MRI. One scheme, called ADF, efficiently enhances SNR, at the same time preserving edges through the process of averaging the pixels in the direction orthogonal to the local image signal gradient. ADF can potentially take away tiny characteristics and adjust the image statistics, even though adaptively accounting for MRI’s spatially changing noise features can provide considerable improvements, this is practically challenged by the inaccessibility of the image noise matrix. With this scheme, it is examined that the selection of filter for the purpose of enhancing the MRI image based on the category of the filtering technique is utilized. It is significant that it considerably saves the processing time. This scheme launches a hybrid filtering technique which combines PSO and TVF to generate a noise reduced MRI image.

In the midst of the complete feature selection schemes available in the literature, TV filter is selected, since it possesses the following properties:

- Among the entire the variational PDE based schemes, the TV minimization scheme provides the better combination of both noise removal and feature preservation, and
- It provides a remarkable bias-variance trade-off.

This chapter clearly discusses the preprocessing method using PSO based TV filter. This chapter mainly focuses on the pre-processing and at the same time, several algorithms have been proposed for the purpose of image denoising. The problem of noise image suppression remains an open challenge, because noise removal introduces artifacts and causes blurring of the images. The proposed pre-processing method finds the optimal value
of the regularization parameter of total variation method. The proposed pre-processing approach consists of the following steps:

- Discussion and analysis of popularly available denoising filters for MRI are Non-local Means, Anisotropic, Bilateral and Total Variation filter, and
- Proposal of PSO based Total Variation Filter.

4.2.2.1 Non Local Means Filter

The NLM filter is a kind of neighbourhood filter (Yaroslavsky, 1985) which completes denoising through averaging related image pixels in accordance with their intensity similarity. The foremost variation, among the NLM and previous related filters is that, the similarity among pixels has been made more robust to the noise level with the help of region comparison rather than pixel comparison; in addition, pattern redundancy has been not controlled to be local (non-local). To be exact, pixels distant from the pixel being filtered are not penalized owing to its distance to the existing pixel, as for instance takes place in the bilateral filter (Tomasi and Manduchi, 1998). The NLM filter (Coupé et al., 2008; Buades et al., 2005), completely based on the redundancy of information is included in the images to eliminate noise. The filter brings back the intensity of the voxel \( x_i \) through computing a weighted average of the entire voxels intensities in the image \( I \).

Here, shown a few heuristic is set, intuitive statements and also how they underlie the NLMeans scheme. Subsequently, the way to adjust the NLMeans to Rician-corrupted data is shown.

Gaussian NLMeans

Consider that an MR image is distorted with Gaussian noise \( \mathcal{N}(0, \sigma^2) \). When a homogeneous area is given with \( n \) voxels \( v_1, \ldots, v_n \) (or consistently, \( n \) measures of the similar voxel value), a probabilistic interpretation is to observe the voxel values \( x_1, \ldots, x_n \) as the realisations of \( n \) independent random variables \( X_i \) next to the similar Gaussian law \( \mathcal{N}(\mu, \sigma^2) \). A normal method to restore the value \( \chi \) of voxel \( \psi \) in the area is subsequently to replace it through the average \( \hat{x} = \sum \frac{1}{n} x_i \). This estimate is extremely satisfying since it is the Maximum Likelihood (ML) estimate of \( \chi \). It can subsequently be observed that, provided some weights \( w_p \), \( E(\Sigma w_i x_i) = \mu \), even when \( w_i \neq \frac{1}{n} \), given \( \Sigma_i w_i = 1 \).
In actual fact, no such homogeneous region is available within reach, and numerous measures of the similar voxel value are infrequently obtained. On the other hand, when one has a method to assess the probability of every voxel value in the overall image (or in a search volume \( V \)) to have been drawn from the same distribution as the existing voxel \( v \), and to reproduce this probability in a weight \( w_i \), subsequently the voxel value \( x \) can be restored, by means of the abovementioned remark, as given below:

\[
NLM_G(x) = \sum_{\bar{x} \in V} w_i x_i
\]

