2 CHAPTER

THEORETICAL BACKGROUND

Highlights of the Chapter

- *Understanding of noise estimation and de-noising of MRI data*
- *Classical MRI enhancement approaches and importance of Stochastic Resonance based enhancement technique*
- *Outline of segmentation methods and the need of fuzzy c-mean for the segmentation of MRI data*
- *Significance of cluster quality index for unsupervised segmentation of real MRI data*
- *Overview of evolutionary computation based optimization and its requirement in medical image processing*

This chapter covers the background ideas of de-noising, contrast enhancement and automatic segmentation of MRI data. The discussion on noise estimation follows the popular de-noising algorithms, and the contrast enhancement follows the some facts necessity of the DSR. The present chapter discusses fundamentals of evolutionary computation techniques and most importantly the role of optimization techniques in the area of medical image analysis.

The acquired *k-space* data is a Fourier transform data, which is commonly known as raw data. This raw data is complex and known to be corrupted by white Gaussian noise. After the inverse Fourier transformation of this data, the real and imaginary data is still corrupted with Gaussian noise. Further, the computation of a magnitude data is a non-linear operation, which changes the distribution of the data. This data distribution is hence no longer remains Gaussian, but Rician distributed [22]. Further, to remove the noise from the image data the blind suppression of noise based on local means [23] and non-local means [24] were the popular choices, however, these algorithms do not estimate the noise. Hence, these algorithms are susceptible to degrade the fine structures of the MRI data.

2.1 Noise estimation techniques

Noise estimation is an essential parameter for many reasons such as restoration, de-noising, and enhancement of the image. Previously, many filtering methods have considered noise estimation as an integral part of de-noising and have shown significant de-noising results with a minimum loss of structure [25-27].

Henkelman R. M. [28] was probably first to estimate the true signal intensity from noisy MRI data. McGibney et al. have been directly estimated noise from the non-signal MRI data [29], this simple and effective technique is shown in Fig 2.1. The relation between noise and signal can be established with the help of second-order moment of Rician distribution, and expressed as follows:

$$\mu_2 = E\{M^2\} = A^2 + 2\sigma_n^2$$

Hence, $A^2 = \mu_2 - 2\sigma_n^2$

where A is signal level without noise, σ_n^2 is noise variance and μ_2 is the second order moment.

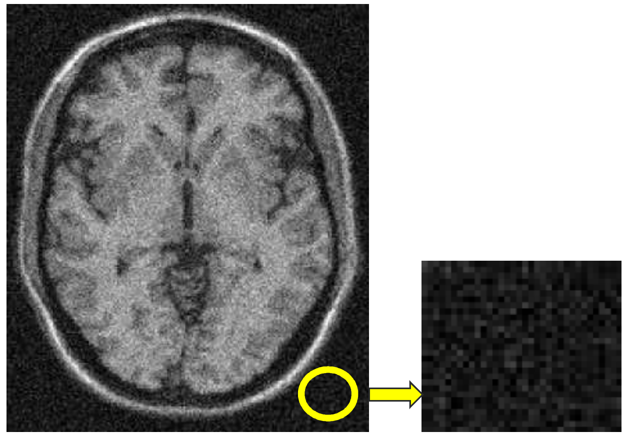

Figure 2-1: The estimation of σ_n^2 has been derived from the background of the magnitude MRI Rician distribution data where signal is not present [29].

A large amount of homogeneous non-signal regions are often hard to find for the calculation of noise variation. In this view, few methods have been proposed, which are based on the estimation of the signal from multiple samples such as maximum likelihood estimation [30] and expectation maximization [31]. However, local statistics need to be calculated if only one image is available. These previously proposed approaches have assumed that the signal in the MRI data is corrupted from noise only. Further, the real MRI data may affect from bias field or some other artifacts as well. This issue needs to be encountered with the help of adaptive de-noising of MRI data.

