International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

December 2012 | Issue 13 | Volume 4 | Number 4 | Pages 60-66

REVIEW OF INTENSITY INHOMOGENEITY CORRECTION METHODS FOR BRAIN MRI IMAGES

M.A. Balafar

Department of Computer, Faculty of Engineering, University of Tabriz, Tabriz, Iran, balafarila@yahoo.com

Abstract- Intensity inhomogeneity is a smooth intensity change inside originally homogeneous regions. The intensity inhomogeneity degrades performance of image processing algorithms. Intensity inhomogeneity correction methods are important image processing algorithms which are used to reduce the inhomogeneity. Brain image intensity inhomogeneity correction is one of the most important parts of clinical diagnostic tools. Brain images mostly contain inhomogeneity. Therefore, accurate process of brain images is a very difficult task. However, accurate process of these images is very important and crucial for a correct diagnosis by clinical tools. A review of intensity inhomogeneity correction methods for brain MRI images is presented. The review covers methods for intensity inhomogeneity correction and their comparative evaluations based on reported results.

Keywords: Inhomogeneity Correction, Brain, MRI, Image Segmentation.

I. INTRODUCTION

Generally, researchers consider intensity inhomogeneity as a smooth spatially varying intensity inside originally homogeny regions. They consider inhomogeneity as multiplicative or additive field. In addition, they consider inhomogeneity independent of noise and model image with inhomogeneity as multiplicative of image and inhomogeneity field plus noise. Inhomogeneity is one of obstacle for automatic image processing applications such as image segmentation [1-4]. Usually, Inhomogeneity correction methods categorized as follow:

Phantom based method is used to estimate device-induced inhomogeneity field. It estimate inhomogeneity field by taking image of a uniform phantom and subtracting smoothed result image from original image of phantom. Usually, researchers use image of oil or water as phantom and use median filter for smoothing. Multicoil method combines surface and body coil images. Usually, body coil has low inhomogeneity but poor SNR and surface coil is vice versa. Therefore, multicoil produces image with high SNR and low inhomogeneity [5]. This method estimates inhomogeneity field by dividing the filtered surface coil image on the body coil image. Afterwards, the result is smoothed.

Special sequences consider device-induced inhomogeneity. For certain pulse sequences, inhomogeneity can be calculated by estimating spatial distribution of the flip angle. Surface Fitting Methods estimate inhomogeneity field using image features which have information about inhomogeneity. These methods fit parametric surface to the mentioned features. Usually, intensity or gradient features are used in these methods. The methods, which use intensity, fit surface in one dominant tissue, then, they distribute obtained surface to all image. In [6], a surface fitting approaches for inhomogeneity correction is proposed namely the white matter (WM) which searches the parameters by fitting with respect to a set of user selected tissue points.

Segmentation based methods: Segmentation of inhomogeneity corrected image is much easier and give better results. Inhomogeneity correction of image with segmentation in hand is very simple. These methods combine segmentation and inhomogeneity correction to benefit from each other. These methods are classified based on to the image segmentation method they use:

Maximum-likelihood (ML) or maximum a posterior probability (MAP): ML or MAP may be used to estimate image intensity probability distribution. Usually, Gaussian mixture model is used and modified to incorporate inhomogeneity in clustering process [7]. The expectation-maximization (EM) algorithm can be used to estimate parameters of this model. In order to use EM algorithm for simultaneously segmentation and inhomogeneity correction, EM was modified to iterate between two processes. In [8], Wells proposed an inhomogeneity correction method namely the expectation maximization (EM) which combines classification with inhomogeneity correction, and models the entire log-transformed bias field as the Gaussian distribution. Biased MAP (BMAP) [9] iterates two interdependent estimations: The MAP estimation of the image classification given an inhomogeneity estimation, and the ML estimation of the inhomogeneity given classification result of MAP.

FCM based methods: The FCM is a soft fuzzy classifier. It allow a pixel belong to several classes and is robust against partial volume effect. Biased FCM (BFCM) [10] is representative of the fuzzy clustering MRI segmentation methods which adapt FCM object function to consider inhomogeneity in clustering process. An adaptive FCM based inhomogeneity correction method is proposed [11] which updates objective function of FCM by multiplication centre of clusters by a function of location representing inhomogeneity. In order to preserve smoothness of objective function, a spatial regularization term is added to objective function which penalizes first and second derivatives of the inhomogeneity function.