The concept of the NL Means filter is to consider every voxel value \( x_i \) in \( V \) in the restoration of \( x \) by means of the similarity (based on intensity) among their spatial neighbourhoods \( N \) and \( N_i \) of size \( S \) as given below:

\[
w_i = \frac{1}{Z(i)} e^{-\frac{1}{2h} \sum_{k=1}^{S} (y_k - z_k)^2}
\]

where \( Z(i) \) indicates a normalization constant with \( Z(i) = \sum_i w_i \), \( y_k \) and \( z_k \) represent the values of the \( k \)-th voxels in the neighbourhoods \( N \) and \( N_i \), and \( h \) operates as a filtering parameter (for more information notice Coupé et al., 2008). The filtering parameter \( h \) is associated with the noise variance \( \sigma^2 \) (Kervrann et al., 2007), and is estimated by means of the pseudo-residual technique proposed by Gasser et al. (1986).

**Figure 4.7: NL Means principle: A Two-Dimensional Illustration**
In Figure 4.7, the restored value of voxel \( v \) with value \( x \) is a weighted average of every bit of intensities \( x_i \) of voxels \( v_i \) in the search volume \( V \). The weight \( w_i \) depends on the similarity of the intensities in cubic neighbourhoods \( N \) and \( N_i \) in the region of \( v \) and \( v_i \).

**Rician NL Means**

In the scenario of Rician noise, there is no closed-form for the purpose of ML estimate of the true signal \( \mu \) provided \( n \) such measures \( x_i \) (Sijbers and Dekker, 2004). On the other hand, the even order moments of the Rician law have extremely uncomplicated expressions. Particularly, the second-order moment is: 
\[
E(X_i^2) = \mu^2 + 2\sigma^2
\]
where \( \sigma^2 \) indicates the variance of the Gaussian noise of complex MRI data. The measured rate of \( x_i^2 \) (and that of \( x_i \)) is hence generally overestimated compared against its true, unknown value, which is pointed out as a Rician bias in the following. Using the similar remark like in the Gaussian case, to be precise 
\[
E(\sum_i w_i X_i^2) = \mu^2 + 2\sigma^2
\]
it subsequently seems natural to restore \( x \) as 
\[
\sqrt{\sum_i w_i x_i^2} - 2\sigma^2
\]
the weights \( w_i \) being cautiously selected and summing to 1.

The voxel value \( x \) can be restored as given below:

\[
NLM_R(x) = \left\| \sum_{\dot{x} \in V} w_i x_i^2 \right\| - 2\sigma^2
\]  

(4.9)

where \( \sigma^2 \) represents the noise variance. As observed by many, in the scenario of random variables \( X_i \) and with \( w_i = \frac{1}{n} \), the term under the square root has a non-null probability to be negative, which reduces at the time where \( n \) is large. In such scenarios, the restored value is fixed to 0. In actual fact, in the scenario of real data, negative values are primarily found in the background of the images.

**4.2.2.2. Anisotropic Diffusion Filter**

Anisotropic filter is a kind of non-optimal for MRIs with spatially changeable noise levels of these sensitivity-encoded data and intensity in homogeneity corrected images. Persona and Malik formulated the anisotropic diffusion filter as a diffusion course of action that promotes intra-region smoothing, at the same time inhibiting inter-region smoothing. Mathematically, the process is given as below:
\[ \frac{\partial}{\partial t} I(\bar{x}, t) = \Delta \left( c(\bar{x}, t) \Delta I(\bar{x}, t) \right) \] (4.10)

In this scenario, \( I(\bar{x}, t) \), indicates the MRI, \( \bar{x} \) indicates the image axes and \( t \) indicates the iteration phase. \( c(\bar{x}, t) \) represents the diffusion function and is a monotonically decreasing function of the image gradient magnitude.

\[ c(\bar{x}, t) = f(|\Delta I(\bar{x}, t)|) \] (4.11)

It permits close by adaptive diffusion strengths and edges are carefully smoothed or improved in accordance with the evaluation of the diffusion function.

4.2.2.3. Bilateral Filter

Bilateral filtering is a kind of scheme for the purpose of smoothing images, at the same time preserving edges. The utilization of bilateral filtering has developed quickly and is at present employed in the field of image processing applications like image denoising, image enhancement, etc (Tomasi and Manduchi, 1998). Numerous qualities of bilateral filter are enlisted below which demonstrates its achievement:

- It is uncomplicated to formulate it. Every pixel is substituted through a weighted average of its neighbours,
- It relies simply on the two parameters that point out the size and contrast of the features to preserve, and
- It is a kind of non-iterative scheme. This makes the parameters simple to maintain, in view of the fact that their effect is not cumulative over quite a few iterations (Liao et al., 2010).