2.2 Methods to De-noise the MRI data

In the literature, several MRI de-noising approaches have been proposed. The previously proposed MRI de-noising filters can be categorized in following three primary methods:

(i) Spatial domain-based filtering

(ii) Transformed domain-based filtering

(iii)Filters exploiting the statistical properties of the image data

Local averaging based smoothing filters [23] have been employed to de-noise the MRI data; these filters eliminated the high-frequency noise. However, the local averaging produced the blurring effects on fine details and sharp edges. Further, the edge-preserving methods such as anisotropic diffusion filters [32] and adaptive de-noising [33] have been proposed to overcome the blurring effects. Recently, José V. Manjón et al. has been proposed non-local principle component analysis based de-noising [25]. This method has utilized the sparseness property of the MRI data that has achieved state-of-the-art results.

The transformation-based filters are more natural segregation of noise from the signal. Filters working in a transformed domain are classified according to the adopted space basis, e.g., obtaining curvelet-based [34], contourlet based [35] and wavelet based approaches [36]. However, these methods achieved the limited effectiveness to de-noise the MRI data.

Another very useful way of designing the MRI de-noising filters is to exploit the statistical properties of the noise. Krissian and Aja Fernandez [27] proposed a very effective anisotropic diffusion filter based on a linear minimum mean squared error estimation (LMMSE) technique for the removal of Rician noise. The maximum likelihood method has been estimated the true underlying intensity for each pixel [31]. This filter has been applied to a set of non-local pixels, and the selection of these pixels is based on the intensity similarity of the pixel neighborhood. These statistical properties based de-noising methods have been proved to be very useful in de-noising of the MRI data. Further, recently proposed de-noising of MRI data based studies have been extended in Table 2-1. Even on the close estimation of noise the filters may suffer over or under smoothing of the data, the primary reasons may be the presence of other degradations such as bias field and poor contrast in the image data. The de-noising results should not affect from these degradations. The optimal design of de-noising filter can avoid the over or under smoothing of MRI data. The Fig 2.2 shows that under smoothing of the MRI data results in sub-optimal de-noising.

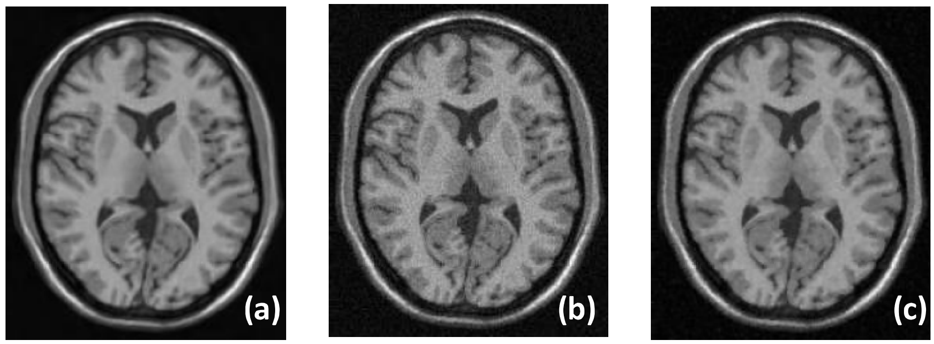

Figure 2-2: Example of sub-optimal de-noising: (a) Ground truth MRI data, (b) noisy data with variance of 10, and (c) recursive LMMSE based filtering (for 50 numbers of iterations and window size of [7, 7])

Table 2-1: Selected previous significant work for de-noising of MRI data

Author (Year)	Method	Application	Remarks
José V.Manjón et al. (2012) [37]	Sparseness and self-similarity	BrainWeb T1, T2, and PD weighted simulated image data	Slightly over-smoothing on edges and fine details in case of ODCT3D
José V.Manjón et al. (2015) [25]	Nonlocal PCA, estimating the local noise	BrainWeb T1 weighted simulated weighted image data	Noise estimation within non-local PCA, good performance
José V.Manjón et al. (2013) [38]	Local PCA	Real clinical data of Diffusion-Weighted Images, synthetic data	Analyzed tractography results as well
Baselice F et al. (2016) [39]	a posteriori estimator in the Bayesian framework	Real clinical data of T1 and T2 weighted image, synthetic data	Provided effective results while preserving details

