5 CHAPTER

ENHANCEMENT AND INTENSITY INHOMOGENEITY CORRECTION OF DIFFUSION-WEIGHTED MR IMAGES OF NEONATAL AND INFANTILE BRAIN

Highlights of the Chapter

- *The data has been segmented according to the mean intensity and PSO based DSR applied to maximize the information within the region and minimize the mean intensity between the different regions*
- *The algorithm has been tested on real Diffusion weighted sequence of neonatal/infantile brain and found highly valuable*
- *The algorithm is capable to reduce the intensity inhomogeneity along with the feature enhancement*

Abstract

Imaging of infantile/neonatal brain mandates tailored radio frequency coils (RF coils) to achieve a homogeneous field over a small region of interest (ROI). Most centers, however, perform pediatric imaging using adult RF coils only as procurement of tailored pediatric coils might prove quite expensive. This practice may not scientifically justified, whereas the image

post-processing techniques reduce the deleterious effects of magnetic field inhomogeneity due to a small ROI being scanned in a large RF coil. Further, the eccentric placement of ROI within the RF coil perpetuates the field inhomogeneity within the scanned region. Hence, the structures closer to the coil appear brighter than those farther away giving rise to a 'shading artifact'. This effect even accentuates in weak signal sequences like diffusion-weighted imaging (DWI). The proposed method significantly removes shading artifact of real DWI and synthetic T1 and T2 weighted magnetic resonance (MR) images. Dynamic stochastic resonance (DSR) intelligently uses the coefficient of discrete cosine transform of an image for brightness normalization and image enhancement simultaneously. The quality of the output image depends on the bi-stability parameters associated with the dynamic equation. Particle swarm optimization (PSO) tunes these bi-stability parameters for the entropy minimization of different group of tissues. The proposed algorithm outperforms the post processing based homomorphic filtering, local entropy minimization with spline model (LEMS) and multiplicative intrinsic component optimization (MICO) methods. PSO based DSR approach may be helpful in accurate diagnosis.

5.1 Introduction

Diffusion-Weighted Imaging (DWI) reflects the Brownian motion of water molecules and gives the potentially unique information about brain tissues. Infantile/neonatal DWI helps to evaluate the nervous system disorders in young children and newborns. Notably, there is increased utilization of DWI in the evaluation of pediatric brain within first two years of life, for commenting on hypoxic brain injury and normal myelination. Fast (echo-planar) imaging technology helps to avoid motion artifact in infantile/neonatal DWI. In eco-planner imaging (EPI) k-space data transverses in one excitation or a small number of excitations called single shot EPI, and multi-shot EPI respectively. These imaging techniques are very useful to assess infarction and metabolic disorders in the neonatal brain [170-173], however not suitable to study anatomical details, as these images have the inherent low signal to noise ratio (SNR).

The anatomy of interest should be placed at the center of the coil to keep uniformity of signal in MR image. The small size of the infantile/neonatal head, when scans using the full size of scanner causes one side of the head away from coil whereas another side closer to the coil. The lower SNR far from the coil and higher SNR near to it results in inhomogeneous intensity on the images, which makes poor gray-white matter differentiation. The diagnosis of the lesion becomes difficult, especially when it lies in the bright region. However, this artifact can be reduced with the help of high-density coils specifically designed to kept close child's head. However, the exclusive installation of such coils is quite expensive. There were various methods proposed to address the issue of intensity inhomogeneity artifacts in MR images. These methods broadly classified into experimental and post-processing techniques. The empirical approaches involve scanning oil or water phantom earlier to the clinical examination to obtain the scanner's bias field [174, 175]. These methods obtain measurement of the scanner's bias field without any assumptions about the patients' anatomy or bias pattern. However, these techniques are time-consuming, require a mathematical model and do not consider the influence of anatomy of interest [176, 177]. These problems can be solved using post-processing techniques such as surface fitting and spatial filtering to remove this artifact. Surface fitting approximates the non-uniform intensity of the image, where pixels of the image are divided according to the surface. Methods based on these techniques use spline basis function and polynomial basis function to perform surface fitting [178, 179]. Parameters are usually related to the expected dynamics of the bias field is the primary drawback of these methods. Spatial filters such as low-pass filters and homomorphic filters are used to remove the bias field. Spatial filtering uses the assumption that the bias field has low spatial frequency intensity variation. Low pass filtering based approach divided into single step based on median filtering [180] and multiple steps based on filtering followed by estimating the non-uniformity [181-183]. These methods considered an assumption that the imaged anatomical structures does not have low frequency components. The limitation of this approach is that it undesirably removes low frequency components of image, which may also removes the useful information correspond to the same. In addition, low pass filter distorts homogeneous tissues near the edges. These shortcomings limit the feasibility of filtering approaches, especially for DWI images, where intensity variation within the image is small. Previously, many methods have been proposed to address the intensity inhomogeneity, however the issue of correcting it is still a challenge [19, 184] i.e. to achieve good quality corrected images.