Nonparametric segmentation: These methods are more general and do not consider any prior knowledge about tissue distribution. These methods use intensity and second derivatives of intensity. These methods iteratively minimize inhomogeneity caused class error. In [12], an energy function is defined by incorporating smoothness constraints into the classification error function of the inhomogeneity corrected image. Gradient descent of this energy function relative to the inhomogeneity field is used for inhomogeneity estimation. This approach is called adaptive field rule (AFR). Also, several algorithms for estimation of the mean intensity of each tissue which is used in inhomogeneity estimation process are presented. One of these algorithms is using gradient descent of the energy function relative to the intensity class means for the intensity class means estimation. This algorithm is called AFR-U.

Histogram Based Methods: These methods usually do not use a priori information about image and use histogram of image to estimate inhomogeneity. These methods do not produce segmentation result. Three histogram based inhomogeneity correction methods are reported in next paragraphs:

High-Frequency Maximization methods: This method does not use any knowledge about image and iteratively, estimate inhomogeneity by maximizing the high frequency information of tissue distribution. This method assumes inhomogeneity as low frequency and image information as high frequency, and maximizes high frequency information. Therefore, it may eliminate low frequency information of image. In [13], a nonparametric none-uniform intensity normalization (N3) method is proposed which models inhomogeneity field as a Gaussian distribution with small variance to constrain the solution space. N3 estimates the inhomogeneity field by maximizing the frequency content of the image intensity distribution.

Information Minimization: These methods consider inhomogeneity as extra information and minimizing information for inhomogeneity correction [14]. They use distribution entropy or log of it to measure information. In [15], a nonparametric coarse to fine approach is proposed which in each scale estimates inhomogeneity using entropy minimizing. If entropy in two scales does not change, interpolate inhomogeneity estimation to original scale.

Histogram matching methods: In these methods, image is divided into sub volumes. These methods assume sub volumes have constant inhomogeneity and use histogram of image to initialize a finite Gaussian mixture model and fit the model to histogram of sub volume to estimate local inhomogeneity. The estimated local inhomogeneity is checked for outliers. At last, the result is interpolated to produce the final inhomogeneity field of input image. In [16], a histogram matching inhomogeneity correction method (called bfc) proposed which divides the image into small sections with relatively constant intensity inhomogeneity. In order to estimate local intensity inhomogeneity, the intensity histogram model (a finite Gaussian mixture) is fitted to the actual histogram of a section by least square fitting. The final inhomogeneity is produced by interpolation of local estimates in sections.

Filtering Methods: These methods consider inhomogeneity a low-frequency artefact and use low-pass filter to inhomogeneity field detection [17]. If there were any low frequency image information, these methods might eliminate them. Other drawback of these methods is producing a streak artefact on edges known as edge effect which causes distortion of homogeneous tissues near the edges. Homomorphic filtering [18] and homomorphic unsharp masking (HUM) method are two most important filtering inhomogeneity correction methods. In homomorphic filtering, subtraction of log-transformed of input image from log-transformed of its low-pass filtered is considered as corrected image [19]. Homomorphic filtering produces edge effect on boundary between tissues. Guillemaud proposed to apply filter just to object to reduce this artefact [20]. In homomorphic unsharp masking (HUM), the inhomogeneity correction field is obtained by low-pass filtering of the input image, divided by the constant to preserve mean or median intensity. In [21], mean filter is used as low-pass filter and the background are masked out from HUM input for reducing edge artefact. In [22], a algorithm namely eq uses multiplication in Fourier domain for low-pass filtering and uses average intensity value to replace background pixels from HUM input for reducing edge artefact. Also in [18], average intensity value replaces background pixels for reducing edge artefact. In [23], median filter is used as low-pass filter. Table 1 lists state-of-art inhomogeneity correction algorithms.

Table 1. Advantages and disadvantages of inhomogeneity correction methods

Inhomogeneity correction method	Advantages	Disadvantages
Phantom-based methods [19]	These methods are simple.	It just considers device-induced inhomogeneity. It is difficult to match the images of a phantom due to the coil profile temporal and spatial variation.
Multi-coil methods [5]	This method combines surface and body coil images resulting an image with high SNR and low inhomogeneity	These methods take more time and do not totally remove inhomogeneity of body coil.
Special sequences methods [19]	These methods are useful in specific acquisition designs.	These methods just consider device-induced inhomogeneity.