On the other hand, the bilateral filter is not parameter-free. The collection of the bilateral filter constraints has a considerable control on its behavior and working. The constraints are window size \( W \), standard deviation \( \sigma_d \) and \( \sigma_r \). In the process of noise removal, the constraints have to be adjusted to the noise level. At the same time the bilateral filter adjusts itself to the image aspects content. The disadvantage of this kind of filter is that it cannot eliminate salt-and-pepper noise (Wei, 2009). It also roots for spread of noise in medical images (Liao et al., 2010). One more disadvantage of bilateral filter is
that it is single resolution in nature indicating it is not right to use the dissimilar frequency constituents of the image (Roy et al., 2010). It is effective to eliminate the noise in high frequency area. However it provides poor performance to eliminate noise in low frequency area.

Bilateral Filtering is accomplished by the integrations of two Gaussian filters (Zhang et al., 2009). One filter functions in spatial domain and second filter functions in intensity domain. This filter uses spatially weighted averaging smoothing edges. In the case of conventional low pass filtering (Liao et al., 2010), it is presumed that the pixel of any point is comparable to that of the close by points:

\[
h(x) = k_d^{-1}(x) \int_{-\infty}^{\infty} f(\xi) c(\xi, x) \, d\xi
\]

(4.12)

where \( c(\xi, x) \) determines the geometric closeness among the neighborhood center \( x \) and a nearby point \( \xi \). Both input \( f \) and output \( h \) images might be multiband. In addition,

\[
k_d(x) = \int_{-\infty}^{\infty} c(\xi, x) \, d\xi
\]

(4.13)

However, practically the pixel of points at boundaries is unrelated to the close points. As a result, the boundaries are blurred. Bilateral filter integrates gray levels depend on both geometric closeness and photometric resemblance and it desires close by values in both domain and range (Liao et al., 2010). Range filtering is similarly which is given as:

\[
h(x) = k_r^{-1}(x) \int_{-\infty}^{\infty} f(\xi) s(f(\xi), f(x)) \, d\xi
\]

(4.14)

where \( s(f(\xi), f(x)) \) computes the photographic resemblance among the pixel at the neighborhood center \( x \) and that of close by point \( \xi \). In this scenario, the kernel computes the photometric similarity among pixels. The normalization constant in this scenario is,
The bilateral filtering described as given below:

\[ h(x) = k^{-1}(x) \left( \int_{-\infty}^{\infty} f(\xi) c(\xi, x) s(f(\xi), f(x)) d\xi \right) \]  

(4.16)

where \( k(x) = \int_{-\infty}^{\infty} c(\xi, x)f(f(\xi), f(x)) d\xi \) integrates domain and range filtering will be represented as bilateral filtering (Tomasi and Manduchi, 1998). It substitutes the pixel value at \( x \) with an average of related and close by pixel values. In case of smooth regions, pixel values in a small neighborhood are related to each other, and the bilateral filter operates basically as a standard domain filter, averaging away the small, inadequately correlated differences among pixel values caused with noise. Bilateral filtering is a kind of non-iterative scheme. Dissimilar to conventional filters, it eliminates the noise and protects the edge details. However, the optimal performance of the bilateral filter is completely based on the constraints of the filter.

### 4.2.2.4. Proposed Total Variation Filter

Total Variation filter is a kind of scheme that was primarily developed for the purpose of image denoising in AWGN by Rudin, Osher and Fatemi in 1992. The TV regularization scheme is one of the most common and successful schemes in the field of image denoising. In this scheme, the energy model is created through the categories of two terms: one is regularization term and the second one is fidelity term. The regularization term takes part a vital responsibility in realizing the right amount of noise removal and the fidelity takes part a vital responsibility in preserving edges. The TV is given as the following variation model:

\[
\min_u \left\{ \int_\Omega |\Delta u| d\Omega + \frac{1}{2\lambda} \int_\Omega |u - f|^2 d\Omega \right\} 
\]

(4.17)

where \( \Omega \) indicates the image domain, \( f \) represents the observed image function which is presumed to be distorted with additive white Gaussian noise, and \( u \)
indicates the sought solution. The parameter $\lambda$ is employed to manage the quantity of smoothing in $u$. The working of TV filter is shown in Figure 4.9.