One of the newer technique for image enhancement using the DSR phenomena has considerable potential for application to functional and molecular imaging. Double well bistable model of DSR is commonly used a non-linear model that enhances the SNR by utilizing the appropriate amount of noise. Previously, double well bistable based DSR technique employed to improve the contrast of MR images [54], ultrasound images [109] and CT-Scan images [49]. The performance of DSR greatly depends on DSR parameters and number of iterations, to achieve the best results. The drawbacks of previously proposed techniques are the non-optimized DSR parameters and observation based manual selection of number of iterations. This chapter proposes a method to correct the shading artifact in infantile/neonatal brain MR images using the post-processing principle based on PSO optimized DSR. This approach adaptively selects bistability parameters and number of iterations to produce an optimal image and does not need any phantom measurements to determine the bias field for compensation neither needs any analytical function to describe the RF response. The proposed method uses the image properties to reduce the shading artifact by filtering out the bias field intensity and enhances the image in a single step. The algorithm is suitable to remove the inhomogeneity of low signal sequence DWI, T1 and T2 weighted MR images while preserving the useful details. The rest of the chapter organized as follows. Section 5.2 describes mathematical formulation to compensate the bias field function. Section 5.3 gives the methodology of proposed algorithm. Section 5.4 demonstrates the experimental results and efficiency of the proposed algorithm for intensity inhomogeneity correction. The presented approach has been extensively tested and validated on a large dataset of real and simulated images this section. Finally, Section 5.5 concluded the chapter.

5.2 Mathematical formulation for removal of shading artifact

This work includes standard simulated dataset of noisy T1 and T2 weighted images suffering from different level of intensity inhomogeneity and real DWI. The slow varying bias field presents with these images reduces the difference between the brain tissues, which may lead to the poor diagnosis and inaccurate segmentation [19, 189]. The poor perceptibility of image modeled as degradation, which is considered as a noisy image, hence DSR as presented in Equation (4.6) can be re-written as:

$$\frac{d}{dt}\,x(t) = a\,x - b\,x^3 \; + \; input \tag{5.6}$$

In above equation the last term $input$ represents the image I in spatial domain (x, y). The zero mean of discrete cosine transformed image $\acute{I}(u, v)$ serves as $input$. Equation (5.6) discretizes in k steps using Euler-Maruyama's method [185] to process the coefficients that are discrete in nature:

$$x(n+1) = x(n) + k\ [a\ x(n) - b\ x^3(n) + \acute{I}(u,v)\ ] \tag{5.7}$$

Further, bias field distributed on different group of tissues, which requires variable filtering. For this purpose, proposed method implements following two strategies:

(i) The image divided into the different homogeneous regions according to mean pixel intensity level.

(ii) The number of DSR iterations keeps decreasing for minimum to maximum intensity regions.

5.3 Material and Methods

EPI DW (b=1000) MR images of neonatal and infantile brain obtained from 1.5 T MRI scanner (Siemens MAGNETOM Avanto) in DICOM format. Image slices were subjected to processing which had localized and strong inhomogeneity. Additionally, images available at BrainWeb dataset (http://www.bic.mni.mcgill.ca/brainweb/) used to compare segmentation results of proposed algorithm with recent existing methods. The four sets were formed from the downloaded simulated dataset. First set has 12 T1 weighted images with 20% inhomogeneity with 3% noise whereas the second set contains 12 T1 weighted images with 40% inhomogeneity with 3% noise. The third set contains 12 T2 weighted 20% inhomogeneity with 3% noise, whereas forth set has 40% inhomogeneity with 3% noise. All 48 images were obtained in the size of 217×181.

The flow chart presented in Fig. 5.1 describes the proposed methodology for the correction and enhancement of the images. The input image has broken into four regions using intensity histogram. The coefficients of DCT undergo DSR with least number of iterations (n) for the region that has maximum mean intensity and highest number of iterations (n) for the region that has minimum mean intensity. PSO tunes the DSR parameters for $entropy$ minimization of each region individually of input image. Variable n and entropy minimization helps to normalize the tissue intensity within the same region and enhance the contrast between different tissues. The reconstruction of processed regions produces the final output image.