II. COMPARATIVE STUDY

The reported results for intensity inhomogeneity correction algorithms are presented. In order to investigate their effectiveness, the quantitative and qualitative results of the algorithms are presented.

A. Simulated Images

In [28], three inhomogeneity correction methods (the expectation maximization (EM) [8] , the white matter (WM) [6], and the N3 method [13]) are compared. EM iterates between classification and filtering stages. Filtering stage smoothes the field estimate and utilize a Gaussian filter with truncated kernel to remain within interested volume, WM, first, segment white matter using an artificial neural network classifier, then, removes partial volume voxels using gradient information.

Afterwards, a smooth field is fit to the remaining white matter voxels and extrapolates this field to the rest of the volume. N3 iterates between estimating intensities of the corrected volume and smoothing the estimated volume. The N3 does not rely on explicit tissue classification.

The methods are applied on phantom based T_1, T_2, and PD weighted data. The WM method outperforms competing methods on T_1 weighted volumes. The high contrast between the WM and other tissues in T_1 weighted images could be the reason for superiority of WM method. The most stable performance in this experiment is for the N3 method. The voxels outside the classifier’s tissue model are corrected excessively by the expectation maximization method.

In [29], six inhomogeneity correction algorithms, N3 [13], bfc [16], SPM [30], and low pass filter based methods (hum [21], eq [22] and cma which is available in the Nautilos Library from the Center for Morphometric Analysis at the Massachusetts General Hospital) were compared. Of the compared methods: hum and cma filter image data in the spatial domain, while, eq filters in the frequency domain. The cma filters white matter and then extrapolating the estimated field to the whole volume.

The bfc algorithm Normalize regional tissue intensity histograms to global values. The methods are applied on image volume from BrainWeb. The correlation of the extracted with the applied bias field is used to evaluate the methods. The N3 and the bfc methods outperform other competing methods.

The bfc performs better than N3 at low inhomogeneity but worse than N3 at high inhomogeneity. The filtering based methods produce inhomogeneity field contains higher-frequency structures from brain. Also, contrary to N3 and bfc, the filtering-based methods are not adaptive and the filtering strength is not depended to data quality.

In [31-33], adaptive filter based methods has been presented to overcome this problem. The SPM utilize the mixture Gaussian classifier, which could be inadequate to model the image intensity distribution. Moreover, at low inhomogeneity the spm method may be unstable. None of the methods produce ideal results under all situations (Table 2).

Table 2. Advantages and disadvantages of inhomogeneity correction methods-continue

Inhomogeneity correction method	Advantages	Disadvantages
Surface Fitting Methods (intensity based) [24]	These methods produce good results when pixels of a dominant tissue are distributed over the image and can be selected.	These methods estimate the inhomogeneity field from one tissue and blindly distribute it over the image.
Surface Fitting Methods (gradient based) [24]	These methods yield good results when an image contains large homogenous areas.	These methods assume there are distinctive and large homogeneous areas in image and may integrate unwilling image information.
Maximum likelihood (ML) or maximum a posterior probability (MAP)-based methods [20]	These methods combine segmentation and inhomogeneity correction. Therefore, they can improve each other.	These methods can stack error of different iterations and need initialisation.
FCM-based methods [11]	These methods are more robust against partial volume effect.	These methods do not produce good results in the presence of a high-level of noise and inhomogeneity.
Nonparametric segmentation-based methods (nonparametric max-shift or mean-shift clustering) [25]	These methods are more general and do not consider any prior information about tissue distribution.	These methods are expensive.
High-Frequency Maximization methods (Histogram Based Methods) [19]	This method does not use any knowledge about an image.	They may eliminate low-frequency information of an image.
Information Minimization methods (Histogram Based Methods) [26]	They use only the information that is present in an image, without making assumptions on spatial and intensity distributions.	They need a constraint to preserve contrast in image. The nonlinear log-transformation of image intensities makes the numerical computation of entropy challenging.
Histogram matching methods (Histogram Based Methods) [27]	These methods need no initialisation and prior information making these methods fully automatic and general	They assume that sub-volumes of images have constant inhomogeneity.
Filtering Methods (Homomorphic filtering and Homomorphic un-sharp mask) [26]	They are simple in concept and fast.	These methods might eliminate low-frequency image information. They produce a streak artefact on the edges, known as the edge effect.

