Accurate tissue segmentation from magnetic resonance (MR) images is an important step in the quantitative brain image analysis for the detection of the epilepsy disease. But, the accuracy of many segmentation algorithms is only limited because of the presence of noise and the intensity irregularity in brain MR images. Medical image segmentation has huge impact on the digital image processing, owing to its spatial resolution enhancement and image sharpening. It has been employed for deriving helpful information from the medical image data, which in turn provides the most precise and reliable method for diagnosis. This procedure is a critical challenge on account of the existence of in-homogeneities in the intensity of images. The elimination of the spatial intensity irregularities from MR images is a difficult task, since the in-homogeneities could vary with different MRI acquisition parameters from one patient to another and from slice to slice. Conventional method in hospitals is based on the manual segmentation of the medical image considered. This again relies on the perceiving capabilities of the physician in getting the required region extracted out from the image. But this is made difficult due to minute variations and resemblance between the actual and affected biological region in the image.

The insufficient number of radiologists and the huge volume of MRI to be analyzed result in intensive labor and is also highly uneconomical. It also reckons on the expertise of the technician analyzing the images (Masroor and Dzulkifli, 2008). The estimates also show that between 10% and 30% of tumors escape the eyes of the radiologists during the routine screening. In the acquisition stage of medical images, there are chances that the medical image might be tampered because of issues occurring during the acquisition stage. Hence, the original image may not be useful for examination. Image segmentation can be defined as the partition or segmentation of a digital image into same type of regions with an important goal of simplifying the image considered, into something that can be comprehended and easy for visual analysis. Image segmentation is a highly significant process in the whole field of medical image analysis.
There are various methods available for the segmentation of an image into subregions, so that homogeneity is maintained in each region. Due to the complexity and inaccuracy, not every technique is suitable for the examination of medical image. Also, there are no benchmarked image segmentation techniques which can yield satisfying results. Segmentation method with accuracy is an item of research. MR Image segmentation is a highly demanding issue because of its complexity. Segmentation of brain MR images is an extremely important step and has widely gained the attention of many researchers during the past decade. This chapter gives a detailed account of a few of the image denoising techniques, image segmentation making use of clustering methods, segmentation utilizing optimized clustering techniques and random optimized clustering approaches for segmentation. This chapter targets a review of the various methods of segmentation, and their drawbacks are discussed as comparison based analysis. Also, the idea of a novel algorithm which is more accurate, effective and also fast for epileptic tissue segmentation using MR images is introduced.

2.1. Image Denoising Techniques in Various Preprocessing Approaches

The image under test obtained by the acquisition device is vulnerable to damage by the environment. The restoration of images attempts the minimization of the effects of these degradations with the help of a filter (Elsherif and Elsayad, 2001; Zong et al, 1996). Hence, a basic issue in the image processing is the enhancement of their quality by the removal of the noise. A large variety of techniques devoted for carrying out this task is available. All of them depend on the type of the noise in images (Wirth et al, 2004). Image preprocessing techniques are useful for the improvement of the quality of an image before getting it processed in an application. This utilizes a small neighborhood of a pixel in an input image to obtain new brightness value in the output image. These preprocessing methods are also referred to as filtration and resolution enhancement. The medical image quality parameters are noise and resolution chiefly. The important aim of this section is the improvement of the image quality by de-noising and resolution enhancement. Many of the imaging techniques are deteriorated by noise. For the preservation of the edges and contour information of the medical images, effective denoising and an improved enhancement technique is necessary. Image denoising techniques and their illustrations of the techniques in the corresponding works are represented in Figure 2.1.
2.1.1. Preprocessing using Filtering Techniques

The denoising of magnetic resonance (MR) images is a significant issue to be resolved. It has been often in discussion in the recent times because of its importance for many clinical and research purposes. Denoising is applied as a preprocessing step in many image processing and analysis operations such as registration or segmentation for reducing the random noise which arises from the acquisition process. One technique that has found extensive application in MRI preprocessing is the Gaussian filter (Ashburner and Friston, 2000). This technique, even though is able to reduce some image noise (particularly in homogeneous areas), and also eliminates high-frequency signal components, produces blurred edges in the images. Hence, this filter has been generally used for regularization purposes, such as in Voxel Based Morphometry (VBM) (Ashburner and Friston, 2000), for reducing anatomical irregularities. A big number of edge-preserving techniques have been proposed for overcoming the observed blurring effects. Still, this filter takes a long time for the removal of noise, during which a few significant details would also be reduced in the denoising process.

Other transforms that have been employed for denoising images are Principal Component Analysis (PCA) (Muresan and Parks, 2003) and the Discrete Cosine
Transforms (DCT) (Yaroslavsky et al., 2000). Most of the transform domain filters have evolved from variations of the transform threshold-inverse transform principle. Based on this principle, local transform approaches (i.e., sliding window with or without overlapping) have yielded very good results recently (Guleryuz, 2003; Guleryuz, 2007; Yaroslavsky et al., 2000). In Guleryuz’s (2007) technique for Gaussian noise reduction, the image noise is eliminated by making use of overcomplete linear transforms and thresholding. Actually, Guleryuz employed a classical sliding-window DCT thresholding as in Yaroslavsky et al. (2000), but overlapping estimations adaptive combination was applied for the reduction of the Gibbs effects.

Other recently introduced approaches make use of learned image patch dictionaries (Aharon et al., 2006; Elad and Aharon, 2006; Mairal et al., 2008) in the place of DCT bases for performing the denoising. All these approaches come up from the fact that an image can be represented as the linear combination of a set of image bases with very less non-null co-efficients. This characteristic, referred to as sparseness, is the heart of the JPEG and JPEG2000 compression standards. For instance, anisotropic diffusion filters (Gerig et al., 1992) are capable of removing noise by making use of gradient information without damaging important image structures.

Even though many algorithms have been innovated to serve the purpose of image de-noising, the issue of noise image suppression has remained a challenge unresolved, since noise removal brings in artifacts and leads to blurring of the images. Few popular denoising filters for MRI are Non-local Means, Anisotropic Diffusion, Bilateral and Total Variation filter. In this section, focus is on these four filtering methods for the reduction of the image artifacts and noise in MRI images.

Kaur and Mittal (2014) examined a MRI tumor detection technique where denoising was performed with 3*3 mean filter. In this technique, all images were applied to denoising filter for eliminating white Gaussian noise. 2D-mean filter is utilized for denoising the image. Here, the summation of the elements and then division by their number is the outputs referred to as average or mean output. The 2D window or mask which is selected for filtering process is of 3*3 size. The choice of window size only determines the elements selection. The image de-noising is done using mean filter rather
than median filter as it does the smoothing of the grayscale image data with more accuracy, conducts spatial filtering on each unique pixel and then chooses the average value of the window elements and not just the median value. But the only drawback is that it lets in autocorrelations. This may also result in misleading visual impression of importance, as the smoothness of the resulting curve may often be taken as an indication that few visible features would be important, even if they are just normal noise.

Hence, the Non Local Means (NLM) filter, a novel technique proposed by Buades et al. (2005), has emerged as a very easy and effective means of limiting noise with minimal deterioration to the actual structures of the image. This method is in accordance with the original redundancy of patterns within the images. Enhanced recently, the NLM filter has been employed for the denoising of MR images and has been proved with better results in comparison with other available methods (Coupé et al., 2008, Manjón et al., 2010; Wiest-Daesllé et al., 2008).

In the recent times, denoising techniques using nonlocal means (NLM) (Perona and Malik, 1990) were employed to raise the MRI-SNR (Signal - to - Noise Ratio) by decreasing the variations between pixels in the image with near similarity indices (Nowak, 1999). The reliability of the evaluation of pixel similarity is improved by comparison of the small image regions having its center at each pixel, instead of pixel-by-pixel comparisons. The performance obtained by the realisation of NLM is good for images degraded by both Gaussian and Rician noise. But the computational complexity is huge, since a large number of elementary operations are necessary for denoising of each pixel.

According to Wiest-Daesllé et al (2008) Non-Local Means (NLMeans) filter has been introduced recently for the denoising of MRI with high SNR. But, for Diffusion Weighted Magnetic Resonance (DW-MR) images with high b-values (and hence low SNR), the noise, which is purely Rician-distributed, can no more be approximated as additive white Gaussian, as assumed implicitly in the traditional formulation of the NLMeans. High b-values are normally made use of in High Angular Resolution Diffusion Imaging (HARDI) or Q-Space Imaging (QSI), for which an optimal restoration is crucial. For adapting the NLMeans filter to Rician noise degraded data, a novel method is presented. Validation is carried out on synthetic data and on real data for both traditional
MR images and DT images. The adaptation performs better than the actual NLMeans filter with regard to Peak-Signal-to-Noise Ratio (PSNR) for DW-MRI.

Zhang et al (2014) examined a Rician NLM (RNLM) employing Combined Patch and Pixel (CPP) similarity, where only the pixels having pixel and neighbourhood similarities at the same time will have their assignment of higher weights in the average. To conclude, the enumerated results indicate that the RNLM-CPP algorithm can maintain small high-contrast particle details, which are clinically related, but generally blurred by the actual RNLM algorithm.

Hu et al (2012) presented the integration of a discrete cosine transform (DCT) into NLM filter to have an improvement over its limitation, and suggested a new filter. In the new filter, during the denoising, transformation of image patches are first done from time domain to frequency domain, making use of DCT, and lower-dimensional frequency co-efficients subspace of DCT is got by Zigzag scan. As a result, similarity weights are calculated in this subspace with being hard to noise instead of the full space. Hence, the accuracy of similarity weights is enhanced and same kind of more pixels can be found in the search window. Lastly, taking the characteristics of Rician noise into consideration in MR image, the unbiased correction operation is carried out for the elimination of the biased deviation. The filter proposed has been compared with many methods introduced recently, which show that the proposed filter outperforms the rest of the methods with regard to both vision and complexity.