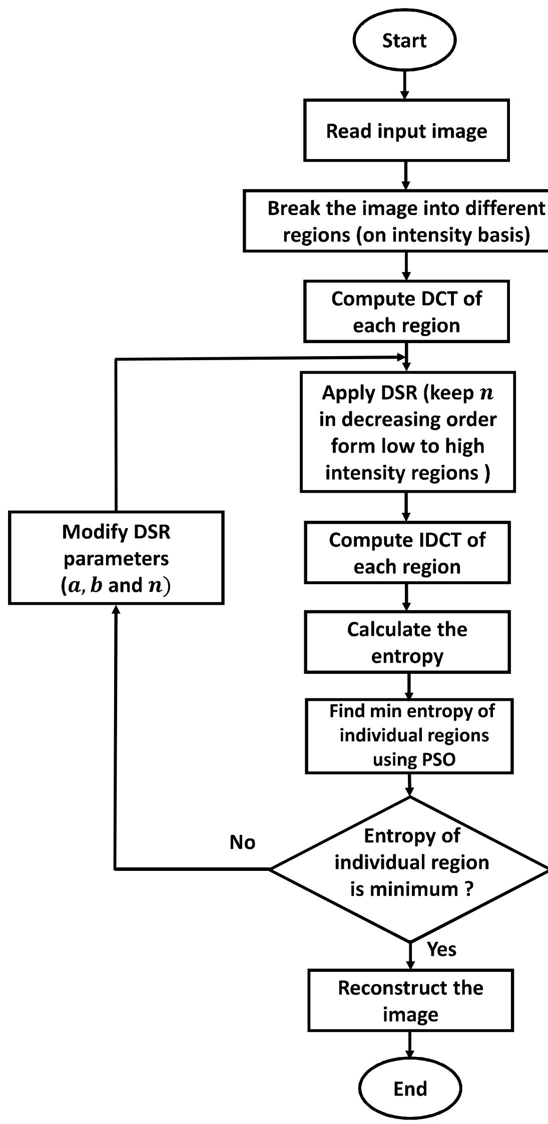

Figure 5-1: Flowchart of DSR based correction of shading artifact

5.3.1 Particle Swarm Optimization

PSO is a population-based computational algorithm inspired by social behavior of bird flocks [94]. PSO initializes with the population of arbitrary solutions called particles, and these particles evolve over the generations. Each particle has a velocity and a position vector that empowers it to fly over the problem space in search of optima. Adjustment of the position of a particle determines by the information of its previous position and its current velocity. The dimension of position and velocity vectors depend on the number of decision variables in the problem. The best location recognized by each particle denotes the personal best ($pbest$). Moreover, best among all the $pbest$ values represents a global best ($gbest$) value. The particles determine the better location based on these pbest and gbest values.

5.3.1.1 Objective function

Image entropy is a quantity, which describes the variation of information in an image. Previously, entropy has been used as the quality measure for intensity inhomogeneity reduction [186], hence, present study have chosen entropy as the objective function for PSO. The objective function optimizes with the objective of minimum entropy for different regions in the image, which is defined as:

$$H\ (I) = \sum_{i} h_I(i) \, log \frac{N}{h_I(i)}$$

$where\ h_I(i)$ denotes the histogram count of intensity value i in the image, I and N is the total number of pixels of I.

5.3.1.2 Algorithm

Step 1 Divide the image into the regions according to the tissues intensities using histogram, say $R_1, R_2 \ldots R_p$, where R_1 has least mean intensity and R_p has maximum mean intensity (Here, the value of $p = 4$)

Step 2 Compute DCT transform of all the regions

Step 3 Apply DSR on the coefficients of transformed regions

(a) Initialize $\mathrm{x}(0) = 0,\ \mathrm{k} = 0.015$

(b) Use iterative equation given in Equation (5.7) to update the cosine coefficients for the region of image having least intensity

$$\mathrm{x}(\mathrm{n}+1) = \mathrm{x}(\mathrm{n}) + \mathrm{k}\,[\mathrm{a}\,\mathrm{x}(\mathrm{n}) - \mathrm{b}\,\mathrm{x}^3(\mathrm{n}) + R_1]$$

Step 4 Optimize number of iterations, a, and b using PSO for the minimization of the objective function

Step 5 Repeat step 3 (b) for the next region R_2 and decrease the number of iterations by one up to the last region

Step 6 Reconstruct the different regions of image with the help of inverse DCT

Step 7 Combine all the regions

Step 8 Analyze the performance measures of the enhanced image

5.4 Results and Discussion

The methodology has been tested on (i) broad range of simulated dataset (T1 and T2 weighted images) obtained from BrainWeb to show the effectiveness of the proposed algorithm, (ii) the real data of the infantile/neonatal brain DWI used for the considered application. First part of this section shows the qualitative and quantitative results for simulated dataset. The results obtained by proposed method are quantitatively compared with recent popular methods. Further, the presence of noise in addition to intensity inhomogeneity affects the segmentation results. At present, we have performed segmentation using Fuzzy c-mean method [187] and have chosen Jaccard coefficient and global consistency error for its quantitative evaluation. The second part of section shows the application of the proposed algorithm for real DWI of neonatal/infantile brain and the quantitative results shown in terms of image quality are promising.