In the proposed method, the best value of the regularization parameter ($\lambda$) is approximated and optimized with the help of PSO. PSO is one of well-organized search and optimization techniques (Kennedy and Eberhart, 1995) depending on the progression and intelligence of swarms. This scheme is completely based on a swarm of particles flying in the search space (Ibrahim and Shafaf, 2010). The location of every particle indicates a possible solution to the optimization setback. With the intention of applying the PSO parameters like representation of the preliminary population, fitness function recognition, representation of location and velocity policies, and initially the constraint, should be taken into account. PSO possess several similarities with evolutionary computation approaches like GA. The system is initialized with a population of random solutions and looks for optima through the process of updating generations. On the other hand, distinct to GA, PSO does not include any evolution operators like crossover and mutation. In case of PSO, the potential solutions are known as particles, which fly through the problem space by following the existing optimum particles. Every particle controls its co-ordinates in the problem space which are connected with the best solution (fitness) it has realized to this point. (The fitness value is also accumulated.) This value is known as pbest. An additional "best" value that is tracked in the PSO is the best value, obtained to this point by any particle in the neighbors of the particle. This location is known as lbest. When a particle considers all the population as its topological neighbors, the best value is a global best and is known as gbest.

The PSO conception includes, during each time step, varying the velocity of each particle in the direction of its pbest and lbest positions (local version of PSO). Acceleration is weighted through a random term, which keeps away random numbers being produced for acceleration in the direction of pbest and lbest locations. During recent times, PSO has been productively implemented in several research and application areas. It is revealed that PSO obtains better results in a quicker, inexpensive manner when compared against other schemes. Furthermore, PSO is attractive since there are only few parameters to handle with. One version, with small deviations, performs better in an extensive range of applications. PSO has been employed for approaches that can be utilized across an
extensive range of applications, in addition for particular applications concentrated on a particular requirement.

The proposed scheme is suited well for the purpose of denoising in MR images. The regularization parameter ($\lambda$) is a positive value indicating the fidelity weight which manages the quantity of denoising. The parameter, can be adjusted the large value of lambda, it eliminates a huge quantity of noises, simultaneously it helps to smoothen the image. The regularization parameter is not determined by means of standard estimators. When the value of the parameter becomes zero ($0=\lambda$) the estimated solution is extremely influenced with noise, to be exact, at the same time when ($1=\lambda$), the estimated solution is going to be very smooth. Hence, the regularization parameter is tuned by PSO, the obtained solution gives the fidelity weights ranges from 0.0147 to 0.0829, the estimated solution correctly reflects the original image without noise and it takes a significant part in the denoising process. The visual appearance of NLM, ADF, BF, TV, and proposed OTVF filter images are as shown in Figure 4.8.

![Figure 4.8: (a) Original Noisy MRI Image (b) Non Local Means Filter (c) Anisotropic Diffusion Filter (d) Bilateral Filter (e) Total Variation Filter (f) Proposed Optimized Total Variation Filter](image-url)
The final output of OTVF filtered image is given as input for skull stripped process is illustrated in Figure 4.9, which helps to obtain clear segmentation of brain cerebral tissues.

![Figure 4.9: (a) OTVF image (b) Denoised Skull Stripped image](image)

4.3. SUMMARY

This chapter intensely focuses on developing an efficient preprocessing method to reduce the noise and increase the image quality, which improves the result of segmentation accuracy of MRI images. Since the noise in MRI images reduces the segmentation accuracy, an efficient preprocessing method is introduced in this research work to improve the segmentation of MRI image samples. To improve denoising results, the total variation, using PSO, is proposed for image denoising. In the proposed system, the total variation method is best suited for denoising the MR brain images, and the PSO algorithm is used for computing an optimal value of the regularization parameter. The regularization parameter may be tuned the lambda value, and also used to control the amount of smoothing. From the result, one can conclude that the performance of PSO-TVF is superior to the other filtering methods such as NLM, ADF, BF, and TV filter. The design of the MRI Brain Segmentation using Clustering techniques is presented in the next chapter (Chapter 5).