Hwuang et al (2013) evaluated the Anisotropic Smoothing Regularizer (AnSR) which uses edge-detection and denoising inside the Demons framework for the regularization of the deformation field at each iteration of the registration in a more aggressive manner in homogeneously oriented displaced regions. Simultaneously it regularizes in a less aggressive manner in areas comprising of non-homogeneous local deformation and tissue interfaces. On the contrary, the traditional Gaussian Smoothing Regularizer (GaSR) performs a uniform averaging over the entire deformation field, with no care in considering transitions across tissue boundaries and local displacements in the deformation field. In this work AnSR is applied within the Demons algorithm and performs pairwise registration on 2D synthetic brain MRI, with and without noise, after the induction
of a deformation that simulates shrinking of the target region anticipated from Laser-induced Interstitial Thermal Therapy (LITT). The Demons with AnSR are employed for registration of clinical T1-weighted MRI for one epilepsy and one (GBM) patient pre and post LITT.

Tristán-Vega et al (2012) gave the introduction for a method for heavily accelerating the computation of patch distances and hence in NLM, considering only the difference between important features related to the pixels to be weighed. In comparison to other related works, the technique has a number of key benefits that are tested over the usual MRI data sets: first, the calculation maintains the statistical characterization of patches in the original NLM, and thereby its optimality properties. But, this approach is chiefly oriented to MRI, which is implicitly non-textured.

Lately, Krissian and Aja-Fernandez (2009) showed a new anisotropic diffusion filter in accordance with linear minimum mean squared error estimation and partial difference equations for Rician noise elimination, with highly standardized results. Wavelet-based filters have also been applied successfully to the denoising of MR images (Pizurica et al., 2003). Such filters are rooted on the technique of image processing in a transformed domain.

Another method, Anisotropic Diffusion Filtering (ADF) (Perona and Malik, 1990), is efficient in the improvement of SNR while maintaining edges by the averaging of the pixels in the direction orthogonal to the local image signal gradient. ADF can largely remove small features and produce alterations to the image statistics. Although by adaptively accounting for MRI’s spatially changing noise characteristics, this can yield improvements; the unavailability of the image noise matrix is a practical challenge.

Gopinath (2011) innovated a graph based MRI image segmentation, where the preprocessing is conducted by making use of Anisotropic Filtering. Anisotropic filter helps to smooth within the regions of an image without producing any blurs to the edges. For Normalized MRI Prostate image, the intensity values and its Standard deviation values are replaced in the diffusion equation. The diffusion equation considers smoothing within a region rather than smoothing across boundaries. This equation will not result in any inter-
regional blurring as caused by Gaussian smoothing frequently. An anisotropic diffusion filter keeps up the edges of images, but eliminates small features and produces a mask effect in the regions of the denoised images in a uniform manner. These denoising methods eliminate noise substantially but have the setback of producing blurred images and addition of artifacts to the images.

Deepika (2012) introduced segmentation of noisy MRI images using anisotropic diffusion filter for brain tumor. It can be noticed that anisotropic diffusion filter performs better than other filtering technique in denoising of medical images. Furthermore, denoising performance can be enhanced by the modification of some parameters of filtering technique. Gallea et al (2008) assessed a method with the purpose of noise removal in MRI. An implementation of an improved version of Perona and Malik's anisotropic diffusion filter is realized. In this schema, the modified diffusion equation of the filter is useful for considering the edge’s direction. This permits the filter only to blur uniform areas, while preserving the edges. Palma et al (2014) gave a quantitative analysis which describes ADF limitations and a new framework on the basis of both the strongest edges and on planar regions of the image, for the optimal setting of the parameters.

Tabik et al (2006) studied a parallel implementation of the Anisotropic Nonlinear Diffusion (AND) for 3D images filtering. AND is a highly capable noise reduction technique in the domain of computer vision. This method is in accordance with a Partial Differential Equation (PDE) tightly mated with a massive set of eigen systems. Denoising large (3D) images in biomedicine and structural cellular biology by AND filter involves huge computational expense. In consequence, a suitable parallel realization of AND is the best technique for reducing its runtime. Wu et al (2014) suggested the improvement of the structure-adaptive anisotropic filtering approach on the basis of the Non Linear Structure Tensor (NLST) analysis technique. Based on the anisotropic measurements of image structures, a novel kernel construction approach is developed, for making the filter shape fine tuned to image characteristics. Through the accurate estimated orientation of the image structures, the filtering process is carried out with the proper alignment of the filter kernels. Nevertheless, the conventional anisotropic diffusion filter has many drawbacks, like the sensitivity to noise.
Walker et al (2006) showed the preprocessing, based on bilateral filtering, that can localize activated brain near to regions of abnormal tissue such as tumors with more accuracy. In comparison with Gaussian spatial smoothing, this has better performance believing that activation signal does not create any blur across sharp intensity “edges” produced by tissue interfaces. This alternative technique of spatial smoothing may be helpful, especially for comparatively stronger activation signal as needed at higher field strength. Bilateral filtering is shown to increase the statistical importance of activated areas, while preserving boundaries between tissue classes and between activated versus non-activated regions inside the same tissue class.

McPhee et al (2011) presented the use of the bilateral filter for the purpose of high-pass filtering of magnetic resonance phase images whose implementation is easy. A bilateral filter weighs a pixel's vicinity based on the spatial distance in addition to the similarity in intensity. Bhonsle et al (2012) showed the implementation of bilateral filtering for medical image de-noising. Its conceptualization and execution are simple but the performance of bilateral filter relies on its parameter. Hence, for yielding the optimum results, the parameter must be estimated. The bilateral filtering is applied on medical images which are degraded by additive white Gaussian noise with different values of variances. The filter acts like a spatial Gaussian filter in areas with same pixel values, but it limits artifacts at boundaries between areas with pixel values with huge difference, such as the brain surface.

Ryan and Laidlaw (2014) studied and produced the assessment of a bilateral filter for the smoothing of diffusion MRI fibre orientations preserving anatomical boundaries and supporting multiple fibres per voxel. In this technique, distances and local estimators of weighted collections of multi-fibre models are defined and are shown that these provide the ground for effective bilateral filtering algorithm for orientation data. This method has significant applications in diffusion MR tractography, brain connectivity mapping, and cardiac modeling.

Anand (2008) presented a useful technique for the improvement of noisy magnetic resonance image utilizing bilateral filter in the undecimated wavelet domain. The extent of the restored magnetic resonance image is helpful for diagnosis and automated
computer analysis. Undecimated Wavelet Transform (UDWT) is applied for effectively representing the noisy co-efficients. The filter co-efficients of the UDWT are not up-sampled with a raise in the level of decomposition. Application of bilateral filter on the transformed approximation co-efficients effectively maintains the related edge features and eliminates the noisy co-efficients.

Mustafa and Kadah (2011) explained an extension to the bilateral filter: Multi Resolution Bilateral Filters (MRBF), with Wavelet Transform (WT) sub-bands mixing. They suggested that wavelet sub-bands mixing is on the basis of a multi-resolution technique for boosting the quality of image denoising filter, which, in turn, is very robust in the reduction of noise in noisy images. Quantitative validation was conducted on synthetic datasets produced with the help of the Brain Web simulator. Lastly, the effect of the presented multi-resolution approach based on wavelet sub-bands mixing should be examined further, as in combination with the nonlinear diffusion filter and the total variation minimization.

Wang and Zhou (2006) studied a denoising algorithm for medical images with a combination of the total variation minimization technique and the wavelet scheme. The scheme offers good noise removal in really noisy medical images, still preserving the sharpness of objects. Mainly, this scheme allows implementation of an efficient automatic stopping time criterion.

Varghees et al (2012) suggested an automatic, adaptive image denoising approach for the elimination of of Rician noise from MRI images. The suggested technique is in accordance with the discretized Total Variation (TV) minimization model and the local noise estimation scheme. The regularization parameter of the TV based denoising technique is in conformance with the standard deviation of noise in MRI image. The performance of the presented technique is assessed using the brain MRI images affected by Rician noise with standard deviation in the range from 2 to 30. The validation of the quality of the denoised image is done by the use of both subjective visualization tests and objective quality metrics. The experimental results reveal that the method proposed yields a substantial improvement in maintaining the edges while reducing the Rician noise from a MR image at the same time. The adaptive TV filtering technique has reasonably better
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performance compared to the other available methods such as non-local filter, bilateral filter and multiscale Linear Minimum Mean Square-error Estimation (LMMSE) approach.

Garg and Kaur (2013) developed a technique which is a combination of Interpolate Median Filter (IMF) with Anisotropic Diffusion Total Variation FCM (ADTVFCM) for the improvement of the segmentation accuracy for brain MRI images as it is required for medical images to be noiseless for correctly detecting brain disorder or injury in brain so that the right diagnosis can be planned. Hence, this presented technique is expected to provide better segmentation results when compared to previous ones. Then again, this filter is affected by the stair-casing effect, which results in gradual contrast variations in homogeneous objects, particularly near curved edges and corners. The popularly adopted TV filter is not optimum for MRI images with spatially altering noise levels, along with artifacts. It selects reliable edges and in the initial step itself, makes the study of noise/artifact distribution from the noisy image. Then, the spatially variant parameters are defined based on it, thus making it adaptive. Furthermore, the proposed technique aligns its significant parameter via a data-driven approach without the need of user’s inputs, thus making it automatic.