In [34], a parametric intensity inhomogeneity correction algorithm namely GradClassLeg is applied on the image from BrainWeb corrupted by variant distortion (correlation between corrupted image relative to the original image).

The correlation between corrected images with the original image is used to evaluate inhomogeneity correction algorithms. GradClassLeg performance is compared with reported results for integrated segmentation and inhomogeneity correction algorithms (Wells [8], BMAP [9] and BFCM [10]). GradClassLeg outperforms the other algorithms. These results confirm that the gradient descent approach assumed by GradClassLeg is robust enough to estimate strong inhomogeneity fields.

In [12], adaptive field rules for non-parametric MRI intensity inhomogeneity estimation algorithm (AFR and AFR-U) are compared with basic supervised Gaussian (BGAUSS) (the classification based on the classes means without bias correction) on the image from BrainWeb corrupted with intensity inhomogeneities of magnitude 20% and 40% of the original clean image.

Dice similarity index for different methods in 20% are: BGAUSS (0.95, 0.88, 0.92), AFR (0.94, 0.89, 0.92) and AFR-U (0.94, 0.90, 0.94) and for 40% are: BGAUSS (0.91, 0.79, 0.85), AFR (0.89, 0.83, 0.90) and AFR-U (0.89, 0.85, 0.92). AFR-U outperforms competing algorithms and AFR has the second performance. The improvement of AF-U and AFR over BGAUSS are greater for the 40% inhomogeneity than for the 20% inhomogeneity.

In [15], A nonparametric MRI inhomogeneity correction method is applied on the image from Brainweb corrupted by a realistic bias field from the Brainweb site with amplitudes ranging from 0% to 100% and Additive Gaussian noise from 0% to 10% of the maximum intensity in the volume. The proposed method based on intensity-gradient entropy was compared with two widely used inhomogeneity correction methods with their default parameters: N3 [13] and the bias correction method of the SPM2 software [35].

The coefficient of variation (CV) was used for the methods comparison. The average CV value of different inhomogeneity correction methods for all the random noise and bias field amplitude levels was: SPM2 = 0.030 $\pm$ 0.020, N3 = 0.025 $\pm$ 0.017 and the proposed method = 0.024 $\pm$ 0.016. The three methods provide well and almost similar performance in all situations. However, the proposed method outperforms competing methods on average.

B. Real Images

In [36], four inhomogeneity correction methods (a phantom method [37], two low pass filter methods [18, 23], and a surface fitting method with reference points selected from white matter [6]) were evaluated in brain tumour segmentation. All competing methods outperform the surface fitting method which could be related to the way the reference points were generated.

The inhomogeneity correction did not improve tumour assessment [36]. The tumour segmentation mostly is affected by the localization of the tumour region and the intensity contrast with surrounded tissue. Thus, the inhomogeneity has less effect on tumour segmentation.

In [34], a parametric intensity inhomogeneity correction algorithm namely GradClassLeg is applied on 20 normal images from IBSR. GradClassLeg performance is compared with reported results for integrated segmentation and inhomogeneity correction algorithms (Wells [8], BMAP [9], BFCM [10] and Siyal and Yu method [38]). The average Jaccard indexes are: Wells = 0.5655, BMAP = 0.56, BFCM = 0.67, Gred = 0.739 and Siyal and Yu = 0.737. The GradClassLeg algorithm provides results comparable to the best reported results.

In [12], An adaptive field rule for non-parametric MRI intensity inhomogeneity estimation algorithm (Adaptive field rule) is applied on 20 normal images from IBSR. Adaptive field rule performance is compared with reported results from IBSR. Jaccard similarity index of this method for different images are: (0.61, 0.645, 0.715, 0.6, 0.485, 0.735, 0.71, 0.54, 0.59, 0.455, 0.575, 0.5, 0.585, 0.465, 0.54, 0.625, 0.6, 0.54, 0.495). The average Jaccard indexes are: 0.5715. The Adaptive field rule algorithm provides results comparable to the best reported results.

In [15], A nonparametric MRI inhomogeneity correction method is applied on a set of 13 subjects with hepatic encephalopathy. The coefficient of variation (CV) for white matter and gray matter and the coefficient of joint variation (CJV) were used for the methods comparison. The average value of normalized CJV for different inhomogeneity correction methods was: the proposed method using intensity-gradient based entropy = 0.74 $\pm$ 0.09, proposed method with classic entropy = 0.98 $\pm$ 0.09, SPM2 = 0.97 $\pm$ 0.05 and N3 = 0.98 $\pm$ 0.04. The proposed method based on intensity-gradient entropy outperformed other competing methods in all cases.