At first step, the performance of the algorithm depends on the settings of PSO parameters, like inertia weight (w), learning rates (c_1, c_2), population size (p) and the number of generations (i). The experiment considered w as adaptive in nature, which started from 0.9 and linearly decreases to 0.4 with the increase in the number of generations. The local and global behavior constants c_1 and c_2 have been set to 0.8 and 0.9 respectively. PSO produced results with good repeatability and accuracy for 60 number of generation and 25 size of population. The graphs shown in Fig. 5.2 (b, f) confirm that chosen PSO parameters are appropriate, as the entropy reduced below to 0.005 for image shown in Fig. 5.2(a), and image shown in Fig. 5.2(b) for generation band 50 to 60. For the above settings, PSO finds the DSR parameters a, b and n for a given input image to keep entropy low within the region of same type of tissues.

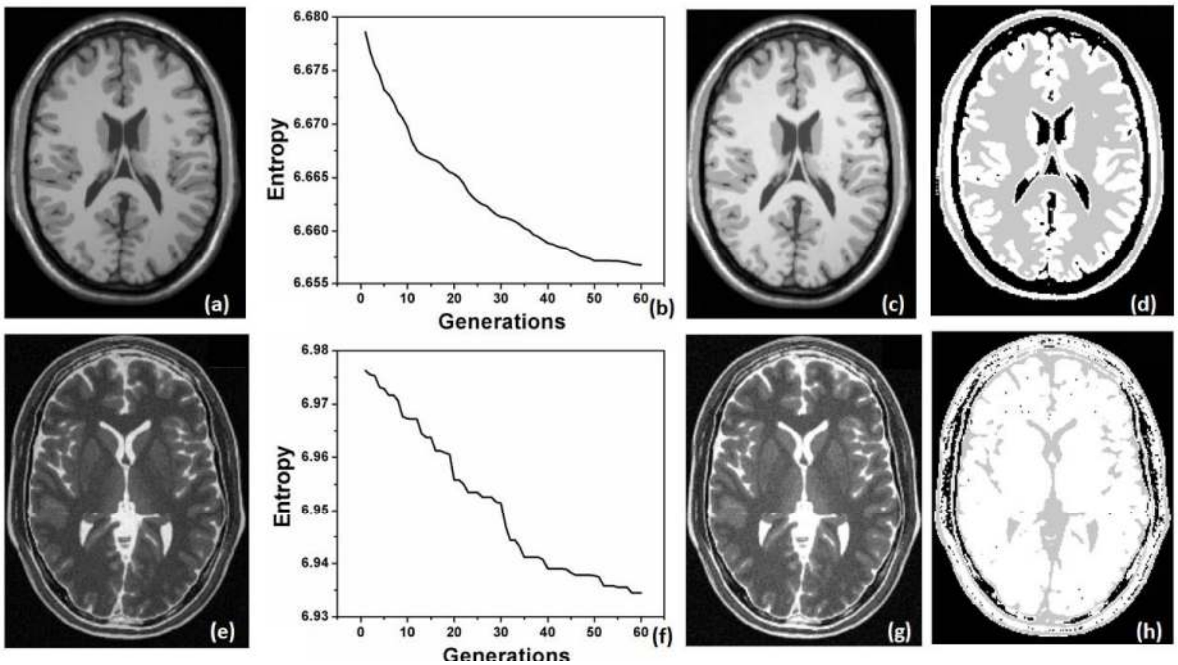

Figure 5-2: (a) T1 weighted image (40% inhomogeneity and 3% noise), (e) T2 weighted image (40% inhomogeneity and 3% noise), (b, f) obtained curve for number of generation against the objective function for image (a, e) respectively, (c, g) are the SR processed images, (d, h) are the segmented images

Figure 5.2 shows the outputs after inhomogeneity correction with enhancement and segmentation steps. Images in the first column are original input images having 40% inhomogeneity with 3% noise. Images shown in Fig. 5.2 (c and e) are the bias field corrected images. It can be visually observed that the obtained images from proposed technique are intensity homogeneity corrected and having better contrast. The segmentation results of these images in the last column shows distinct gray-white matter of brain. The segmentation results shows that 3% noise in T1 weighted image has not much effect on the output, however, the same amount of noise has slightly effected the output in T2 weighted image. This indicates that the methodology works efficiently even in the presence of noise.

5.4.1 Comparative study

Present qualitative comparison includes the quality of processed images and the segmentation results obtained from following intensity correction methodologies: (i) Homomorphic filtering (HmF) [183], (ii) local entropy minimization with a spline model (LEMS) [188] and (iii) multiplicative intrinsic component optimization (MICO) [189]. The post processing HmF is a non-linear mapping technique uses the log transformation of intensity. The effectiveness of HmF based algorithms to remove intensity inhomogeneity in MR images shown in Fig. 5.3 (b, l). The LEMS used to remove the shading artifact present in different weighted contrast images of MRI. The MICO based correction demonstrated good accuracy on synthetic and real MRI data. The proposed SR-PSO based algorithm has been compared with above mentioned methods for 48 simulated test images and real images. As discussed earlier these images have different level of inhomogeneity and noise.