J.Mohan et al. (2013) [40]	Nonlocal neutrosophic set Wiener filtering	Simulated and clinical MR images	Visual and diagnostic quality of the denoised image well preserved
JenyRajan et al. (2012) [26]	Nonlocal maximum likelihood estimation	Simulated and clinical MR images	Non-central-χ distribution and spatially varying nature of the noise is considered
Hosein M.Golshan et al. (2013) [41]	Linear minimum mean square error estimation	Simulated and clinical MR images	Removed the noise and preserved the anatomical structures
M M-Fernandez and Sergio Villullas (2015) [42]	Expectation maximization in Probabilistic Wavelet	BrainWeb T1 weighted simulated and clinical MR images	Requires generalization of distribution models of the wavelet coefficients
S. Aja-Fernández et al. (2008) [43]	Linear minimum mean square error estimation	BrainWeb MRI data and real DWI data	Restoration of DWI, more accurate tensor estimations
S. Aja-Fernández et al. (2008) [27]	Recursive Linear minimum mean square error estimation	Simulated and clinical MRI data images	Uses information of the sample distribution of local statistics of the MRI data
Kenneth Kagoiya and Elijah Mwangi (2017) [44]	Non-Local Means Wavelet with Bilateral Filter	BrainWeb MRI data	Slightly over-smoothing on edges and fine details

2.3 Enhancement of MRI data

Dynamic contrast-enhanced magnetic resonance imaging (DCE-MRI) is a well-established technique to enhance the tissue contrast, which helps in the examination of the microstructure of the tissues [45]. In this technique, a gadolinium-based contrast agent requires to inject into the tissues using oral or intravenous. Instead of contrast based enhancement or the techniques rely on expensive scanner upgrades, the present study has considered the post-processing contrast enhancement technique to improve the visual quality of the MRI data.

Previously, many post-processing contrast enhancement techniques have been proposed such as weighted threshold histogram equalization, which can control the enhancement process with the help of an adaptive enhancement strategy [46]. Zuo et al. proposed range limited bi-histogram equalization to improve the contrast of the images [47]. This technique has suggested a threshold, which minimizes the intraclass variance, and is used for the separating point for this histogram equalization. The techniques mentioned above based on the unique characteristics of the image data, and hence are susceptible to noise amplification. In this regard, Hossian et al. proposed a method to the obtained optimum value of contrast, brightness and detail, which is based on the optimum separating point for segmenting the histogram of Ultrasound knee joint cartilage image data [48]. Recently, it has been found that the stochastic resonance based enhancement techniques are more capable of controlling multiple properties of MRI data and these techniques are more tissue adaptive [49]. Previously proposed enhancement of MRI data based studies have been extended in Table 2-2.

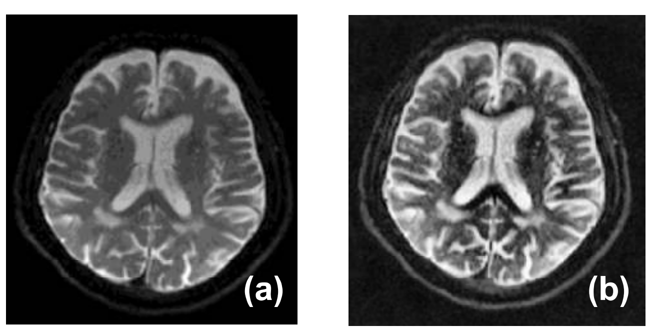

Figure 2-3: Example of sub-optimal tissue contrast enhancement leads to artifacts and noise: (a) real T2 weighted MRI data, (b) contrast enhancement using classical adaptive histogram equalization

Table 2-2: Selected previous significant work for post-processing enhancement of MRI data