In [39], 20 normal images from IBSR are categorized in two groups: contaminated and uncontaminated image volumes based on their quality. The ten contaminated image volumes contain either the smooth intensity inhomogeneity, or rapid interslice intensity variation. A bias correction method is incorporated to remove contamination before image segmentation. N3 has virtually become the standard method against other inhomogeneity correction methods [19]. However, N3 does not take the rapid inter-slice intensity variations into account. Therefore, not only N3 but also a 3-D wavelet-based bias correction method [40, 41] is utilized which is useful for correcting not only the smooth intraslice inhomogeneity, but also the rapid interslice intensity variation.

After inhomogeneity correction, a Gaussian mixture is applied on 10 contaminated images (1_24, 2_4, 4_8, 5_8, 6_10, 7_8, 8_4, 15_3, 16_3, 17_3). Jaccard similarity index of contaminated images for different methods are: N3+ Gaussian mixtures (0.64, 0.512, 0.48, 0.49, 0.42, 0.61, 0.535, 0.54, 0.51, 0.5) and wavelet + Gaussian mixtures (0.63, 0.665, 0.63, 0.51, 0.525, 0.57, 0.58, 0.625, 0.625, 0.61). The average Jaccard indexes are: N3 + Gaussian mixtures = 0.525, wavelet + Gaussian mixtures = 0.595.

III. CRITERIA

For evaluate inhomogeneity correction algorithms, two criteria, Jaccard similarity [19] and Coefficient of Joint variation (C) [14] commonly are used. The Jaccard similarity: The inhomogeneity corrected image is segmented, and then similarity is defined as follow:

$$J(S,S')=\frac{|S\cap S'|}{|S\cup S'|} \quad (1)$$

where S is a tissue in segmented image and S' is the same tissue in ground truth.

The higher similarity produces better inhomogeneity correction. In this research, average of Jaccard similarity for tissues is used to evaluate different algorithms as follow:

$$J(S_1,S_2,S_3)=(J(S_1,S_1')+J(S_2,S_2')+J(S_3,S_3'))/3 \quad (2)$$

Coefficient of Joint Variation (C): Grey n-homogeneity increase in-tissue variation. Inhomogeneity correction should decrease grey variation as much as possible. In order to calculate in-tissue grey variation, C is defined as follow:

$$C(C_1,C_2,C_3)=V/M \quad (3)$$

where V and M are joint variance and mean of tissues, respectively. They are defined as follow:

$$V=\sigma(C_1)+\sigma(C_2)+\sigma(C_3) \quad (4)$$

$$M=\mu(C_1)+\mu(C_2)+\mu(C_3) \quad (5)$$

where σ, μ and C_i represent variance, mean and ith tissue, respectively. The lower value of C shows better inhomogeneity correction.

In high neighborhood size, some inhomogeneity correction algorithms produce image with zero contrast. The C doesn't consider contrast between tissues. In order to overcome this shortcoming, the C is modified as follow:

$$Contrast=|\mu(C_1)-\mu(C_2)|+|\mu(C_1)-\mu(C_3)|+ +|\mu(C_2)-\mu(C_3)| \quad (6)$$

$$C_{contrast}(C_1,C_2,C_3)=\frac{V}{M.Contrast}$$

IV. DATABASES FOR INHOMOGENEITY CORRECTION ALGORITHMS VALIDATION

A. BrainWeb

BrainWeb (www.bic.mni.mcgill.ca/brainweb), a synthetic image database has been developed by the McConnell Brain Imaging Centre of the Montreal Neurological Institute (MNI). A manually segmented head image passes through an MR simulator to produce the synthetic images. MR simulator allows producing synthetic images with different levels of noise and intensity inhomogeneity. At first version, Brainweb provided two anatomical models, one of a normal brain and the other of a brain with multiple sclerosis lesions. The ground truth (manual) segmentation has nine normal tissue classes. Additionally, it has partial-volume content levels for each image pixel. Recently, other twenty normal models have been added. Currently added models have 11 normal tissue classes [42, 43].

