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# Unsupervised segmentation of noisy and inhomogeneous images using global region statistics with non-convex regularization

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ABSTRACT

Improving the segmentation of magnetic resonance (MR) images remains challenging because of the presence of noise and inhomogeneous intensity. In this paper, we present an unsupervised, multiphase segmentation model based on a Bayesian framework for both MR image segmentation and bias field correction in the presence of noise. In our model, global region statistics are utilized as segmentation criteria in order to classify regions with similar mean intensities but different variances. Additionally, we propose an edge indicator function based on a guided filter (instead of a Gaussian filter) that can preserve the underlying edges of the image obscured by noise. The proposed edge indicator function is integrated with non-convex regularization to overcome the influence of noise, resulting in more accurate segmentation. Furthermore, the proposed model utilizes a Markov random field to model the spatial correlation between neighboring pixels, which increases the robustness of the model under high-noise conditions. Experimental results demonstrate significant advantages in terms of both segmentation accuracy and bias field correction for inhomogeneous images in the presence of noise.



## 1. Introduction

Image segmentation is a fundamental task that separates magnetic resonance (MR) images into non-overlapping regions. In real MR imaging applications, such as for anatomical medical images, image segmentation plays a critical role in quantitative analysis [1], diagnosis [2], and treatment evaluation [3]. However, image artifacts such as noise, inhomogeneous intensity and texture often cause tissue to be misclassified, which can hinder accurate segmentation. In fact, intensity inhomogeneities often occur in image because of spatial variations in illumination (natural images), radio-frequency coils, and acquisition sequences (medical images). Hence, automatic segmentation in the presence of noise and inhomogeneous intensity remains a challenge in the field of MR imaging. Fig. 1 shows the taxonomy of existing methods for noisy and inhomogeneous image segmentation.

To resolve the challenge of inhomogeneous intensity, many bias field correction methods have been introduced over recent decades. These have been reviewed by Vovk et al. [4], who divided the existing bias field correction techniques into prospective and retrospective methods. Retrospective methods, which are currently more widely used, can be further categorized as filtering [5], surface fitting [6], histogram analysis [7,8], or segmentation [9–24] methods. Among these retrospective methods, segmentation-based techniques are the most popular, as they allow segmentation and bias correction to be combined in an iterative process, thereby achieving optimal solutions. These segmentation-based approaches are either local or global region-based methods. Because of the slowly varying bias field, existing local region-based methods [10–17] assume the bias fields to be almost constant within a small window. Li et al. [10] proposed a variational level-set method (VLS) to simultaneously perform multiphase segmentation and bias correction. Using local mean intensities, the VLS method allows for the management of inhomogeneous intensity. However, the technique is insensitive under conditions of high noise. Furthermore, as the energy function of the VLS method is not convex, this method could become trapped around local minima [12]. Motivated by the VLS model [10], Zhan et al. [13] exploited local image region statistics to describe the local image region. Their method allows for the identification of regions with the same mean intensity but a different variance. More recently, Zhang et al. [12] defined a transformed domain to improve the robustness of the model, employing the maximum likelihood in the transformed domain (MLTD). One problem with MLTD is that local region-based methods are often very sensitive to the window radius. In addition, local region-based approaches tend to be computationally complex, as they calculate local information for each pixel in an image. Statistical methods for local regions rely on the

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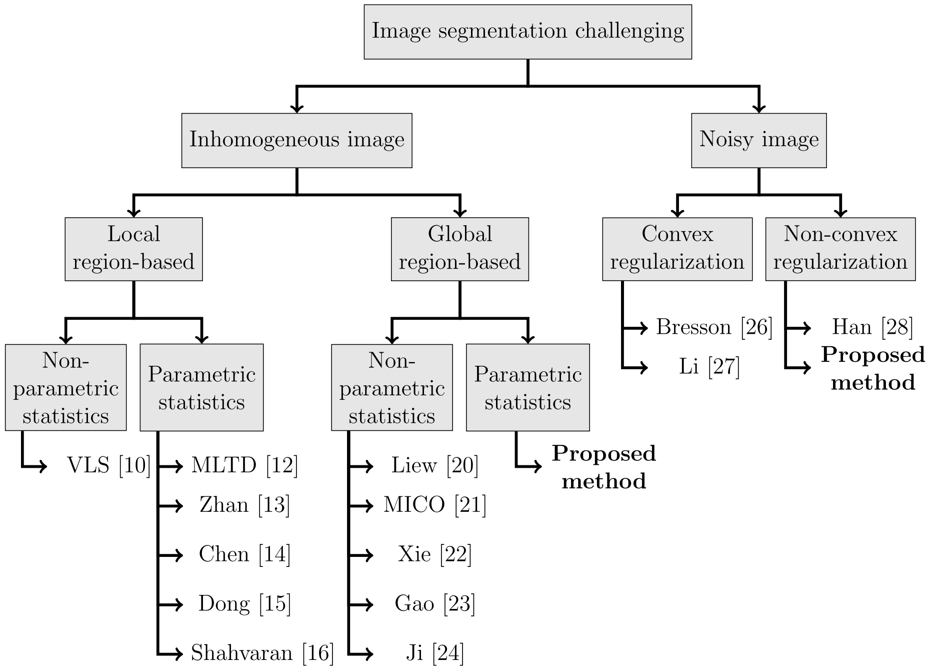