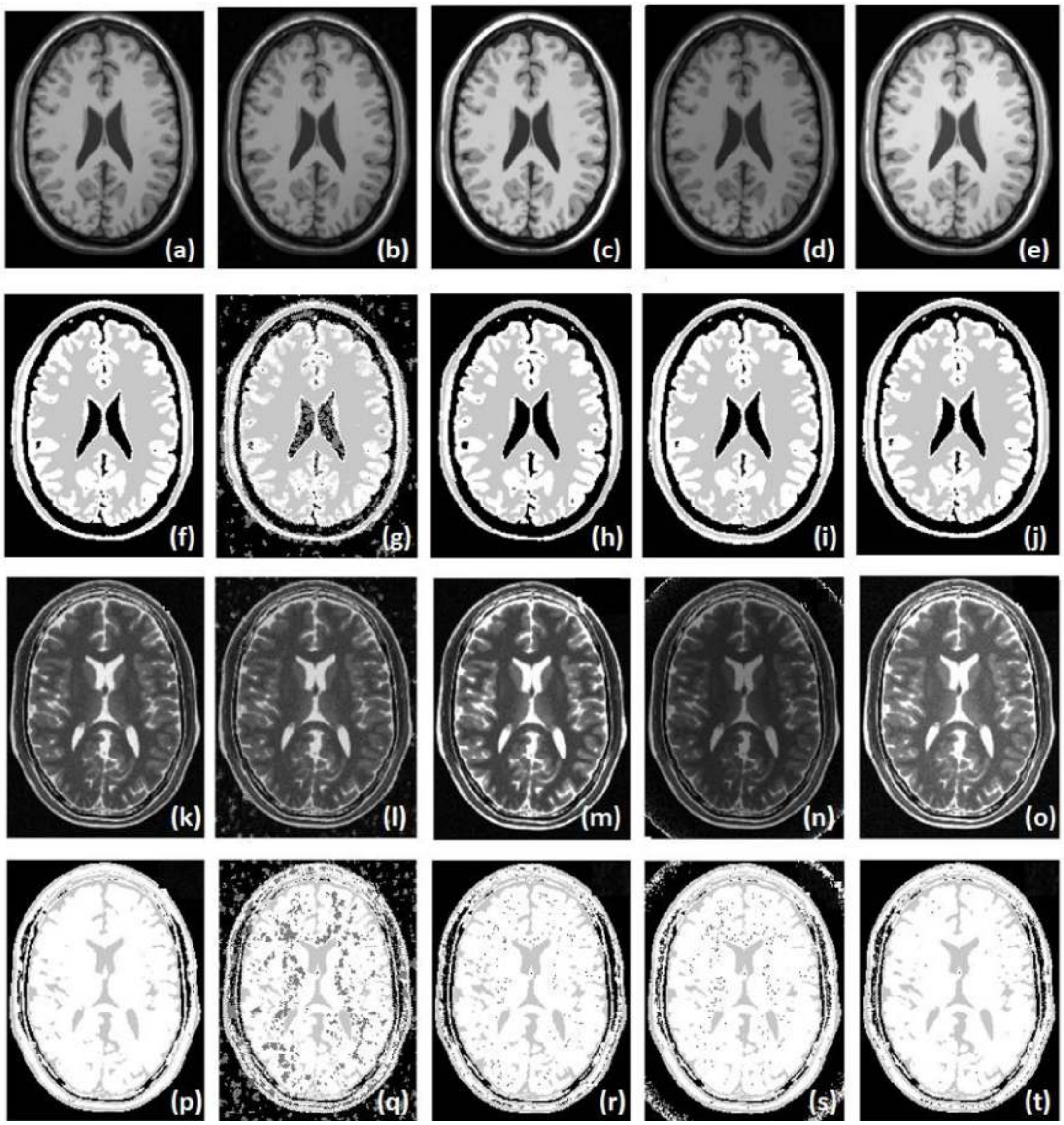

Figure 5-3: (a) Simulated input T1 weighted image with 20% inhomogeneity and 3% noise, (k) simulated input T2 weighted image with 40% inhomogeneity and 3% noise, images (f) and (p) are respective segmented images, image obtained using (b, l) Gaussian HmF, (c, m) LEMS method, (d, n) MICO method, (e, o) proposed method, (g, q), (h, r), (I, s) and (j, t) are respective segmented images