B. The Internet Brain Segmentation Repository (IBSR)

The Center for Morphometric Analysis (CMA) at the Massachusetts General Hospital (MGH) provides the Internet Brain Segmentation Repository (IBSR) (www.cma.mgh.harvard.edu/ibsr/), an on-line database of head MR images of more than 40 subjects along with truth model for segmentation. Truth models for some of MR images have 43 individual structures and for others have three tissue classes, gray matter (GM), white matter (WM), and cerebrospinal fluid (CSF).

C. Section for Biomedical Image Analysis (SBIA)

For generating simulated inter-subject head deformations, software has been developed by the Section for Biomedical Image Analysis (SBIA) in the department of Radiology at the University of Pennsylvania (www.rad.upenn.edu/sbia/). Xue et al. [44] used these simulated inter-subject head deformations for validation studies of atlas-based segmentation methods.

V. CONCLUSIONS

Inhomogeneity degrades medical dignosis tools results. Inhomonegeity correction is a neccessary stage to improve the accuracy of these tools. This field is a research area for many decades and lots of research has been done in this area. In this paper a critical review of inhomogeneity correction methods for brain images is presented. This paper review recent works in this area. Also, this paper presents Advantages and disadvantages of inhomogeneity correction methods. Moreover, the paper presents comparative study of these methods.

REFERENCES

[1] M.A. Balafar, A.R. Ramli, M.I. Saripan, S. Mashohor, "Review of Brain MRI Image Segmentation Methods", Artificial Intelligence Review, Vol. 33, pp. 261-274, 2010.

[2] M.A. Balafar, A.R. Ramli, M.I. Saripan, S. Mashohor, R. Mahmud, "Medical Image Segmentation Using Fuzzy C-Mean (FCM) and User Specified Data", Journal of Circuits, Systems, and Computers, Vol. 19, pp. 1-14, 2010.

[3] M.A. Balafar, A.R. Ramli, M.I. Saripan, S. Mashohor, R. Mahmud, "Improved Fast Fuzzy C-Mean and its Application in Medical Image Segmentation", Journal of Circuits, Systems, and Computers, Vol. 19, pp. 203-214, 2010.

[4] M.A. Balafar, A.R. Ramli, S. Mashohor, "Medical Brain Magnetic Resonance Image Segmentation Using Novel Improvement for Expectation Maximizing", Neurosciences, Vol. 16, pp. 242-247, 2011.

[5] W.W. Brey, P.A. Narayana, "Correction for Intensity Falloff in Surface Coil Magnetic Resonance Imaging", Medical Physics, Vol. 15, pp. 241-245, 1988.

[6] B.M. Dawant, A.P. Zijdenbos, R.A. Margolin, "Correction of Intensity Variations in MR Images for Computer-Aided Tissue Classification", IEEE Transactions on Medical Imaging, Vol. 12, pp. 770-781, 1993.

[7] J.D. Gispert, S. Reig, J. Pascau, J.J. Vaquero, P. Garcia-Barreno, M. Desco, "Method for Bias Field Correction of Brain T_1-Weighted Magnetic Resonance Images Minimizing Segmentation Error", Hum. Brain Mapp., Vol. 2, pp. 133-144, 2004.

[8] W.M. Wells, W.E.L. Grimson, R. Kikinis, F.A. Jolez, "Adaptive Segmentation of MRI Data", IEEE Transactions on Medical Imaging, Vol. 15, pp. 429-442, 1996.

[9] J.C. Rajapakse, F. Kruggel, "Segmentation of MR Images with Intensity Inhomogeneities", Image Vision Comput., Vol. 16, pp. 165-180, 1998.

[10] M.N. Ahmed, S.N. Yamany, N. Mohamed, A.A. Farag, T. Moriarty, "A Modified Fuzzy C-Means Algorithm for Bias Field Estimation and Segmentation of MRI Data", IEEE Transactions on Medical Imaging, Vol. 21, pp. 193-199, 2002.

[11] D.L. Pham, J.L. Prince, "An Adaptive Fuzzy C-Means Algorithm for Image Segmentation in the Presence of Intensity Inhomogeneities", Pattern Recognition Letters, Vol. 20, pp. 57-68, 1999.

[12] M.G. Sebastian, A.I. Gonzalez, M. Grana, "An Adaptive Field Rule for Non-Parametric MRI Intensity Inhomogeneity Estimation Algorithm", Neurocomputing, Vol. 72, pp. 3556-3569, 2009.