Author (Year)	Method	Application	Remarks
Chiao-Min Chen et al. (2015) [50]	Hierarchical correlation histogram analysis	MRI data on Parkinson's disease	Edge information of specific cells effectively increased
I. Isa et al. (2016, 2017) [51, 52]	Average Intensity Replacement based on Adaptive Histogram Equalization	FLAIR sequence of MRI data	Natural brightness improvement on the WMH of the periventricular region
N. Senthilkumaran and J. Thimmiaraja (2014) [53]	Compared different histogram equalization techniques	Brain MRI data	Specific contrast enhancement measures requires specific enhancement techniques
VP Rallabandi and PK Roy (2010) [54]	Dynamic Stochastic Resonance (DSR) technique	Clinical brain MRI data	Contrast enhancement without amplification of noise, improved results
Ebenezer Daniel and J.Anitha (2016) [55]	Optimum Wavelet-Based Masking (OWBM) algorithm	BrainWeb and MIAS data set	Optimization algorithm has been used to find appropriate parameters
Yunlan Tan et al. (2013) [56]	Wavelet Homomorphic Filtering Transform	Clinical MRI data and other medical images	MRI of the temporomandibular joint has shown that this method can effectively eliminate the non-uniform luminance distribution
Bo Li and Wei Xie (2015) [57]	Adaptive fractional differential approach	Clinical radiological data including MRI	Better enhancement by making edges clearer and textures richer

Kai-jian Xia et al. [58]	Improvement correction strategy in wavelet transform domain	Medical image data including MRI	Effective improvement in the image quality, performed non-reference evaluation, and the reference evaluation
A. Gandhamal et al. [59]	Local Gray Level Transformation using S-curve technique	MRI data of Knee Osteoarthritis	Attempted to resolve improper brightness and contrast distribution issues
S.Jeevakala and A.Brintha Therese (2017) [60]	Laplacian pyramid and singular value decomposition to improve the visibility	Simulated and clinical MRI data images	Enhancement method improved segmentation accuracy
T. Gong et al. (2017) [61]	The improved clonal selection algorithm	Harvard University MRI dataset	Addressed noise as well as contrast enhancement

2.4 Segmentation of MRI data

Segmentation of MRI data is an essential task in the automatic disease diagnosis and has a high impact on the overall analysis of pathology and treatment planning. In automatic image segmentation, the partition of an image into homogeneous and meaningful regions is fundamental but a challenging problem. Segmentation methods can be broadly sub-divided as follows:

A. Thresholding based segmentation
B. Region growing segmentation
C. Atlas-based segmentation
D. Active contours based segmentation
E. Classification/clustering of the data

Thresholding based segmentation methods are simple and computationally efficient, however, in these methods, spatial information of data are not included [62]. Hence, these methods are sensitive to even a small amount of noise and intensity inhomogeneity. In region growing based segmentation methods, the region starts growing from the seed point and add the image pixels while examining the properties of neighborhood pixels. Previously, region growing based methods have been used for different applications of MRI segmentation [63]. The major disadvantage of this method is the selection of seed point, which significantly influences the segmentation results. The atlas-based segmentation is similar to supervised classification method, however, this segmentation approach employed in the spatial space instead of in feature space. In this technique, the atlas is the template of the anatomy of interest for a specific population. The aligned probabilistic atlas is used as prior information for the segmentation [64]. The accuracy of this segmentation approach decreases in case of deformation in the image or anatomy of interest [12]. In case of active contours methods, a closed curve has been drawn around a region of interest, where the internal and external forces deform this curve iteratively for the objective of minimization of energy function [65]. Previously, many deformation models have been studied for the segmentation of MRI data [66, 67].

Further, from a classification point of view, the segmentation algorithms can be classified into two categories:

(i) Supervised segmentation, where algorithms required a priori knowledge about the ground truth image.

(ii) Unsupervised segmentation, where algorithms itself learn from the data. These algorithms produce the resultant based on the cluster features.

Unsupervised segmentation is quite challenging, but are highly useful for automated segmentation, as eventually, ground truth segmented image is not available in case of specific disease diagnosis using radiological image data. In this regard, the expectation-maximization (EM) method [68], k-means [69] and fuzzy c-means (FCM) segmentation [70] are the most popular unsupervised segmentation techniques. In the case of the EM-based algorithm, initially, the Gaussian mixture model (GMM) is used to estimate the model parameters. Further, the algorithm iterate for the convergence and utilizes expectation step and maximization step. In k-means segmentation, each point of the data completely belongs to one of the clusters, whereas in the case of FCM each point has a probability of belonging to each cluster. Hence, k-means is known as a hard clustering method whereas FCM is known as soft clustering method of segmentation.