Liu et al (2014) introduced the denoising method on the basis of the assumption on spatially changing Rician noise map. A two-step wavelet-domain estimation technique is designed for the extraction of the noise map. In accordance with a Bayesian modeling approach, a generalized total variation-based MRI denoising model is presented on the basis of global hyper-Laplacian prior and Rician noise assumption. The model proposed has the characteristics of backward diffusion in local normal directions and forward diffusion in local tangent directions. In order to further enhance the denoising performance, a local variance estimator-based technique is brought in for the calculation of the spatially adaptive regularization parameters relevant to local image features and spatially changing noise map. The important advantage of the new method is that it takes full benefit of the global MR image prior and local image properties. Many experiments have been carried out on both artificial and real MR data sets for the comparison of the proposed model with few of the highly standardized denoising techniques.
In order to get over the above mentioned issues, Optimized Total Variation Filter (OTVF) denoising is introduced. This technique boosts the actual MRI images in two steps, which comprise of denoising and edge enhancement. Many of the denoising solutions focus mainly on noise reduction and neglect the edge information. Few techniques employ different algorithms for each of these two steps. This work presents a single process which performs these two operations simultaneously making use of a combination of image preprocessing techniques. Regularization parameter (lambda), a positive value which specifies the fidelity weights provides control towards the amount of de-noising. The smoothing and optimization of fidelity weights are done using Particle Swarm Optimization (PSO) for the restoration of a regularization parameter ranging from 0 to 1.

**TABLE 2.1: Merits and Demerits of Denoising Methods**

<table>
<thead>
<tr>
<th>Denoising Filtering Methods</th>
<th>Merits</th>
<th>Demerits</th>
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| Mean Filter                 | • The computation in mean filter is done using convolution.  
                                • Similar to other convolutions it is in accordance with a kernel, representing the shape and size of the vicinity to be sampled when computing the mean.  
                                • It is to be noted that a small kernel can be employed more than once for producing the same but does not produce identical effect as a single time with a large kernel. | • The mean filter eliminates both the noise and the minute detail as it cannot distinguish between the two. Anything that is comparatively small in size to the size of the neighbouring area will have less effect on the value of the mean, and will be filtered out. |
| Non Local Means Filter | • Conducts denoising for AWGN noise even at larger variances.  
|                        | • This technique produces very good results in images with huge redundancy.  
|                        | This technique poses two major drawbacks,  
|                        | • The computation involved is very huge in number.  
|                        | • Therefore the simulation time increases with the size of the degraded image.  
|                        | • Removes non redundant details. Additionally, computation cost is high.  

| Anisotropic Diffusion Filter | • Averaging is good for the removal of random noise.  
|                            | • Easy realization along with the chance of discretization of the problem on a varying grid, adaptive to the local image structure.  
|                            | • It provides smoothening of an image, but simultaneously blurs significant features such as edges, thus making it hard for the identification of the next stage of image analysis, that is segmentation.  
|                            | • In order to get over this issue, a nonlinear filter, that is adapted to the local structure of an image, should be considered.  

| Total Variation Filter | • This noise reduction method is advantageous over simple techniques such as linear smoothing or median filtering that eliminate noise.  
|                       | • Highly efficient at preserving edges and smoothing away noise in flat regions at the  
|                       | • Blurring fine image structure or introducing artifacts.  
|                       | • It is assumed that the underlying image has piecewise constant regions. This assumption is no more valid resulting in the solutions affected due to
### PCA Filter
- Operates directly on the Color Filter Array data utilizing a supporting window for the analysis of the local image statistics.
- Exploitation of the spatial and spectral correlations which exist in the CFA image can help in efficiently suppressing noise and maintaining color edges and details simultaneously.
- Removes the noise without causing any blur towards the edges and the significant features of the images.
- Less effective on the MRI for the detection and characterization of small or non-homogeneous lesions.
- Computation is not economical.

### Anisotropic Nonlinear Diffusion Filter
- It removes noise in flat regions and maintains edges to a higher extent.
- Setting different parameters, such as the number of iterations, is a hard task. It deteriorates the fine structure, thereby leading to reduction in the resolution of the image.

### Bilateral filter
- A bilateral filter maintains the edges.
- Simple to understand, Operation according to weighted mean of neighboring pixels.
- Slow in operation compared to a Gaussian filter.
- Staircase effect - intensity plateaus that result in images to appear like cartoons.
- Gradient reversal - insertion
| Median Filter | • Setting up is easy due to being non-iterative. |
|              | • The median is a more reliable average than the mean and so a single negligible pixel in vicinity will not have any effect on the median value significantly. |
|              | • As the median value must really be the value of one of the pixels in the vicinity, the median filter does not involve any creation of new imaginary pixel values when the filter spans along an edge. Due to this reason the median filter is good at preservation of the sharp edges than the mean filter. |
| Gaussian Filter | • Has no overshoot to a step function input during the minimization of the rise and fall time. |
|                | • Gaussian filter has less possible group delay. |
|                | • It is an ideal time domain filter. |
|                | • One of the main issues with the median filter is its complexity in computation. For finding the median it is sorting of all the values nearby into numerical order is required and this is again slow, even with fastly sorting algorithms such as quick sort. |
|                | • Any structure that takes up less than half of the filter’s neighborhood will be removed. |
|                | • The Gaussian filter is non-causal meaning that the filter window is symmetric about the origin in the time-domain. This result in the Gaussian filters not being practically realizable. |
|                | • In real-time systems, a delay is unavoidable since the incoming samples are required to fill the filter window before the
application of the filter to the signal.
- No amount of delay can yield a theoretical Gaussian filter causal (since the Gaussian function is non-zero everywhere).
- The convergence of Gaussian function to zero is so rapid that a causal approximation can accomplish any necessary tolerance with a moderate delay, even to the precision of floating point representation.

<table>
<thead>
<tr>
<th>Proposed Denoising Filter</th>
<th>Merits</th>
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<tbody>
<tr>
<td>Optimized Total Variation Filter (OTVF)</td>
<td>The performance and the effectiveness of the different de-noising techniques have been computed so that it can be used for the identification of the quality of MRI images.</td>
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<tr>
<td></td>
<td>The local interactions brought in by TV do not reach much longer distances practically; hence the TV model can nearly be a local filter. This issue and normalizing the Regularization parameter ($\lambda$) by making use of the PSO in TV for neighborhood of each pixel.</td>
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<td></td>
<td>From this viewpoint, performance of the proposed and available TV is computed in terms of Peak Signal to Noise Ratio (PSNR), Root Mean Squared Error (RMSE) and Structured Similarity Index Metrics (SSIM).</td>
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2.1.2. Preprocessing Using Skull Stripping

Brain is the region of the central nervous system situated in the skull. For the diagnosis of human brain affected with tumor, skull stripping plays a significant preprocessing role. Skull stripping is the procedure of separating the brain and non-brain tissues of the head, which is a crucial processing step in analyzing the neuro imaging data. Challenges still persist, even though many algorithms have been proposed to deal with this issue.

Segonne et al (2004) demonstrated a new skull-stripping algorithm, which is based on a hybrid approach combining watershed algorithms and deformable surface models. This technique possesses the advantage of the robust nature of the former, in addition to the surface information available to the latter. During the implementation of this new skull-stripping algorithm, an automated algorithm is able to segment the whole brain successfully, without any manual intervention.

Mohsin et al (2012) enhanced the effectiveness of stripping skull in MRI by making use of the systematic employment of “Erosion” with Area of Interest (AOI) technique after detecting false-background. Before the application of “Erosion”, a false background is found out. The identification of skull boundary is done through Dilation and then scan line algorithm is used for the filling of the false background area. As a result, “Erosion” algorithm will only erode the AOI, and leads to the stripping of skull without any damage to the other tissues of the brain.

Roslan (2010) gave the introduction for skull stripping of MRI brain images, utilizing mathematical morphology. Skull stripping is an important phase in MRI brain imaging applications, and it denotes the removing the non-cerebral tissues. The important issue in skull-stripping is the segmentation of the non-cerebral and the intracranial tissues because of their homogeneity intensities. As morphology necessitates the binarization of the image in the previous step, this paper presents mathematical morphology segmentation using double and Otsu's thresholding. The purpose is the identification of reliable threshold values for the removal of the non-cerebral tissue from MRI brain images. Ninety collected samples of T1-weighted, T2-weighted and FLAIR MRI brain images are brought into use in the experiments.
Somasundaram and Kalavathi (2011) proposed a new skull stripping method for magnetic resonance image (MRI) of human head scans on the basis of 2D region growing. This is an entirely automated technique for the segmentation of the brain portion from T1, T2 and PD weighted MR images. This method includes two important processes. As the first step, the part of the brain in the middle slice is extracted and then the portions of the brain in the remaining slices are extracted. In this technique, the binary form of the brain image is treated first to detect the rough brain. Then, by utilizing the 2D region growing technique, the fine brain area detection in the rough brain is carried out. A circle is set inside the rough brain for the selection of the seed points for region growing. The geometric similarities of the nearby slices are made use of for the extraction of brain portions in the leftover slices. The proposed technique yields the extraction of the brain in T1, T2 and PD weighted images with accuracy.

Shanthi and Sasikumar (2007) gave the introduction for skull stripping and automatic segmentation of brain MRI, employing seed growth and threshold techniques. Segmentation of human brain from MRI scan slices without manual intervention is the goal of this research work. An easy and precise method is designed for the extraction of the brain tissues from the T1 weighted MR Images. A blend of threshold and seed growth techniques is applied for the classification of the brain tissues into white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF).

Sadananthan et al (2009) showed new, fully-automated skull stripping algorithm, that is influenced by the previous work, consisting of intensity thresholding and elimination of narrow connections, employing morphological processing. In place of morphological operations, a superior graph theoretic segmentation is applied with appropriately modified edge weight assignment for enabling the accurate reduction of narrow connections and dura attachments.