Figure 5.3 (a) and Figure 5.3 (k) are T1 and T2 weighted input images undergo different intensity correction methods. Images shown in second column onwards in first and third row of Fig. 3 are inhomogeneity corrected images using HmF, LEMS, MICO and proposed method respectively. Images shown in second and fourth rows are the segmented images of first and third rows images using Fuzzy c-mean method. It is noted from the corrected images that all considered methods successfully removed the intensity inhomogeneity, however, produced different image quality. HmF has been applied on the test image with 1.02 maximum gamma value and 0.98 minimum gamma value. As seen in figure, the output images from HmF filter are suffering with low contrast. Additionally, the effect of noise is also appearing on the segmented images. LEMS method has been directly applied without using any filtering because it removed edge details. The produced images have better contrast than the images obtained using HmF method. LEMS yielded satisfactory results in presence of 3% noise in T1 weighted image, but the effect of 3% noise on T2 weighted image can be clearly visualized on its segmented image. The output images obtained from MICO method are good in bias correction however the contrast is low. This method performs significantly satisfactory in presence of noise 3% in T1 weighted image. However, the same amount of noise affects the segmented T2 weighted image. The performance of our proposed method is producing qualitatively better results as compared to the previously proposed methods. The processed T1 and T2 images have shown better contrast and edge details. The output of algorithm is least affected by the presence of noise, the result of same is reflected in the output segmented images.

The quantitative comparison of segmentation results have been extensively performed in two stages. At the first stage, the comparison was performed on overall segmented image in terms of global consistency error (GCE) [190]. Further, segmented gray matter (GM) and white matter (WM) individually compared in terms of Jaccard similarity (JS).

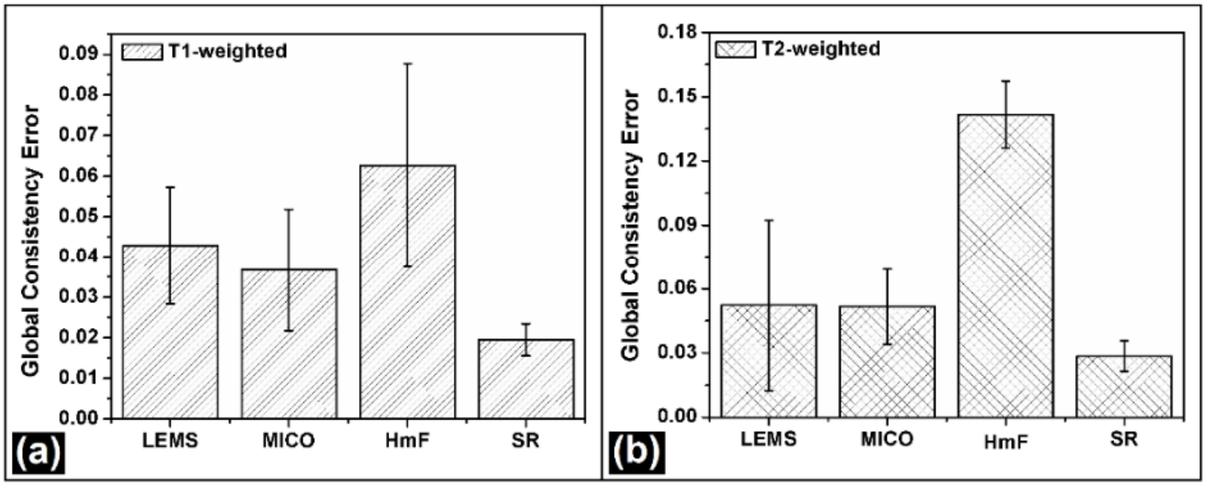

Figure 5-4: Quantitative comparison of LEMS, MICO, HmF and proposed SR based method in terms of global consistency error for (a) segmented T1 weighted image and (b) segmented T2 weighted image

GCE of all four sets were obtained against the respective segmented ground truth images. The lower values of GCE indicate the accurate segmentation. Figure 5.4 (a) shows the mean GCE for 24 T1 weighted images of set 1 and set 2. The HmF method shows highest GCE, whereas the proposed SR based method shows minimum GCE with least standard deviation. Figure 5.4 (b) shows the mean GCE for 24 T2 weighted images of set 3 and set 4. The GCE for T2 weighted images is relatively higher than the T1 weighted images, as Fig. 5.3 already demonstrated the lower segmentation performance of T2 weighted images in presence of 40% inhomogeneity and 3% noise. The proposed method has minimum mean GCE for T2 weighted images with least standard deviation.