Table 2-3: Selected previous significant work for fuzzy c-means based segmentation of MRI data

Author (Year)	Method	Application	Remarks
M. Gong et al. (2012) [71]	Fuzzy c-means with local information, implemented kernel distance measure as a fitness function	Synthetic data and brain MRI data	Good accuracy, Robust to noise
S. K. Adhikari et al. (2015) [72]	Conditional spatial fuzzy C-means	BrainWeb simulated MRI brain images	Reduced sensitivity to noise and intensity inhomogeneity
Zexuan Ji et al. (2012) [73]	Generalized rough fuzzy c-means	BrainWeb simulated and clinical brain MRI data	Robust to the initialization, Bias field correction incorporated
Zexuan Ji et al. (2012) [74]	Fuzzy c-means clustering with weighted image patch	Synthetic data and BrainWeb simulated MRI	Robust to noise, improved the segmentation accuracy

		data	
M. K. Alsmadi (2014) [75]	Firefly algorithm based fuzzy-C mean algorithm	MBIC, IBSR simulated and real MRI data	Better tumor segmentation, need to improve the robustness
A. Elazab et al. (2015) [76]	adaptively regularized kernel-based fuzzy c-means	BrainWeb simulated MRI data	Suggested trade-off between segmentation accuracy with computation cost
M. Forouzanfar et al. (2010) [77]	Parameter optimization of improved fuzzy c-means	BrainWeb simulated MRI data	A hybrid GAs/PSO has been employed to improve the segmentation accuracy
W. Cai et al. (2007) [78]	Local information based robust fuzzy c-means	Synthetic data, simulated BrainWeb data, and clinical MRI data	Require filtering as a pre-processing step for better segmentation accuracy in the presence of mixed noise
A.N. Benaichouche et al. (2016) [79]	Multi-objective improved spatial fuzzy c-means	BrainWeb simulated MRI data	Combined Pareto fronts for better segmentation results
J. Aparajeeta et al. (2016) [80]	Modified possibilistic fuzzy C-means	Synthetic data and simulated BrainWeb MRI data	Capable of estimating the bias field followed by segmentation

The soft clustering methods are less sensitive to noise and have advantages over the hard clustering based segmentation. The soft clustering based method such as FCM is based on the compactness of the cluster, which may not yield the appropriate segmentation across different weighted sequences of MRI data having multiple numbers of degradations. Further, the unsupervised segmentation methods such as K-Mean and FCM requires prior knowledge of the number of clusters (or regions) in an image. However, in most of the practical situations, the number of clusters is unknown or not possible to determine. Previously proposed FCM based segmentation of MRI data based studies have been extended in Table 2-3.

2.4.1 Cluster quality index for unsupervised segmentation

The selection of the number of clusters affect the segmentation quality and has impacts on the segmentation results. In this view, there is a need for an index that can automatically and accurately determine the number of clusters, which would help to avoid over-segmentation or under-segmentation of an image data.

Previously, there are many cluster validity indexes have been proposed to find the optimum number of segments in the image. The cluster validity indexes can be classified into the four categories based on the following criterions:

(i) Partition degree

(ii) Classification entropy

(iii) Intra and inter-cluster distance

(iv) Hybridization

Cluster validity indexes based on partition degree and classification entropy such as partition coefficient [81] and partition entropy coefficient (PE) [81] show monotonicity and lack of geometrical connection of the objects in an image. However, J. M. Chen attempted to reduce the monotonicity of partition entropy coefficient and proposed its modified form [82]. The Xie-Beni index (XB) is based on intra and inter-cluster distance, which is formulated in terms of cluster compactness and the separation between the clusters [83]. XB index reduces the monotonicity tendency and relates the geometrical connection of the data. The fuzzy hyper-volume (FHV) follows the concept of distance, which calculates the hyper-volume and density of the clusters [84]. Previously, many cluster validity indexes were also proposed while considering the hybridization of two or more validity indexes to obtain the better performance such as partition density index [81] and PBM index [85].