Hwang et al (2011) proposed a technique, which includes a speedup operator to the conventional 3D level set technique, for accelerating the level set evolution. In addition to the processing time for brain extraction being reduced by the speedup operator, the accuracy of brain extraction is also enhanced by the adoption of a refinement process. Galdames et al (2012) introduced an automatic skull stripping method which is in
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Somasundaram and Kalavathi (2012) developed an automated technique for the segmentation of the brain regions from T1-weighted MRI human head scans. This methodology comprises of two stages. In Stage-1, the extraction of the brain portion in the middle slice of the volume is carried out. The remaining brain regions slices are extracted in Stage-2. In each stage, the processing of the binary form of the brain image is carried out for finding the rough brain mask. The detection of the boundary of the fine brain region in the rough brain is done using the contour lines. The method proposed exhibits robust behavior to the variability of brain anatomy and image orientation.

Mahapatra (2012) proposed a new technique for skull stripping of infant (neonatal) brain magnetic resonance images making use of previous shape information within a graph cut framework. Skull stripping has a huge role to play in brain image analysis, and is a challenging task for neonatal brain images. Mostly, employed methods like the Brain Surface Extractor (BSE) and Brain Extraction Tool (BET) do not yield desirable results for neonatal images because of poor tissue contrast, weak boundaries between brain and non-brain regions, and low spatial resolution. The accurate identification of brain and non-brain tissues can be accomplished by inclusion of prior shape information. Prior shape information is got from a set of labeled training images. The probability of a pixel inside the brain is found from the prior shape mask and admitted in the penalty term of the cost function. An extra smoothness term which bases itself on gradient information helps the identification of the weak boundaries between the brain and non-brain region.

Galdames et al (2011) developed an automated accurate skull stripping technique on the basis of deformable models and histogram analysis. A pre-segmentation step is helpful for finding the optimal starting point for the deformation, and is in accordance with thresholds and morphological operators. Thresholds are calculated

accordance with deformable models and histogram analysis. A rough-segmentation step is useful for finding the optimal starting point for the deformation on the basis of thresholds and morphological operators. Thresholds are calculated with comparisons made with an atlas, and modeled by Gaussians. The deformable model is according to a simplex mesh, and the image local gray levels control its deformation and the information obtained on the gray level modeling of the rough-segmentation.
employing comparisons with an atlas and modeling by Gaussians. The image local gray levels control its deformation and the information obtained on the gray level modeling of the pre-segmentation. The Simplex Mesh and Histogram Analysis Skull Stripping (SMHASS) method was examined on the following international databases generally employed in scientific articles: BrainWeb, Internet Brain Segmentation Repository (IBSR) and Segmentation Validation Engine (SVE).

Bauer and Reyes (2011) showed a reliable and fully automated method for skull-stripping, achieving better results in comparison to the standardized methods on tumor-bearing brain images. Computation time is quite faster on 3D MRI volumes. Hahn and Peitgen (2000) proposed a technique for the elimination of non-cerebral tissue in T1-Weighted Magnetic Resonance (WMR) brain images with robustness. This process, frequently called as skull stripping, is a significant step in neuroimaging. The new technique comprises of a single morphological operation, viz, a modified three-dimensional fast watershed transform that is perfectly desirable for locating the brain, along with the cerebellum and the spinal cord.

Lee (2013) assessed the accuracy and effective behavior of both automatic and semi-automatic skull-stripping techniques. The assessment was conducted on both simulated and real data with the ground truth in skull-stripping. Though automatic technique has showed better results, it requires additional interference. On the contrary, semi-automatic technique revealed better accurate results, though it was time consuming and affected by operator bias. Hence, it might be practically suitable to use the semi-automated method as the post-processing for the automatic one.

Benson and Lajish (2014) proposed a technique for MR Image contrast enhancement and skull stripping on the basis of the morphological image processing technique. The method proposed operates on T1, T2 and FLAIR axial images. Experimental results reveal that the proposed technique effectively works for the enhancement and skull elimination of brain MR Images.

Tao and Chang (2010) introduced an automatic skull stripping algorithm by making use of deformable surface models and fuzzy tissue classification. Deformable
surface based methods chiefly depend on image gradient and surface internal forces for moving the deformable surface towards the regions of interest. Here it is the brain tumor. The image gradient information is usually extracted from the MRI modalities which are used for the task at hand which are T1, T2, and FLAIR. Additionally, internal forces are brought into use for guiding the evolution of the deformable surfaces and enforce certain topological constraints such as smoothness, convexity or shape prior on them. Criticisms on this type of techniques are that the initial surface position should be near enough to the tumor volume to avoid local minima and failure in converging.

Ali et al (2014) developed two methods for the extraction of the brain tissues as primary step. The next step was the utilization of the resultant skull stripped images as input to four segmentation algorithms for the extraction of the tumor region and computing the area value of it. The resulting skull stripped images for entire set of T2-weighted images and the adaptive K-Means clustering techniques showed the robust performance of these presented algorithms.

Somasundaram and Shankar (2014) presented an automatic technique for the segmentation of brain from T1 weighted MR images. Primarily, Otsu thresholding technique is made use of for finding the threshold value to eliminate low intensity pixels such as air and CSF from the image. K-Mean clustering technique is then used for the classification of the image into three portions such as brain tissues, non-brain tissues and background. For eliminating the non-brain pixels, histogram of the image is examined, and lastly, Largest Connected Component (LCC) is used for the segmentation of the brain.

2.2. Impact of Preprocessing in Segmentation

Image preprocessing is a significant and challenging area in the computer-aided diagnostic systems. In medical image processing and particularly in MRI segmentation task, preprocessing the image is highly necessary so that segmentation algorithms perform correctly. The accuracy of segmentation is increased by right detection and segmentation of the tissue. The accurate tissue segmentation can take place only if image is pre-processed as per image size and quality. In this chapter, section 2.1 provides the description of the pre-processing method which consists of two phases. In the first phase, the elimination of noises in the image samples are performed by using various filters. The second phase
discusses the algorithm that is used for the removal of unnecessary skull/ribcage portion. This, in turn, eliminates the false positive results in the final stages of processing in the computer aided diagnostic systems. Both algorithms are employed on MR images of brain affected by epilepsy. The efficient preprocessing should remove the over segmentation issue in further processing, while the tissues are retained.

2.3. Segmentation using Clustering Techniques

One significant area of research is the application of image segmentation in the evaluation of the similarity between the regions that is useful for automatically segmenting the images into parts with meaning. Image Segmentation is a basic procedure in digital image processing which comprises of many application areas such as Medical Image Computing, Remote Sensing, Face recognition, etc. The important aim of image segmentation is the extraction of the similar regions which is then utilized for subsequent processing, including object representation and description. Clustering is a process where the data or entities are gathered together, forming a number of clusters, such that the entities within a cluster have more similarity to each other than the rest in other clusters. The objects are thus organized into an effective representation that features the population that is being sampled. Other clustering processes have been in development for such diverse fields as Statistical data analysis, Medical Imaging and Pattern Recognition. The important advantage of clustering is that interesting patterns and structures can be detected directly from very large data sets with less or none of the background information. In this section, review of the recent technologies and techniques of semi-automatic and automatic techniques for the segmentation of MRI images are performed. Few of the important problems in MRI image segmentation while making use of different clustering approaches have been discussed.

Selvamani and Geetha (2011) made use of K Means clustering algorithm for the segmentation of the medical image. Thus, an algorithm that can be suitable for large datasets and to detect the initial centroid is proposed. An algorithm is defined to segment the MR brain image into K different tissue types that are GM, WM, and CSF, and maybe other abnormal tissues. The considered MR images can be either scale or multivalued. Each scale-valued image is created as a collection of regions with an intensity that slowly
Hybrid Fuzzy Clustering Technique using Random based Optimization for Segmenting MRI Brain Images

K-means algorithm is a widely known partition algorithm used in cluster analysis, which has few drawbacks when there are some restraints in computing resources and time, particularly due to huge size.

Sharma and Gulista (2011) introduced a segmentation process for the MR images of the human Brain by making use of K means Algorithm and Canny Edge Detection Algorithm. K-means Clustering algorithm yielded the segmented image of an MRI with the same intensity regions. K-means Clustering performs the segmentation of all the three matters of the brain i.e. GM, WM, and CSF. Also, the edge detection algorithm is realized creating the boundaries of the different regions of the MRI on the basis of scale and threshold values applied for the segmentation.

Somasundaram and Genish (2013) demonstrated a boundary detection method for the segmentation of the hippocampus (the subcortical structure in medial temporal lobe) from MRI having inhomogeneous intensity without affecting its boundary and structure. The image is pre-processed by making use of a noise filter and morphology based tasks. An optimal intensity threshold is then calculated employing K-means clustering method. The validation of the technique has been done on human brain axial MRI and is found to provide satisfying performance with heterogeneous intensity.

Taneja and Sahu (2014) introduced the enhanced ACO for tumor segmentation. Ant based clustering is a clustering algorithm that copies the behavior of ants. In this algorithm, ant’s direction and its inclination to move to the next site is considered for the calculation of the probability of selecting the next site by the ant. Moreover, in computing the probability of the ant's next location, a balance is created between the act of the ant direction and the amount of pheromone distribution. This way, the algorithm finds its application for the segmentation of brain images and diagnosis of tumors.

Meena and Raja (2013) demonstrated an automatic localization of epileptic seizures in brain, employed from nuclear medicine imaging technique such as PET. This paper focuses on the research of automatic localization of epileptic seizures in brain functional images making use of symmetry based cluster technique. This technique
proposes a fully automatic symmetry based brain abnormality detection scheme for PET sequences.

Sujitha et al., (2011) proposed the modeling of epileptic seizure prediction, as a classification task and a kind of support vector machine, called fast single shot proximal support vector machine with vector output has been applied for solving multiclass classification issue. Epilepsy is a neurological condition producing disturbances of short duration in the usual electrical functions of the brain and is featured by sporadic firing of neurons abnormally in the brain. MRI is a significant technique employed in epilepsy diagnosis. The detection of the epileptic activity needs a time-exhausting analysis of the whole MRI data with the help of an expert. Therefore, there is a necessity for the generation of an effective prediction model for performing a right diagnosis of epileptic seizure and prediction with accuracy of its type.