[13] J. Sled, A. Zijdenbos, A. Evans, "A Nonparametric Method for Automatic Correction of Intensity Nonuniformity in MRI Data", IEEE Transactions on Medical Imaging, Vol. 17, pp. 87-97, 1998.

[14] B. Likar, M.A. Viergever, F. Pernus, "Retrospective Correction of MR Intensity Inhomogeneity by Information Minimization", IEEE Transactions on Medical Imaging, Vol. 20, pp. 1398-1410, 2001.

[15] J.V. Manjon, J.J. Lull, J. Carbonell-Caballero, G.N. Garciaa-Marti, L.S. Marti-Bonmati, M. Robles, "A Nonparametric MRI Inhomogeneity Correction Method", Medical Image Analysis, Vol. 11, pp. 336-345, 2007.

[16] D.W. Shattuck, R.M. Leahy, "Automated Graph-Based Analysis and Correction of Cortical Volume Topology", IEEE Transactions on Medical Imaging, Vol. 20, pp. 1167-1177, 2001.

[17] M.A. Balafar, A.R. Ramli, S. Mashohor, "A New Method for MR Grayscale Inhomogeneity Correction", Artificial Intelligence Review, Springer, Vol. 34, pp. 195-204, 2010.

[18] B. Johnston, M.S. Atkins, B. Mackiewich, M. Anderson, "Segmentation of Multiple Sclerosis Lesions in Intensity Corrected Multi Spectral MRI", IEEE Transactions on Medical Imaging, Vol. 15, pp. 154-169, 1996.

[19] U. Vovk, F. Pernus, B. Likar, "A Review of Methods for Correction of Intensity Inhomogeneity in MRI", IEEE Transactions on Medical Imaging, Vol. 26, pp. 405-421, 2007.

[20] R. Guillemaud, M. Brady, "Estimating the Bias Field of MR Images", IEEE Transactions on Medical Imaging, Vol. 16, pp. 238-251, 1997.

[21] B.H. Brinkmann, A. Manduca, R.A. Robb, "Optimized Homomorphic Unsharp Masking for MR Grayscale Inhomogeneity Correction", IEEE Transactions on Medical Imaging, Vol. 17, pp. 161-171, 1998.

[22] M.S. Cohen, R.M. Dubois, M.M. Zeineh, "Rapid and Effective Correction of RF Inhomogeneity for High Field Magnetic Resonance Imaging", Human Brain Mapping, Vol. 10, pp. 204-211, 2000.

[23] P.A. Narayana, A. Borthakur, "Effect of Radio Frequency Inhomogeneity Correction on the Reproducibility of Intracranial Volumes Using MR Image Data", Magnetic Resonance in Medicine, Vol. 33, pp. 396-400, 1995.

[24] S.H. Lai, M. Fang, "A New Variational Shape-from-Orientation Approach to Correcting Intensity Inhomogeneities in Magnetic Resonance Images", Medical Image Analysis, Vol. 3, pp. 409-424, 1999.

[25] B. Likar, J. Derganc, F. Pernus, "Segmentation-Based Retrospective Correction of Intensity Non-Uniformity in Multi-Spectral MR Images", Proceeding of SPIE Medical Imaging, Image Processing, San Diego, pp. 1531-1540, 2002.

[26] E. Ardizzone, R. Pirrone, O. Gambino, "Exponential Entropy Driven HUM on Knee MR Images", 27th Annual International Conference of the Engineering in Medicine and Biology Society, pp. 1769-1772, 2005.

[27] D. Shattuck, S. Sandor-Leahy, K. Schaper, D. Rottenberg, R. Leahy, "Magnetic Resonance Image Tissue Classification Using a Partial Volume Model", Neuroimage, Vol. 13, pp. 856-876, 2001.

[28] J.G. Sled, A.P. Zijdenbos, A.C. Evans, "A Comparison of Retrospective Intensity Non-Uniformity Correction Methods for MRI", Information Processing in Medical Imaging, pp. 459-464, 1997.

[29] J.B. Arnold, J. Liow, K.A. Schaper, et al., "Qualitative and Quantitative Evaluation of Six Algorithms for Correcting Intensity Nonuniformity Effects", NeuroImage, Vol. 13, pp. 931-943, 2001.

[30] J. Ashburner, K. Friston, "MRI Sensitivity Correction and Tissue Classification", NeuroImage, Vol. 7, p. S706, 1998.