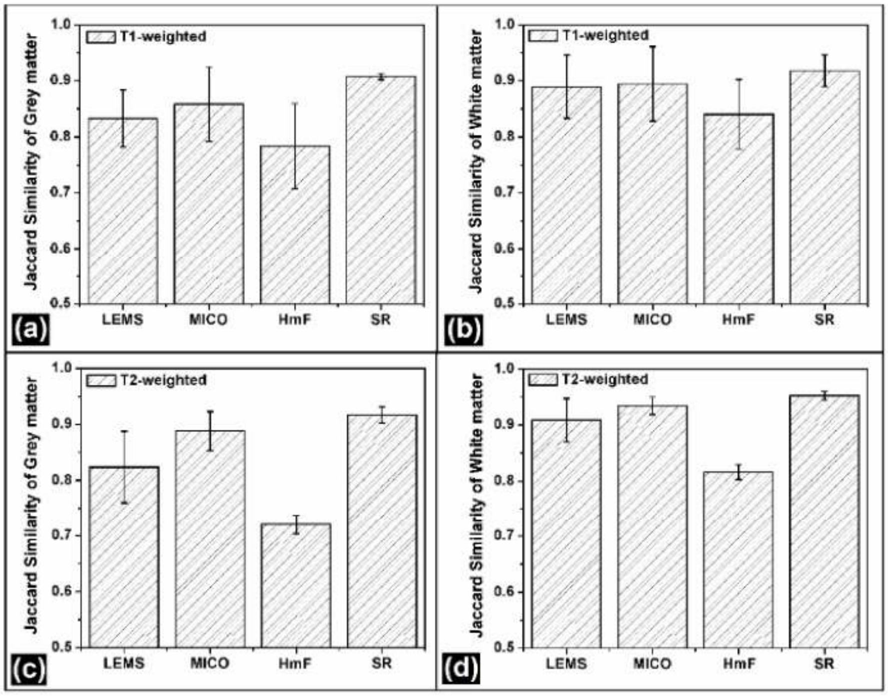

Figure 5-5: Quantitative comparison of LEMS, MICO, HmF and proposed SR based method with ground truth images in terms of JS

Figure 5.5 shows the segmentation comparison of the proposed method with other three tested methods in terms of JS. The higher JS value indicates the segmentation is closer to ground truth image. All 48 images and their respective ground truth images were segmented into the GM and WM. The JS was computed individually for GM of T1, WM of T1, GM of T2 and WM of T2 weighted images. Figure 5.5 shows the highest accuracy and robustness of the proposed methodology for each case, which is closely followed by MICO method. DSR based proposed method produces the better image quality and performed well in the presence of noise. Hence, it performed better than the other considered methods.

5.4.2 Comparative analysis on real DWI of infantile/ neonatal brain

Better image quality leads to improved diagnosis, the blind image assessment methods were used to evaluate the quality of real DWI images. Assessment of the variation of intensity values for two adjacent tissues helps to quantify the image quality and the removal of shading artifact increases the variation in pixel intensity. The value of contrast enhancement factor (F) obtained by calculating the ratio of post and pre-enhancement value of image quality index, (Q) [19], where the value of Q for an image is defined as the ratio of variance (σ^2) and mean (μ) of the pixel intensity, $Q = \sigma^2/\mu$. Anisotropy is another measure, which is capable of differentiating the presence of noise in the images by reducing its value, when noise is present [131].