Mayer et al., (2009) dealt with an automatic technique for MRI brain segmentation. An adaptive mean-shift methodology is employed for the classification of brain voxels into one of three important tissue types: GM, WM, and CSF. The MRI image space is denoted by a high-dimensional feature space including multimodal intensity features along with spatial features. An adaptive mean-shift algorithm groups the joint spatial-intensity feature space, thereby providing the extraction of a representative set of high-density points within the feature space, also known as modes. Tissue segmentation is done by a follow-up phase of intensity-based mode clustering into the three tissue classes. By its nature of being nonparametric, adaptive mean-shift can cope up with non-convex clusters with success. Thus it can produce convergence modes that have better prospects for intensity based classification in comparison to the primary voxels. The validation of the method proposed is performed on 3D single and multimodal datasets, for both imitated and original MRI data.

Sujitha et al., (2010) introduced the implementation of epilepsy prediction by making use of Support Vector Machine (SVM), which is a machine learning algorithm. The prediction model has been created by providing training to the support vector machine with descriptive characteristics obtained from MRI data of 350 patients and was seen that
the SVM based model with a Radial Basis Function (RBF) kernel yields 93.87% accurate prediction.

Xue et al., (2003) dealt with an integrated technique of the adaptive enhanced version for an automatic global-to-local segmentation of brain tissues in three-dimensional 3D MRI images. Three brain tissues are of importance. They are WM, GM, and CSF. In the first step, the denoising process of the images is performed employing a novel diverse type wavelet-based filter, and then the segmentation of the images is done with minimized error global thresholding. Afterwards, a spatial-feature-based FCM clustering, in combination with 3D clustering result weighted median and average filters, is used, for further achieving a locally adaptive improvement and segmentation. This integrated technique provides a reliable and precise segmentation, specifically in noisy images.

Goldberg et al., (2014) made the assessment of the degree of tissue-specific and structural brain atrophy in patients with TLE in comparison with Idiopathic Generalized Epilepsy (IGE) and age-matched controls. An automatic software instrument is employed for brain MRI segmentation into various portions of interest for enabling quantitative analysis of the various brain structures. All epilepsy groups had substantially lower NBV and NWMV when compared to HC (p < 0.001). L-TLE had lower hippocampal volume in comparison to HC and IGE (p = 0.001), and all epilepsy groups had considerably lower amygdala volume compared to HC (p ≤ 0.004). In L-TLE, there was proof of atrophy in both ipsilateral and contralateral structures.

Heckemann et al., (2006) conducted an examination on the performance and procedures of label propagation with decision fusion in MR images of the human brain, beginning from elaborated expert segmentations of 30 brains and making use of a registration technique on the basis of free-form deformation (Rueckert et al., 1999). The goal of this work is the evaluation of the accuracy of the technique by computing the agreement between automatically and manually fixed structure labels, it is precision by the measurement of the agreement between independent fused segmentations, and its modes of failure by the analysis of single cases of label disagreement. A model defined that the achievable improvement can be predicted with regard to the number of input segmentations. A significantly enhanced strategy is thus demonstrated for brain labeling.
providing accuracy that can be predicted at a degree that suffices for a total of scientifically and clinically necessary applications.

Zarandi et al., (2012) employed the Type-2 Possibilistic C Means (PCM) clustering technique for the segmentation of the MRI and for the detection of the abnormalities in these images. By utilizing this automated segmentation strategy, the results obtained are good, which does not get affected by the disadvantages of manual segmenting processes. In recent times, neurology and neuroscience have been critically progressed by imaging tools, which usually take large amount of data and many doubts. Hence, Type-2 fuzzy clustering techniques could process these images more effectively, and better performance could be achieved. The aim of this paper is the segmentation of the brain MRI into indispensable clusters according to Type-2 PCM method.

Vasuda and Satheesh (2010) showed the enhanced FCM Algorithm for MR Brain Image Segmentation. Fuzzy clustering by using FCM algorithm showed superiority over the other clustering approaches with regard to effectiveness in segmentation. But the important setback of the FCM algorithm is the huge time taken for computation necessary for convergence. The effectiveness of the FCM algorithm, concerning computational rate, is enhanced by the modification of the cluster center and membership value updation criterion. In this work, comparison of convergence rate between the conventional FCM and the improved FCM is conducted.

Kannan (2008) developed a new technique called Fuzzy Membership C Means (FMCM) for segmenting MRI and an effective program realisation. Traditional unsupervised clustering techniques like the FCM by Bezdek, have many issues that can be partly applied a proper rule for the construction of the initial membership matrix to clusters. This work formulates a particular technique for building the initial membership matrix to clusters for improving the strength of the clusters. The novel FMCM is experimented on a set of standards and then the implementation to the segmentation of MR images is proposed and comparison made with the results got using FCM.

Zanaty et al., (2008) proposed robust algorithms for fuzzy K means and C means that could help in improving MRI segmentation. Since the K means or FCM method
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attempts the minimization of the sum of squared distances from all points to their cluster cores, this should produce compact clusters. Hence, the distance of the points from their cluster core is useful to decide if the clusters are compact. Considering this, the intra-cluster distance measure is utilized, which is just the median distance between a point and its cluster core. The intra-cluster is employed to retrieve the perfect number of clusters automatically, i.e., a centre of the first cluster is used for the estimation of the second cluster, when an intra-cluster of the second cluster is got. Similarly, the third cluster estimation is done based on the second cluster information (centre and intra-cluster) and so on, and they only terminate when the intra-cluster is smaller than a prescribed value. The algorithms proposed are assessed and comparisons are made with the already proven fuzzy K means and C means techniques by employing them on imitated volumetric MRI and actual MRI data for proving their efficiency.

Beevi et al (2010) developed a new and effective fuzzy spatial C means clustering algorithm which has good robustness to noise. The presented clustering algorithm makes use of fuzzy spatial information for the calculation of membership value. The input image is clustered applying the Improved Spatial FCM (ISFCM) algorithm. A comparative analysis has been conducted between the classical FCM and proposed ISFCM. The algorithm is formulated by including the spatial neighborhood information into the standard FCM clustering algorithm with the help of a priori probability. The probability is provided to show the spatial effect of the neighboring pixels on the centre pixel, which can be automatically determined in the realization of the algorithm by the fuzzy membership. The new fuzzy membership of the current centre pixel is then recomputed with this probability received from above. The algorithm is initiated by a given histogram based FCM algorithm, which is used for the speeding up the convergence of the algorithm.

Christe et al., (2010) provided the implementation of brain image segmentation algorithms such as FCM segmentation and Kohonen means (K means) segmentation. Additionally, a novel hybrid segmentation scheme, namely, Fuzzy Kohonen means of image segmentation which is based on statistical feature clustering is presented and realized along with standard pixel value clustering technique. The comparison of the clustered segmented tissue images is done with the Ground truth and its performance
metric is also investigated. It is seen that the feature based hybrid segmentation gives enhanced performance metric and improvement over the classification accuracy compared to the pixel based segmentation.

Ortiz et al., (2011) proposed a segmentation technique which is based on a supervised version of the Self Organizing Maps (SOM). Also, a probability-based clustering technique is introduced for the improvement of the resolution of the segmented image. Image segmentation includes the partitioning of an image into different regions. These regions decide the different tissues available on the image. This gives rise to a very interesting tool for neuroanatomical analysis. This way, the diagnosis of few brain ailments can be worked out by the analysis of the segmented image.

Kumar et al., (2013) demonstrated an automated MRI brain image segmentation framework by making use of a gravitational search based clustering method. This framework comprises of two stage segmentation process. In the first step, removal of non-brain tissues from the brain tissues are conducted employing modified skull-stripping algorithm. Afterwards, the automatic gravitational search-based clustering technique is applied for the extraction of the brain tissues from the skull stripped image. The algorithm has been brought into use on four modeled T1-weighted MRI brain images.

Zanaty (2013) suggested a new fuzzy c-means technique for the improvement of the MRI segmentation. The novel technique known as “Possiblistic Fuzzy C Means (PFCM)” blends the FCM and PCM functions. It is implemented by the modification of the objective function of the traditional PCM algorithm with Gaussian exponent weights for the production of memberships and possibilities at the same time, in addition to the general point prototypes or cluster cores for every cluster. The interpretation of the membership values can be seen as levels of possibility of the points that belong to the classes, i.e., the compatibilities of the points with the class prototypes. For this reason, the presented algorithm is quite capable of avoiding various issues of the available fuzzy clustering techniques resolving the faults of noise sensitivity and helps in preventing the coincident clusters issue of PCM. The effectiveness of the presented algorithm is exhibited by elaborate segmentation experiments by their application to the applications that are
challenging: GM/WM segmentation in MRI datasets and by comparing with other highly standardised algorithms.

Hussain et al., (2012) introduced an highly effective technique for the accurate segmentation of normal and pathological tissues in the MRI brain images. The segmentation technique proposed performs the classification procedure by making use of Fuzzy Inference System (FIS) and FFBNN. Both classifiers use the selected image features as an input for the classification procedure. The features are extracted in two methods from the MRI brain images. The FIS are employed for making the classification process by the generation of the fuzzy rules by making use of the extracted features. Five features are selected from the MRI images. They are, two dynamic statistical features and three 2D wavelet decomposition features. In Segmentation part, the normal tissues like WM, GM and CSF are segmented from the normal MRI images whereas pathological tissues including edema and tumor are segmented from the abnormal images. The non-cortical tissues in the normal images are eliminated by the preprocessing step.