[31] C. Han, T.S. Hatsukami, C. Yuan, "A Multi-Scale Method for Automatic Correction of Intensity Non-Uniformity in MR Images", Journal of Magnetic Resonance Imaging, Vol. 13, pp. 428-436, 2001.

[32] F. Lin, Y. Chen, J.W. Belliveau, L.L. Wald, "A Wavelet Based Approximation of Surface Coil Sensitivity Profiles for Correction of Image Intensity Inhomogeneity and Parallel Imaging Reconstruction", Human Brain Mapping, Vol. 19, pp. 96-111, 2003.

[33] L. Lemieus, A. Hammers, T. Mackinnon, R.S.N. Liu, "Automatic Segmentation of the Brain and Intracranial Cerebrospinal Fluid in T_1-Weighted Volume MRI Scans of the Head, and its Application to Serial Cerebral and Intracranial Volumetry", Magnetic Resonance Medicine, Vol. 49, pp. 872-884, 2003.

[34] M. Garcia-Sebastian, E. Fernandez, M. Grana, F.J. Torrealdea, "A Parametric Gradient Descent MRI Intensity Inhomogeneity Correction Algorithm", Pattern Recognition Letters, Vol. 28, pp. 1657-1666, 2007.

[35] J. Ashburner, "Another MRI Bias Correction Approach", Eighth International Conference on

Functional Mapping of the Human Brain, Sendai, Japan, 2002.
[36] R.P. Velthuizen, A.B. Cantor, H. Lin, L.M. Fletcher, L.P. Clarke, "Review and Evaluation of MRI Nonuniformity Corrections for Brain Tumor Response Measurements", Medical Physics, Vol. 25, pp. 1655-1666, 1998.
[37] D.A.G. Wicks, G.J. Barker, P.S. Tofts, "Correction of Intensity Nonuniformity in MR Images of Any Orientation", Magnetic Resonance Imaging, Vol. 11, pp. 183-196, 1993.
[38] M.Y. Siyal L. Yu, "An Intelligent Modified Fuzzy C-Means Based Algorithm for Bias Estimation and Segmentation of Brain MRI", Pattern Recognition Letters, Vol. 26, pp. 2052-2062, 2005.
[39] J.D. Lee, H.R. Su, P.E. Cheng, M. Liou, J. Aston, A. C. Tsai, C.Y. Chen, "MR Image Segmentation Using a Power Transformation Approach", IEEE Transactions on Medical Imaging, Vol. 28, pp. 894-905, 2009.
[40] H.R. Su, M. Liou, P.E. Cheng, J.A.D. Aston, C.H. Chuang, "MR Image Segmentation Using Wavelet Analysis Techniques", HBM, Neuroimage, Vol. 26, 2005.
[41] J. Shapiro, "Embedded Image Coding Using Zero Trees of Wavelet Coefficients", IEEE Transactions on Signal Processing, Vol. 41, pp. 3445-3462, 1993.
[42] B. Aubert-Broche, A. Evans, L. Collins, "A New Improved Version of the Realistic Digital Brain Phantom", NeuroImage, Vol. 32, pp. 138-145, 2006.
[43] B. Aubert-Broche, M. Griffin, G. Pike, A. Evans, D. Collins, "Twenty New Digital Brain Phantoms for Creation of Validation Image Data Bases", IEEE Transactions on Medical Imaging, Vol. 25, pp. 1410-1416, 2006.
[44] Z. Xue, D. Shen, B. Karacali, J. Stern, D. Rottenberg, C. Davatzikos, "Simulating Deformations of MR Brain Images for Validation of Atlas-Based Segmentation and Registration Algorithms", NeuroImage, Vol. 33, pp. 855-866, 2006.
[45] Y. Fanid Fathabad, M.A. Balafar, "Content Based Image Retrieval for Medical Images", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 12, Vol. 4, No. 3, pp. 177-182, September 2012.
[46] A.U. Jawadekar, G.M. Dhole, S.R. Paraskar, M.A. Beg, "Novel Wavelet ANN Technique to Classify Bearing Faults in there Phase Induction Motor", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 8, Vol. 3, No. 3, pp. 48-54, September 2011.

BIOGRAPHY

Mohammad Ali Balafar was born in Tabriz, Iran, in June 1975. He received the Ph.D. degree in IT in 2010. Currently, he is an Assistant Professor. His research interests are in artificial intelligence and image processing. He has published 9 journal papers and 4 book chapters.