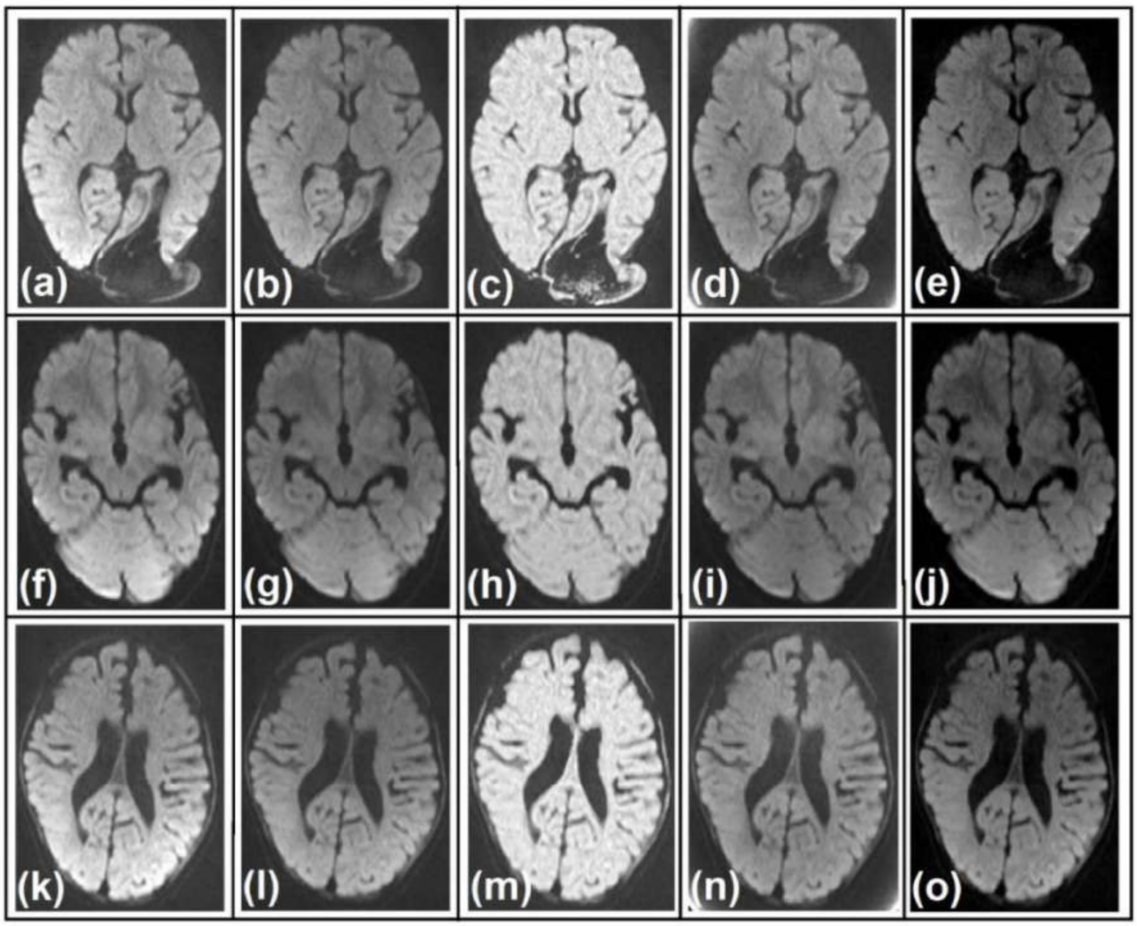

Figure 5-6: Comparison among the correction methods for real DWI Test image 1, Test image 2, Test image 3 and Test image 4. Original input images are shown in [(a), (f), (k)]; images processed using homomorphic filtering are shown in [(b), (g), (i)]; images using LEMS correction are shown in [(c), (h), (m)]; images using MICO method are shown in [(d), (i), (n)] and the corrected images using the proposed method are shown in [(e), (j), (o)]

The variable intensity pattern in original input images is no longer seen in the corrected images using the proposed methodology. The better appreciation of gray-white matter differentiation can be observed in Fig. 5.6 (e, j, o). The input images shown in Fig. 5.6 (a, f, k) is important for lesion detection while the output image obtained by proposed method remains crucial for evaluation of myelination and hypoxic brain injury. HmF removes variable intensity, however the low gray-white matter differentiation leads to loss of information in the images. In addition to reduce gray-white matter differentiation, LEMS based method susceptible to produce artifacts on DWI as seen on Fig. 5.6 (c). This method produced high value of CEF as shown in Table 5-1, however lost the natural look of the images. Image obtained from MICO method looks better than HmF and LEMS method, still the contrast between the tissues is unsatisfactory. All the considered methods removed the inhomogeneity successfully but shows poor image quality and are susceptible to noise, whereas proposed technique simultaneously normalizes the brightness and enhances the image as qualitative results shown in Fig. 5.6 and quantitative results are indicated in Table 5-1.

Table 5-1: Comparative performance evaluation parameters for Test images shown in Fig. 5.6

Correction method	Parameters	Test image 1	Test image 2	Test image 3
HmF method	CEF	0.7160	0.6997	0.7160
	Anisotropy	0.0011	0.0013	0.0011
LEMS method	CEF	1.3842	1.3339	1.3833
	Anisotropy	0.0016	0.0022	0.0028
MICO method	CEF	0.5829	0.5513	0.5610
	Anisotropy	0.0013	0.0013	0.0017
SR based	CEF	1.7578	1.5040	1.5208
	Anisotropy	0.0043	0.0087	0.0074

5.5 Conclusions

The proposed method has been applied on large dataset of images. It has successfully corrected the intensity inhomogeneity present in the form of shading artifact in case of T1, T2 weighted simulated images and real infantile/neonatal brain DWI images. PSO optimized the DSR parameters to minimize the entropy of different image regions based on intensity values. As DSR iteration can also modifies the pixel intensity, the proposed methodology kept DSR iterations to be a variable quantity to obtain its optimum values for each region. This helped to reduce the overall intensity inhomogeneity across the different regions and enhanced the contrast of the MRI data. The obtained results confirm that the proposed method removes inhomogeneity without loss of information and enhances the image features. Further, the intensity inhomogeneity removal algorithm tested on simulated MRI data and helped to achieve better segmentation results. On the other hand, application results obtained on infantile/neonatal DWI brain images using proposed algorithm enhanced the contrast with low anisotropy, whereas HmF, LEMS and MICO algorithms normalizes the brightness at the cost of information loss. The present algorithm can be further enhanced in future to process different image regions simultaneously using parallel computing to reduce the CPU processing time.