W. Wang et al. presented the comparison of eighteen cluster validity indexes and found most of the validity indexes unsatisfactory on the considered dataset [86]. EA. Zanaty presented the comparison of cluster validity indexes on synthetic and simulated MRI dataset images [87]. From experimentation results EA. Zanaty has concluded that the present cluster validity indexes are not working well in different cases and their performance is specific to the dataset and the segmentation algorithm.

2.5 Role of optimization in image analysis

More or less the existing algorithms are unable to accomplish the critical issues of medical image analysis as discussed in Section 2.1, Section 2.2, Section 2.3, and Section 2.4, which result in suboptimal de-noising, contrast enhancement and automatic segmentation of MRI data. For the robust and reliable results, all these issues must be addressed. In this view, the present work suggests evolutionary computation (optimization) technique based MRI image analysis algorithms. The evolutionary computation technique helps to explore all possible solutions within the search boundary and suggest the best one. These algorithms adaptively tune the parameter(s) responsible for producing the optimized solution. Hence, the optimized output results depend only on the fitness functions rather the input data. The non-referential image quality indexes, which are the fitness functions, normally address the specific image qualities. Hence, to improve the overall result, multiple fitness functions need to be implemented. Each of the fitness function should address the different image quality. The optimization based enhancement scheme is presented in the Fig 2.5, where optimization algorithm controls the DSR parameters for optimum values of fitness functions i.e., image quality measures.

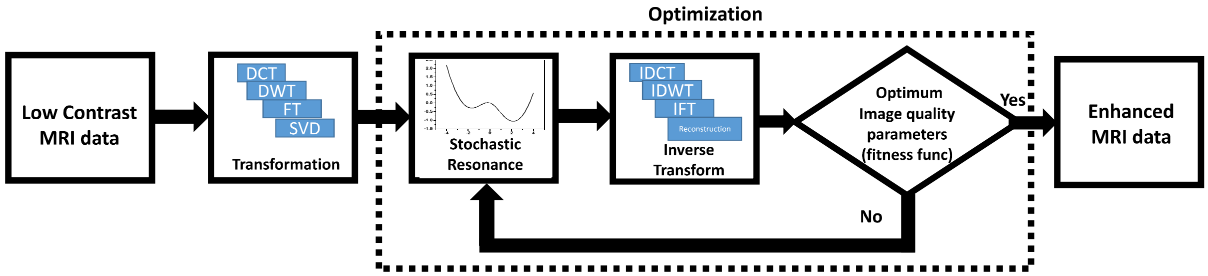

Figure 2-4: Generalized schematic of proposed optimized DSR based image enhancement

Previously, neural network based particle swarm optimization (PSO) approach has been used to de-noise the MRI data [88]. This approach has been demonstrated the robust results for de-noising of different MRI images. Ebenezer Daniel et al. implemented modified cuckoo search optimization for the enhancement of medical imaging data [55]. A. Mustafa et al. have utilized the whale optimization algorithm for the segmentation of liver MRI data [89]. This work has been segmented the liver with the help of a constructed statistical binary image.

The effectiveness of optimization led image analysis algorithm depends on the exploration/exploitation behavior of the algorithm, selection of fitness functions, number of fitness functions and range of search space.

2.5.1 Evolutionary Computation based optimization techniques

Evolutionary computation techniques are based on the powerful principle of evolution, i.e., survival of the fittest. The behavior of these techniques are stochastic in nature, and the search model of these techniques is based on some natural phenomena. In recent time, many evolutionary computation algorithms have been proposed, the popular algorithms are given as follows:

1. Genetic algorithm [90, 91]

2. Ant colony optimization [92, 93]
3. Particle swarm optimization [94, 95]
4. Bat optimization [96, 97]
5. Antlion optimization [98]

The evolutionary computation techniques have received high attention concerning for complex numerical functions. Nevertheless, these techniques have not produced a substantial breakthrough in the area of medical image processing.

