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Correction of inhomogeneous magnetic resonance images using multiscale retinex for segmentation accuracy improvement

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ABSTRACT

The purpose of this study was to improve the accuracy of tissue segmentation on brain magnetic resonance (MR) images preprocessed by multiscale retinex (MSR), segmented with a combined boosted decision tree (BDT) and MSR algorithm (hereinafter referred to as the MSRBDT algorithm). Simulated brain MR (SBMR) T1-weighted images of different noise levels and RF inhomogeneities were adopted to evaluate the outcome of the proposed method; the MSRBDT algorithm was used to identify the gray matter (GM), white matter (WM), and cerebral-spinal fluid (CSF) in the brain tissues. The accuracy rates of GM, WM, and CSF segmentation, with spatial features (G, x, y, r, θ), were respectively greater than 0.9805, 0.9817, and 0.9871. In addition, images segmented with the MSRBDT algorithm were better than those obtained with the expectation maximization (EM) algorithm; brain tissue segmentation in MR images was significantly more precise. The proposed MSRBDT algorithm could be beneficial in clinical image segmentation.

1. Introduction

The segmentation of brain magnetic resonance (MR) images is a pivotal technique in the assessment of volumetric differences for clinical diagnosis, such as brain tissue and brain tumor segmentation [1–4]. Brain tissue segmentation is an important issue among brain MR image segmentation research [5–8]; there exist several brain tissue segmentation methods for MR image studies. Shen et al. [9] proposed an intelligent segmentation technique to identify brain tissues, including the gray matter (GM), white matter (WM), and cerebral spinal fluid (CSF), in brain MR images. A neighborhood attraction, which includes pixel intensities (feature attraction), spatial position of neighbors (distance attraction), and improved fuzzy c-means (FCM), was used to improve segmentation accuracy. In addition, the degree of feature attraction and distance attraction was optimized by an artificial neural-network model. This technique was an improvement from the traditional FCM algorithm; simulated T1-weighted MR images with different noise levels and real MR images were segmented for better results. Vrooman et al. [10] presented a new, fully automatic k-Nearest-Neighbor (KNN) training procedure with non-rigid registration to identify brain tissues; results showed improved accuracy in the segmentation of GM, WM, and CSF. This robust segmentation performance was also evaluated with a similar index (SI). Manjon et al. [11] proposed a tissue type parameter estimation method to estimate mean intensity values of GM, WM, and CSF accurately. As indicated from the preponderous amount of literature, improving the accuracy of brain tissue segmentation in MR images is important for the identification of GM, WM, and CSF for neuro-imaging application.

The signal to noise ratio (SNR) of MR images is sometimes reduced by the receive coils. The image quality is affected by the decreased SNR. In general, the surface coil provides better SNR than the volume coil during MR image acquisition. The surface coil often generates radio-frequency (RF) inhomogeneities when acquiring MR signals. However, RF inhomogeneity, as well as the background noise and partial volume effect, reduces the accuracy of tissue segmentation for brain MR images. Attempts have been

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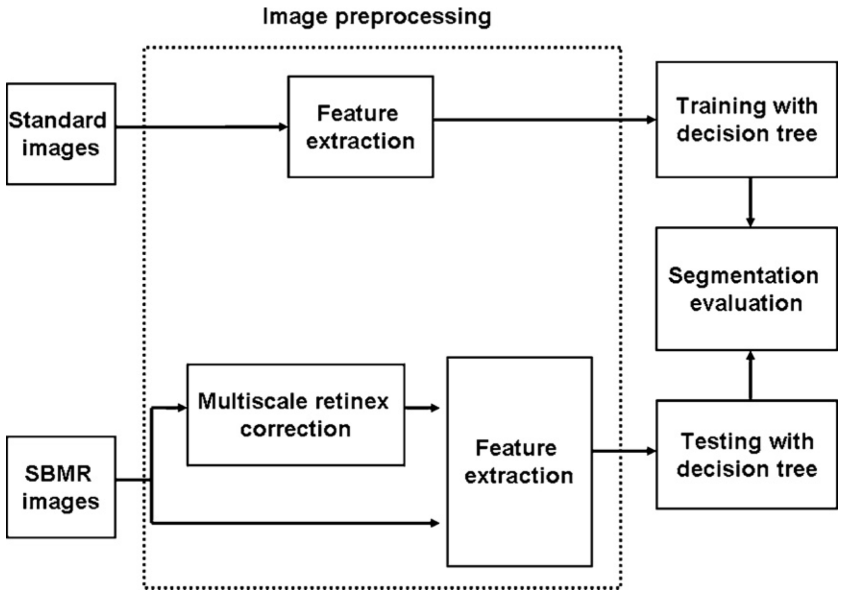