Selvy et al., (2011) conducted the analysis of different clustering methodologies for the tracking of tumor objects in MR brain images. The MR image of axial view of the human brain serves as input to this system. The clustering algorithms which are applied are K means, SOM, Hierarchical clustering and FCM clustering. The given gray-level MR image is transformed to a color space image and clustering algorithms are employed. The location of tumor objects is isolated from an MR image by making use of the clustering algorithms. The above clustering algorithms are assessed and the evaluation of the performance is done on the basis of the time taken for execution and accuracy of the algorithms.

Safa and Bokharaeian (2011) proposed an effective and enhanced semi-automatic Fuzzy EM (Fuzzy E M) based techniques for 3D MR segmentation of human brain images. FEM in addition to histogram based K means in the initiation stage is applied for the labeling of individual pixels/voxels of a 3D anatomical MR image inside the main tissue classes in the brain, GM, WM, CSF. The estimation of FEMs membership function were performed through a histogram-based scheme.
Zanaty and Afifi (2013) introduced a novel modified FCM algorithm which could boost the medical image segmentation. The algorithm proposed is implemented by the modification of the objective function of the traditional FCM algorithm with an adjustable penalty. This penalty is in accordance with a data shape and data size employed for generating the fuzzy terms. The complication of the new algorithm is eliminated by making use of initial seed information into the objective function rather than the entire data set. The algorithm proposed finds its application to MRI datasets. In comparison with the other available approaches, the technique proposed can be used to accomplish the best accurate results.

Tamijeselvy et al (2013) proposed a system used to segment the corpus collapsum and to extract shape features from the corpus callosum. The classification of epileptic and non-epileptic patients using Case Based Reasoning (CBR) classification model has been proposed. This paper compares well-known classification models with CBR. Also, it compares six gray-level image segmentation methods to identify the most suitable method for the segmentation of corpus callosum. Multiscale segmentation has less execution time compared to other methods for segmentation. From the experimental results obtained it is concluded that the threshold interval method is best for the preprocessing, the Multiscale segmentation is suitable for segmentation and CBR is suitable for the classification of the epileptic images from normal images. Thus, through these methods less false positive rate and improved prediction accuracy in diagnosing epilepsy has been achieved.

Tamijeselvy et al (2013) presented a technique which includes the enhanced classification approach for diagnosing epilepsy. The method comprises of the following phases: pre-processing the 2D MR Brain Image utilizing the Threshold Interval Method (TIM) and Min Max (MM). Normalized Segmentation of brain image employing the multiscale segmentation technique for obtaining the segments of corpus callosum. Multiscale segmentation establishes to be better in curvature segmentation with a lesser execution time and 91% of accurate results according to the entropy shape features such as corpus callosum bending angle and Genu thickness. Intelligent Quotient (IQ) is extracted from the segmented corpus callosum diagnosis of epilepsy by employing CBR and genetic
classification. The performance of the CBR classification that is optimized provides a reduction in the false positive rate. The CBR classification model shows a result of about 96.7% of prediction accuracy and the optimized classification technique results reveal 97.3% of prediction accuracy.

FCM is a widely known clustering technique and has been extensively employed in medical image segmentation. Though many researchers have designed multiple clustering algorithms, not one of them is perfect. The FCM algorithm operates without any previous information. The reduction in the complex nature of the algorithm is done by making use of initial seed rather than the whole data set. Also, the FCM technique contains an automated penalty on the basis of data shape and data size used for generating fuzzy terms. The results obtained from the tests prove that the FCM algorithm on actual MRI images come out with 6% noise. The superior nature of the FCM algorithm is exhibited by making its comparison of its performance with the K means, SOM and Hierarchical clustering. Additionally, quantitative results are also produced in the experiments. The segmentation accuracy of the FCM method is raised when compared to the other available methods in the literature. From the quantitative assessment and the visual investigations, it is concluded that FCM algorithm gives a reliable and accurate segmentation. Lastly, it should also be noticed that even though the FCM algorithm can outperform k-Means and other popular algorithms, it is computationwise expensive, and this may reduce its applications in large volume of MRI images.

TABLE 2.2: Merits and Demerits of Cluster based Segmentation

<table>
<thead>
<tr>
<th>Cluster Based Segmentation Methods</th>
<th>Merits</th>
<th>Demerits</th>
</tr>
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</table>
| K means Clustering                | • Faster, robust behaviour and easy in understanding.  
• It is faster in computation rather than other clustering techniques such as | • Various initial partitions can lead to diverse final clusters.  
• The usage of Exclusive Assignment is the |
Hierarchical clustering and tree-based clustering schemes.
- K-means generates tighter clusters compared to hierarchical clustering, particularly if the clusters are globular.

- The presence of two highly overlapping data leads to K-means not capable of resolving that there are two clusters.
- The learning algorithm is varying to non-linear transformations i.e. with diverse representation of data dissimilar results are obtained (Data representation in form of cartesian co-ordinates and polar co-ordinates will produce different results). Euclidean distance measures have unequally weight underlying factors.
- The learning algorithm yields the local optima of the squared error function.
- Random choice of the cluster center cannot provide useful result.
- Can be employed only when mean is defined i.e. does not work for categorical data.
- Not capable of handling noisy data and outliers.
<table>
<thead>
<tr>
<th><strong>SOM based Clustering</strong></th>
<th>• Working procedure of SOM is quite easy to understand and performance is better than the K means, as the number of clusters is decided automatically.</th>
<th>• Failure of Algorithm for non-linear data set.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fuzzy C Means clustering</strong></td>
<td>• Permits a data point to be in multiple clusters.</td>
<td>• Computation is expensive when the training samples become larger.</td>
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<tr>
<td></td>
<td>• A real representation of the gene behavior.</td>
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<td></td>
<td>• Genes generally are involved in multiple functions.</td>
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<td></td>
<td>• Provides best result for overlapped data set and outperforms K Means algorithm.</td>
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<td></td>
<td>• Compared to k-means where data point must be belong to one cluster core exclusively here the assignment of membership to the data point to each cluster center is done. Due to that each data point may be in more than one cluster center.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• A priori specification of the number of clusters.</td>
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<tr>
<td></td>
<td>• Lower value of $\beta$ yields better results but expending more number of iteration.</td>
<td></td>
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<tr>
<td></td>
<td>• Euclidean distance measures can unequally weight underlying factors.</td>
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<tr>
<td>Proposed system</td>
<td>Merits</td>
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<tr>
<td><strong>Fuzzy C Means clustering</strong></td>
<td>• Permits a data point to belong in multiple clusters.</td>
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<tr>
<td></td>
<td>• Faster, robustness and ease of understanding for image segmentation.</td>
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<td></td>
<td>• Yields best segmentation result for river ice images with unique or well isolated textures from each other.</td>
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<td></td>
<td>• Accomplishes more effective accuracy in the result with the reduction in the time taken for data and/or information recovery from large dataset.</td>
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</table>

2.4. Impact of Clustering Techniques in Segmentation

In MR images, the amount of data is huge for human interpretation and analysis. Segmentation is a significant procedure in most of the Medical Image Analysis. Clustering to MR brain tumors preserves efficiency. Clustering is desirable for biomedical image segmentation as it makes use of unsupervised learning. In this chapter, section 2.3 provides the analysis of different clustering methods for the tracking of tumor objects in MR brain images. The input to this system is the MR image of the human brain. The clustering algorithms utilized are K means, SOM, Hierarchical Clustering and FCM clustering. The mentioned clustering algorithms are assessed on the basis of time taken for execution and accuracy of the algorithms. Segmentation by clustering can also be utilized for the detection of the three regions at the brain image. MRI of brain is one of medical imaging tools employed for the detection of the abnormality in brain. The radiologist is usually interested to observe three important regions in the MRI brain images. The three parts are WM, GM and CSF.

2.5. Segmentation Using Optimized Clustering Techniques

FCM is a general clustering algorithm used for segmentation of elliptic seizure from MR images. But in the case of noisy MR images, efficiency of this algorithm is very much reduced. FCM algorithm is still affected by many disadvantages, such as low convergence rate, getting stuck in the local minima and prone to initiation sensitivity. In
the current times, researchers have introduced new parameters for the improvement of the performance of conventional FCM in the case of noisy images. Computations of new parameters are performed through the swarm intelligence techniques. SI is a considerable novel subfield of artificial intelligence which is the study of the social behavior of simple agents. It can be observed in ants’ colonies, fireflies, flocks of birds, beehives, etc.

Ghassabeh et al (2007) proposed a novel technique for the effective computation of two parameters including neighboring pixel’s intensities and the positions. GA optimization method is employed and the capacity of GA in getting optimal values of these parameters is established. Simulation results by making use of noisy MR images, proved the efficiency of the method proposed in the computation of unidentified parameters and being robust towards the noise.

Alsmadi (2014) introduced a new dynamic and intelligent clustering method for brain tumor segmentation by making use of the hybridization of FA with FCM algorithm. For the purpose of automatic segmentation of the MRI brain images and improving the ability of the FCM to automatically deduce the proper number and position of cluster centres and the number of pixels in each cluster in the abnormal (multiple sclerosis lesions) MRI images. The results obtained from the experiments reveal the efficiency of the FAFCM in the improvement of the performance of the classical FCM clustering. However; the superior operation of the FAFCM with other benchmark segmentation technique is shown both qualitatively and quantitatively.

Selvy et al (2013) studied the combination of PSO method with the best clustering techniques for getting a global optimal solution. The extraction of centroids is performed in a random manner in clustering schemes. In the method proposed, centroids are selected on the basis of the p_best and g_best value which gives global optimal solution. The sensitivity and specificity for PSO technique has fewer false positives in comparison to the conventional clustering techniques.