**Fig. 1.** Taxonomy of related methods for noisy and inhomogeneous image segmentation.

assumption that each pixel in each region is independent, ignoring the spatial correlation between pixels [16]. Wang proposed a spatial information system using a patch-based sparse representation method; however, this is a supervised method that requires a training database [17]. Since accurate classifiers rely on good training databases, supervised methods should cover all possible cases, and are thus difficult to attain [25]. Shahvaran et al. [16] utilized a Markov random field (MRF) to model the spatial correlation between neighboring pixels/voxels. Their unsupervised model does not require training data, though it retains the disadvantages of local region-based methods.

In contrast to these local approaches, global region-based methods [20–24] model bias fields as linear combinations of polynomials. In these methods, bias field estimation is performed by identifying the optimal coefficients of basis functions. Compared with local region-based methods, global approaches do not require the user to set the window size, thereby permitting fully automated applications. Liew and Yan [20] utilized a B-spline surface to model the log bias field as a stack of smoothing operations for the segmentation of three-dimensional (3D) MR images. Li et al. [21] proposed a multiplicative intrinsic component optimization (MICO) model for multiphase segmentation and bias field correction, in which the bias fields are represented as a linear combination of Legendre polynomials. The advantages of this method include initialization independence and rapid convergence. Xie et al. [22] proposed an interleaved method, combining modified MRF segmentation with bias estimation. However, in two reports [21, 22], the group used global mean intensity information as a criterion for segmentation, which can fail in regions with similar mean intensities but different variances. In addition, as the MICO model is a K-means clustering-based approach, it is sensitive to noise.

To address the problem of image noise, the total variation can be introduced as a regularization term. Classical regularization strategies are either convex [26,27] or non-convex [28]. Bresson et al. proposed a convex regularization scheme for the segmentation of images with only two regions [26]. Motivated by Bresson's method, Li et al. [27] proposed a multiphase image segmentation technique. These convex regularization methods can be simply solved using the Chammbolle dual algorithm [29]. However, there are two inherent drawbacks to these methods: (1) convex regularization of the membership functions causes over-smoothing of edges in disjoint regions; and (2) they require a large number of tuning parameters, resulting in numerical instability [28].

To protect the edges from over-smoothing, Han et al. [28] proposed a non-convex regularization procedure. Their key idea was to identify an appropriate function such that the contribution of the regularization term does not alter information from a strong gradient. Moreover, an edge indicator function (close to zero at edge locations) was incorporated into the regularization as a weighted function, thus preserving the geometric properties of the original features, such as corners [26]. Therefore, a good edge indicator is crucial for the performance and quality of non-convex regularization. The traditional edge indicator function [28] is computed using the gradient magnitude of the convolved image with a Gaussian filter. Unfortunately, if the image is corrupted by noise, the Gaussian filter produces blurred edges, which ultimately result in false edge detection. Over the past decade, edge-preserving schemes such as bilateral filters [30], domain transform filters [31], and weighted least-squares [32] methods have been proposed. More recently, the guided filter [33] has been shown to function as an edge-preserving smoothing operator, much like the popular bilateral filter [30], and hence the performance of edge indicator functions has improved significantly.

The contributions of the proposed method can be summarized as follows:

1. An unsupervised, multiphase segmentation model is proposed for simultaneous MR image segmentation and bias field correction in the presence of noise based on a Bayesian framework. In our model, global regional statistics such as intensity means and tissue variations are described by Gaussian distributions.
2. Based on a guided filter, rather than a Gaussian filter, an edge indicator function is proposed that can preserve strong image edges in the presence of underlying noise. The proposed edge indicator function is integrated with non-convex regularization to overcome the influence of noise.