Fig. 1. Image processing procedures.

made to minimize segmentation errors of MR images with correction algorithms. A robust automatic algorithm with correcting radio-frequency (RF) inhomogeneity has been designed to segment GM, WM, and CSF of MR images in phantom studies and clinical experiments [12]. Gispert et al. [13] proposed a nonuniform intensity correction (NIC) algorithm (bias field estimation and tissue classification) to segment the phantom dataset and the real image dataset. The NIC algorithm showed the best performance for classifying GM, WM, and CSF in T1-weighted MR images on phantom and real images. Garcia-Sebastian et al. [14] proposed a parametric intensity inhomogeneity (IIH) correction schema and an online estimation of the image model intensity class means to segment MR images. Several previous studies [12–15] have demonstrated brain tissue segmentation with decreased noise-induced errors. However, segmentation errors were increased due to RF inhomogeneities. In an effort to resolve this problem, we proposed a boosted decision tree (BDT) combined with the multiscale retinex (MSR) algorithm (hereinafter referred to as the MSRBDT algorithm) as a preprocessing process. The retinex algorithm was used to reduce the nonuniformity of MR images caused by RF inhomogeneity in MR image intensity. Land [16] proposed a retinex model based on the neurophysiological processing of brain image information in retinas to describe color constancy in human visual perception. The model was developed according to the concept that human perception is not defined solely by the spectral character of the light that reaches the eye; it includes the processing of spatial-dependant color and intensity information on the retina. The process is accomplished by computing dynamic-range compression and color rendition [16–20]. Accordingly, Hurlbert and Poggio [17] and Hurlbert [18] derived a general mathematical function by applying the retinex properties and luminosity principles. Images from various center/surrounding functions in three gray-level scales show different retinex outputs. Moreover, Jobson et al. [21] found that the selection of surrounding function parameters has a significant effect for the retinex output [21,22]. The dynamic compression and color rendition were then balanced with MSR. Although the inhomogeneities of MR image could be reduced with improved hardware, it would be more feasible to develop a preprocessing algorithm to improve the segmentation of brain MR images. The current MSR was hereby proposed for the preprocessing of brain MR images.

After preprocessing, the brain tissues of MR images were segmented with decision tree algorithms. Two decision trees have been developed in existing literature: the classification and regression tree (CART) and the See5/C5.0 (BDT). The CART is a binary tree that can be used for classification and regression analysis [23–26]; the See5/C5.0 [27–29] was advanced from the ID3 learning tree [30] and has been adopted for various biomedical applications [31]. In the previous study, a BDT was applied as the segmentation algorithm as it can effectively classify data structure, predict the accuracy of non-linear problems, interpret rules in a decision tree rule set, and eliminate outliers [25]. Combining the advantages of the MSR and the BDT decision trees, the MSRBDT algorithm was proposed for the identification of GM, WM, and CSF in brain tissues. The goal of the current study was to improve the accuracy rates of brain MR image segmentation.

2. Materials and methods

Image processing procedures are shown in Fig. 1. The decision tree structure was constructed by a training procedure from a standard image (manually identified by an expert), which was tested to identify different types of brain tissues for all brain MR images. Two image preprocessing methods are available for the testing procedure. The first method applies the MSR algorithm to correct for RF inhomogeneities of MR images; spatial features were extracted from the corrected MR images, the images were then segmented. An alternative method is to segment the brain MR images after extracting spatial features. Two decision trees, CART and BDT, were used to evaluate the results of segmented brain images.

2.1. MR images

The simulated brain MR (SBMR) images obtained from BrainWeb (http://www.bic.mni.mcgill.ca/brainweb) were T1-weighted 3-mm-thick images with 3%, 5%, 7%, and 9% noise levels. At each noise levels, RF inhomogeneities of 20% or 40% were introduced to the SBMR images. Details of the SBMR images are described in Table 1. Segmentation results from images of different qualities were examined. An expert manually identified a standard brain MR image from an original image with no noise and inhomogeneity as a training data; it was adopted as the standard image in the present