2.6 Stochastic Resonance

Stochastic resonance was first examined for the probable description of the periodicity of Earth's ice ages where normal climate and mostly ice-covered states are modeled as two metastable states divided by an energy barrier [99]. Recent studies have shown that DSR helps to amplify a weak signal with the aid of an appropriate level of noise in the existence of the nonlinear system. The added noise to the weak signal must be high enough so that together they can cross the energy barrier and change the state of the Brownian particle in the nonlinear system. Further, the high amount of noise may lead to oscillations between two states and degrades the performance. The stochastic resonance phenomena has been utilized for many engineering applications such as sensory-motor detection [100, 101], enhancement of information transmission in neural network [102], fault diagnosis of train bearings [103], redundant sensor systems [104], energy harvesting [105] and mechanical fault feature extraction [106]. Broadly, stochastic resonance can be classified into the following three categories:

(i) Nonlinear dynamic

(ii) Nonlinear non-dynamic

(iii)Suprathreshold

The non-linear dynamic class of stochastic resonance involves with dynamic systems such as Quartic bi-stable models [107], neuron bi-stable model [108] and tri-stable model [106]. Hence, this stochastic resonance system is known as dynamic stochastic resonance (DSR), and the present work has been restricted to this class of stochastic resonance. Previously, DSR has been proposed for the enhancement of ultrasound [109], CT [49] and MRI data [54]. In these studies, DSR has been found useful for radiological images and accomplished impressive results. The overview of DSR based enhancement is demonstrated in Fig 2.4. However, this approach is suffered from the non-optimal selection of DSR parameters. This drawback restricted DSR based contrast enhancement method to achieve high-quality resultant data.

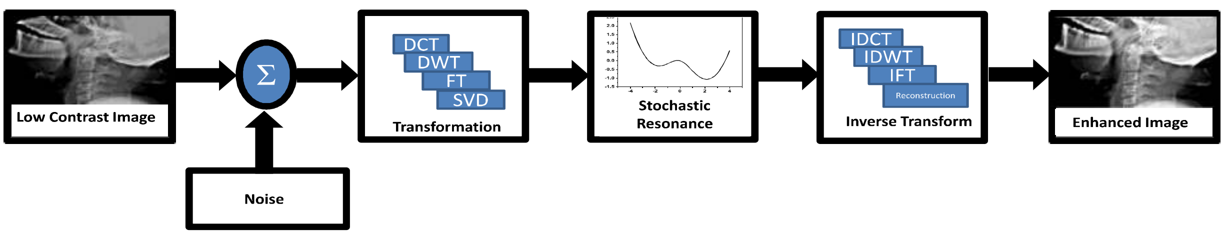

Figure 2-5: Generalized schematic of previously proposed DSR based image enhancement

This chapter outlined the importance of post-processing analysis of MRI data, and discussed the challenges in the post-processing analysis. Critical review of existing algorithms for (i) de-noising, (ii) contrast enhancement and (iii) automatic segmentation of MRI data helped to understand how previously proposed algorithms encounter the major challenges of this field. Further, the concepts of optimization algorithms for de-noising, contrast enhancement, and automatic segmentation has been introduced to meet the goals of the thesis. The proposed approaches in the thesis have been validated on the standard simulated dataset, and the applications of these approaches have been shown on real MRI data from Chapter 3 onwards.

3 CHAPTER

ADAPTIVE NOISE ESTIMATOR FOR THE APPLICATIONS OF DE-NOISING AND SEGMENTATION OF MRI DATA

Highlights of the Chapter

- *Present chapter proposes an algorithm for adaptive noise estimation based on multi-objective particle swarm optimization (MOPSO)*
- *MOPSO based non-local Kalman filter and MOPSO based linear minimum mean square error (LMMSE) filter to de-noise the MRI data*
- *Adaptive noise estimation technique has been found valuable for recursive and non-recursive filters both*

Abstract

The present study proposes the noise estimation of Magnetic Resonance Imaging (MRI) data using multi-objective particle swarm optimisation (MOPSO). This adaptive noise estimation is based on the maximisation of the multiple quality measures, which enable the algorithm to achieve de-noising along with enhancement in the image features. The chapter proposes two filtering approaches to de-noise MRI data. In first, MOPSO based noise estimation is followed by non-local statistics based Kalman filter, whereas, in the second approach,