Soesanti et al (2011) improvised an optimized fuzzy logic technique for MRI brain images segmentation. This is a technique which is based on a modified FCM clustering algorithm. The FCM algorithm incorporating spatial information into the
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Membership function is made use for clustering, whereas a traditional FCM algorithm does not wholly make use of the spatial information in the image. The benefits of the algorithm are lower sensitivity to noise in comparison to other techniques, and it provides the regions with more homogeneity than those of other techniques. Originality of this research is the techniques which are employed on a normal MRI brain image and tumor MRI brain images, and the analysis of the area of tumor from the images that are segmented.

Jagadeesan and Sivanandam (2013) designed an enhanced K means and FCM with firefly algorithm for the segmentation of brain magnetic resonance images. This algorithm is in accordance with the maximum measure of the distance function that is developed for cluster center detection procedure by making use of the Mahalanobis concept. In particular, the firefly algorithm is realized for the optimization of the FCM membership function for accurate segmentation process. Simultaneously, the convergence criteria are determined for effective clustering technique. The Firefly algorithm parameters are adjusted to be fixed and they do not have any adjustment according to the time. As Firefly algorithm does not remember any history of situation that is better for each firefly and due to this reason they travel in any case and they miss their situations. So a better algorithm is necessary which can yield even better resolution than the firefly algorithm. To fulfill this requirement, the Artificial Fish Swarm Algorithm is proposed for the optimization of the fuzzy membership function. During the survey of the previous literature, it has been observed out that no work has been done in the arena of segmentation of brain tumor by making use of AFSA based clustering. In AFSA, artificial fishes behave in complete independence from past during their next movement and the next movement is just related to the current position of artificial fish and its other companions which result in the selection of the best initial centers for the MRI brain tumor segmentation.

Tamijeselvy et al (2013) introduced ACO and PSO technique with the clustering algorithm. The performance of these algorithms are compared and found that FCMPSO performs better than the FCM and FCMACO algorithm. The PSO and ACO are the Swarm intelligence methods that find its implementation in the field of clustering for getting approximated solutions for optimization issues in a quite tolerable amount of computation time. The function of PSO and ACO is the search for the optimized solution according to the movement of the swarm.
Abinaya and Pandiselvi (2014) presented a system possessing three phases. In the first phase, preprocessing is conducted for the removal of the film artifacts and unnecessary skull regions in brain MRI image. In the second phase, enhancement is carried out for the removal of noise in brain MRI image. In the third phase, PSO is realized for the segmentation of tissues such as WM, GM, and CSF in brain MRI image. The segmented brain MRI aids the radiologists in the inspection of brain abnormalities and tumor. The algorithm is tested with 50 real patient’s brain MRI image.

Tamijeselvy et al (2013) proposed an algorithm referred to as TV Regularization for solving the issues in FCM. Here TV is merged with FCM for the elimination of noise but the technique leads to stair casing effect and consumes longer reconstruction time. The hybrid algorithm proposed combines ADF and TVFCM technique, which gets over the issues in conventional TVFCM. ADF technique initially performs the diffusion of the image and then convolution is performed using convolution filter and then TVFCM segmentation is applied.

Alomoush et al (2014) presented a novel clustering technique on the basis of the hybridization of FA and FCM known as FFCM for the segmentation of MRI brain images. This approach makes use of the capability of firefly search towards finding the optimized initial cluster centers for the FCM and thus enhances MRI brain tumor segmentation. The proposed technique was assessed by the application to a MRI brain segmentation issue utilizing a imitated brain data set of McGill University and actual MRI images from Internet Brain Segmentation Repository benchmark data sets. The cluster validity index (Rm) was made use as a fitness function for the determination of the best solutions got from the firefly algorithm. The experiments revealed encouraging results after the application of FFCM, in comparison with the state-of-the-art segmentation algorithms and FCM random initiation of cluster centres.

Anitha et al (2012) showed that white Matter Lesions (WMLs) are small portions of dead cells which are seen in parts of the brain. Generally, it is hard for medical experts to conduct the accurate quantification of the WMLs because of reduced contrast between WM and GM. The goal of this paper is the automatic detection of the WMLs which is observed in the brains of old people. WML detection process comprises of the
following stages: 1. Image preprocessing, 2. Clustering (FCM, GPC, GFCM). The testing of the system is conducted on a database of 208 MRI images. GFCM produces high sensitivity of 90%, specificity of 94% and overall accuracy of 95% over FCM and GPC. The experimental results show that GFCM better localizes the large regions of lesions and provides lower false positive rate in comparison with FCM and GPC which conquers the largest loads of WMLs only in the upper ventral horns of the brain.

Salih et al (2005) demonstrated about intensity group clustering algorithms for achieving further diagnosis for brain MRI, which has been rarely studied. Subjective study has been advised for the evaluation of the clustering group intensity with the purpose of obtaining the best diagnosis along with better detection for the cases under suspicion. This method uses image tissue biases of intensity value pixels for providing 2 regions of interest as approaches. Also, the actual mathematic solution could also be utilized with a particular set of modern sequences. There are many benefits in generalizing the solution, which yields good scope for application and greater accuracy.

Fuzzy clustering algorithms are affected by some weaknesses. The important weakness includes the tendency to be trapped in local optima and vulnerability to initiation sensitivity. This section influenced to present a new technique for solving the FCM initialization issue by making use of firefly algorithm for finding the optimal initial cluster centers for the FCM. Thus, all applications in relevance to fuzzy clustering such as image segmentation are improved. FA has few drawbacks such as getting trapped into many local optimums. FA does local search also and sometimes is not able to remove them since the firefly parameters are constant and they do not vary with time. Hence, the behavior of attraction coefficient and randomization coefficient in firefly can be adjusted to determine the global search mobility for which random based metaheuristic optimization methods are introduced. Random based Optimized Clustering Techniques such as Chaotic and Levy Flights are realized into FA to find the global cluster centers as the beginning cluster value of FCM.
<table>
<thead>
<tr>
<th>Optimized Clustering based Segmentation methods</th>
<th>Merits</th>
<th>Demerits</th>
</tr>
</thead>
</table>
| **K means with FA**                           | • The selection of optimal centroid values are done by using FA which enhances the MRI brain tissues segmentation.  
   • Algorithm is effective. The MSE is lesser than both K-means clustering algorithm and the usual Firefly clustering algorithms. | • Firefly algorithm has few disadvantages such as being trapped into many local optima. Firefly algorithm conducts local search also and sometimes not capable of entirely removing them. |
| **FCM with GA**                               | • The time required to reach an optimum through GA is lower than the time which is necessary for the iterative approach.  
   • Moreover, the number of clusters is lowered.  
   • GA gives higher resolution capacity in comparison with the iterative search because of the fact that the precision is dependent on the step value in the “for loop function” which is max equal to 0.001 for the radius parameter in clustering algorithm. | • The greatest drawback is that there is no other better way for the determination of the C value of clustering and the initial cluster centers significantly.  
   • FCM is a local search optimization algorithm, it will have its convergence to the local minimum point and this clustering effect would have impact on a larger scale if the initial value is not selected properly. |
<table>
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<tr>
<th><strong>FCM with PSO</strong></th>
<th><strong>FCM with FA</strong></th>
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| • The local optimum is avoided, and also is robust towards initialization.  
  • The fluctuation however has shown itself in the new algorithm, which better converges to lower quantization errors.  
  • Better effect in handling data sets that dimension less than the number of sample. | • Low Convergence  
  • Weak local Search capability.  
  • PSO cannot operate on the issue of non coordinate system like solution of energy field and mobile rules for the particles in the energy field.  
  • The method quite easily is affected from the partial optimism, which causes it less perfect at the regulation of its speed and direction. |
| | • Able to make use of the advantages of the firefly search to check many search space regions when concentrating on the most encouraging regions at the same time, which results in the most perfect outcomes to be accomplished by these cases.  
  • Outcomes acquired from the proposed algorithm are superior to those of the FCM algorithm with random initialization across the four quality measurements used here. | • Sensitivity to noise and one expects low (or even no) membership degree for the outliers (noisy points).  
  • Having disadvantages like initialization sensitivity and its resultant local optima problem.  
  • Firefly algorithm does not remember any history of better situation for each firefly and due to this reason they move in any case and hence they miss their situations. |
<table>
<thead>
<tr>
<th>FCM with ACO</th>
<th>FCM with AFSO</th>
</tr>
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</table>
| - Utilized for the clustering of data points into smaller groups with same features that can be managed.  
- Improvement in the performance of FCM algorithm due to its sensitivity to local extreme. | - The FCM algorithm still has other restrictions, for instance, getting influenced by equal partition trend of the data set and sensitivity to initial conditions such as the cluster number and the cluster centers.  
- The computation is time consuming. |
| - Artificial fishes behave in complete independence from past during their next movement and the next movement is just related to the current position of artificial fish and its other companions which result in the selection of the best initial centers for the MRI brain tumor segmentation. With the help of the values of the membership of pixels obtained with FCM Clustering Algorithm, and high capability of AFSO in the global search along with the high ability of K means in performing local search has been used in conjunction for the image segmentation to be achieved. | - An artificial fish swarm algorithm on the basis of chaos search is proposed, which can overcome the drawback of easily falling into the local optimum in the later evolution period, along with keeping the rapidity of the previous period.  
- Nonetheless, it may be get trapped in local optimum in the later evolution period and its search accuracy is less. |
<table>
<thead>
<tr>
<th>Proposed system</th>
<th>Advantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM with FA</td>
<td>• Permits a data point to belong to multiple clusters.</td>
</tr>
<tr>
<td></td>
<td>• Faster, robust in behavior and easy to understand for image segmentation.</td>
</tr>
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<td></td>
<td>• Several variants and modifications are performed to improve its performance.</td>
</tr>
<tr>
<td></td>
<td>• Optimized clustering segmentation results are accomplished by the application of FA to FCM.</td>
</tr>
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2.6. Impact of Optimized Clustering Techniques in Segmentation

Many optimized clustering-based techniques have been developed for image segmentation in medical imaging under discussion in Section 2.5. Segmentation of the images is applied for the diagnosis of many disorders. Also, the task is frequently made harder due to the interference of noise and artifacts, instrumental limitations, reconstruction algorithms and patient mobility. Amidst the fuzzy clustering techniques, FCM algorithm is the widely known technique to be used in image segmentation because of its robust characteristics towards ambiguity and retrieval of much more information compared to the hard segmentation methods. The FCM is regarded as the most desirable technique for the segmentation of MRI brain images. As the FCM method does not always give the best results, the Swarm intelligence methods can find their implementation in the field of clustering for getting estimated solutions for optimization issues in a fair amount of computational time. Recently, many metaheuristic search algorithms have been combined with FCM algorithm for the identification of the optimal cluster centers. These modified algorithms have the capability to explore the whole search space in order to identify the solutions that are likely. The generation of cluster centers are done by the metaheuristic search algorithms and then utilized by the FCM algorithm to be used in image segmentation. This combined technique taps the strengths of the two algorithms, thus assuring superior quality and uniform results in MRI image segmentation.
2.7. Segmentation using Random based Optimized Clustering Techniques

Cheng and Huang (2010) used the n-dimension convergence algorithm for tracking the highly powerful course of evolution in conventional GA by K means clustering method. And, Chaotic algorithm was employed to avoid the new approach from prematuring. With the help of the proposed approach, along with the maintenance of the basic search capability, the flexibility and effectiveness of parametric modeling were enhanced as well.

Chen et al (2008) demonstrated chaos-ant colony algorithm on the basis of an ant colony algorithm, making use of gridding method, and merging it with chaos theory. ACO is a fresh new random optimization algorithm which uses artificial ants ejecting pheromone on the way, portrayed with a positive feedback, distributed computation and parallel algorithm. It is highly robust and is easier to obtain a combination with other techniques in optimization. Slower convergence and easier trapping in local optimum are the few shortcomings, though it finds wide application in optimization issues. In the chaos-ant colony algorithm, some max-min ant system idea is helpful for limiting the pheromone strewn in the path. Enhancements are done in initialization and updation of pheromone.

Min-Yuan and Kuo-Yu (2009) gave the introduction of K means with Chaos Genetic Algorithm (KCGA) to lower the amount of computation and provide improvement in the estimation accuracy for nonlinear optimizations, in which the initial population is developed by chaos mapping and then fine-tuned by competition. Within every iteration of this technique, along with the development of GA, the K means clustering algorithm is employed to accomplish faster convergence and result in a quick generation of the population as well. The important aim of the paper is the demonstration on how the improvement for the GA optimizer be achieved by incorporation of a hybridization strategy.

Ebrahimzadeh and Jampour (2013) generated pseudo random numbers by Lorenz chaotic system for operators of GA for avoiding local convergence. During the recent times, rapidly developing optimization algorithms make use of the GA for the improvement of the result of Optimization issues. Many procedures of the GA are based on
‘Random’, which is basic to evolutionary algorithms, though the main defects in the GA are local convergence and high tolerances in the results, which have happened due to being random.

Zhao et al (2014) introduced an Improved Cuckoo Search (ICS) algorithm to be used for clustering, where the mobility and randomization of the cuckoo is transformed. Cuckoo search (CS) is one among the new swarm intelligence optimization algorithms motivated by the compelling brood parasitic behavior of cuckoo, which made use of the idea of LF. But the convergence and stability of the algorithm is not suitable because of the heavy-tail property of LFs.

Hakli and Uğuz (2013) presented the Levy Flights Artificial Bee Colony (LFABC) algorithm for performing the distribution by making use of the LF method. There are several population based optimization techniques utilized for numeric functions and engineering issues. The greatest problem of these approaches is about determining the balance between exploration and exploitation. The artificial bee colony algorithm, proposed by Karaboga, yields better results, in comparison with other popular nature-influenced methods. Although the ABC algorithm is good in the exploration part, and also known for exploring new places, it is not good enough in the exploitation part, which is described as exploiting the results explored. To get rid of this problem, rather than the random distribution of the scout bees in the search space in ABC algorithm, efforts were made for the ABC algorithm to enhance the exploitation. The two methods were trialed on 10 benchmark functions, and the method proposed was seen to yield better performance.

Husselmann and Hawick (2013) demonstrated a data-parallel algorithmic realization of Lévy-flighted particle swarm optimization and showed how it uses accelerators such as Graphical Processing Unit (GPU). PSO is a potential algorithm for space search issues such as parametric optimization. Particles with Lévy-Flights have a long-tailed probability of outlier jumps in the problem space that yield a good consensus between local space exploration and local minima prevention. However, generation of many particles and their trajectories with Lévy-random deviates involves expensive computation. The computational trade off’s performance that can be achieved using GPUs,
and the scalability of such an approach, utilizing different uni-modal and multi-modal test functions in a range of dimensions are studied.

Liu (2014) threw the focus on to the use of PSO for cluster analysis. Clustering analysis is a hugely known technique in the data mining domain. It is mostly utilized for finding the classes or groups for unlabeled datasets automatically. In standard PSO, the non-oscillatory route can be quick in causing a particle to stagnate and it may also lead to premature convergence on suboptimal solutions which donot even provide the guarantee to the local optimal solution. In this, Lévy mechanism is presented for the PSO algorithm and is employed in the data sets. Results reveal that the new PSO model, named LPSO, is successful in contributing to improved performance for clustering data.

**TABLE 2.4: Advantages of Random based Optimized Clustering Segmentation Methods**

<table>
<thead>
<tr>
<th>Proposed System</th>
<th>Advantages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chaotic map with Firefly Algorithm (CFA) is integrated into FCM</td>
<td>• Chaotic Optimization Algorithm can perform entire searches at much faster speeds than random searches which rely on probabilities.</td>
</tr>
</tbody>
</table>
| Levy Flights with Firefly Algorithm (LFFA) is integrated into FCM | • During the survey of the earlier literature, it has been observed that no research has been done in the area of segmentation of MRI image employing LFFA with fuzzy clustering techniques.  
• Enhance the right segmentation of cerebral tissues by making use of LFFA based FCM is presented. |

2.8. Impact of Random based Optimized Clustering Techniques in Segmentation

Technically though not feasible, it is possible to achieve a global optimal clustering result, with the help of clustering approach by attempting all partitioning possibilities in an exhaustive manner. Since the number of clusters and the number of
data points increase, the combinational number of possible categories also escalates, leading to computational complexity. Hence, the heuristic approach is sought after for finding global optima randomly, thus enhancing the quality of the final clustering results iterationwise. Metaheuristics which help in step by step optimization by design are the suitable prospects for such computation.

A significant collection of nature-inspired optimization techniques aka metaheuristics have evolved in the recent times with designs imitating swarm behavior shown by living creatures. Each of the search agents denote a specific combination of centroid positions; they travel and look for for optimality in their own method, they communicate with each other sometimes and then are guided together towards the aim of global optimization. Till date, the new nature-inspired optimization algorithms have attracted much attention among researchers. The computational advantages have been evaluated mathematically, and due to their practical doability, have been employed in different applications. But, validation of the efficiency of hybrids in combination of such nature-inspired algorithms with traditional clustering algorithms is still at an early stage.

By the design merits, nature-inspired optimization algorithms are conceived to be capable of getting over the shortcomings of K means clustering algorithms due to the problem of getting stuck in local optima. To overcome the setback of slow convergence and random constructions of meta-heuristics, hybrid techniques are used. To provide an increase in the global search mobility and to fine tune the attraction co-efficient behavior and randomization co-efficient behavior of fireflies, random based metaheuristic optimization methods are used in integration with FCM.

2.9. Findings of the Literature Study

Image denoising and segmentation are the two important highly challenging areas in MRI images for the segmentation of cerebral tissues. The presence of noise not only deteriorates the visual quality but also largely affects the accuracies of segmentation, which is significant for medical diagnosis procedure. Though conventional linear noise reduction techniques have been available for quite a long time for their simplicity and ability to achieve critical noise removal when the variance of noise is low, they result in
blurring and smoothening of the sharp edges of the image. Therefore, in the recent years there has been a considerable amount of research on non-linear noise removal methodologies, and most popular among them are the Total Variation based de-noising techniques. It is also seen that MRI brain images are chiefly degraded by AWGN. Without the process of denoising, image details are eroded which, in turn, leads to reduction in the quality of the image and hence improper segmentation. In this chapter, the classification of important image segmentation algorithms is studied. Despite several years of research, there is no universally approved MRI image segmentation algorithm. It is thus deduced that MRI brain segmentation is a challenging issue in image processing and computer vision. Segmentation performed with clustering and optimization techniques are also discussed. Still the global optimization is a highly demanding issue in medical applications. Also, it has been seen that there is no work done in MRI image segmentation with randomization techniques like chaotic maps and Levy flights based optimized clustering method. Hence, the work further is focused on the development of random based optimized clustering technique for increasing the global search mobility, to refine the attraction coefficient behavior and randomization coefficient behavior of fireflies.

2.10. SUMMARY

This chapter studies the overview of all the available methods of MRI image preprocessing, MRI image segmentation based on clustering and MRI image segmentation based on optimized clustering. With the aim of improving the denoising and segmentation results, many techniques have been proposed by making use of various procedures. The underlying merits and demerits of every one of the existing techniques have also been discussed. As a detailed analysis of the available techniques has been made in a systematic manner, it will be very much useful for the present research work gear towards enhancing the performance of de-noising techniques and improving the elliptic seizure segmentation results from MRI images. This is also much helpful to get over the limitations of the existing techniques and thus the improvement in the accuracy of segmentation based optimized clustering method can be achieved with random based optimized clustering methods.