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Tumor or abnormality identification from magnetic resonance images using statistical region fusion based segmentation

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ABSTRACT

In this article, a statistical fusion based segmentation technique is proposed to identify different abnormality in magnetic resonance images (MRI). The proposed scheme follows seed selection, region growing–merging and fusion of multiple image segments. In this process initially, an image is divided into a number of blocks and for each block we compute the phase component of the Fourier transform. The phase component of each block reflects the gray level variation among the block but contains a large correlation among them. Hence a singular value decomposition (SVD) technique is adhered to generate a singular value of each block. Then a thresholding procedure is applied on these singular values to identify edgy and smooth regions and some seed points are selected for segmentation. By considering each seed point we perform a binary segmentation of the complete MRI and hence with all seed points we get an equal number of binary images. A parcel based statistical fusion process is used to fuse all the binary images into multiple segments. Effectiveness of the proposed scheme is tested on identifying different abnormalities: prostatic carcinoma detection, tuberculous granulomas identification and intracranial neoplasm or brain tumor detection. The proposed technique is established by comparing its results against seven state-of-the-art techniques with six performance evaluation measures.

1. Introduction

Image segmentation showed tremendous applications in medical imaging systems for the last few years. It includes delineation of anatomical structures and identification and marking of other regions of interest (ROI). It has numerous applications which includes: quantification of tissue volumes, diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data, computer-integrated surgery, etc.

Segmentation of medical images is one of the challenging tasks in computer vision [1,2]. Automatic segmentation of brain magnetic resonance image (MRI) has a great research importance. It mainly considers separation or classification of MRIs into different classes like gray matter, cerebrospinal fluid, white matter, skull, background, etc. Generally, an MRI is highly affected by noise, intensity inhomogeneity and blurred boundaries which leads to an error in boundary identification during the segmentation process. Few popular existing segmentation techniques for medical image segmentation are: thresholding [3], statistical methods [4,5], clustering [6,7], graph [8,9] and region based methods [10,11].

A simple approach of medical image segmentation is by thresholding based approach, where the threshold value/s are determined by analyzing the peaks and valleys of the histogram of the image [1,12]. Different medical image thresholding techniques are proposed in the medical imaging literature including an early work by Gordon et al. [13]. An adaptive thresholding scheme based on the pixel wise path connection between the pixels is also proposed by Lee et al. in Ref. [3]. Assuming that some prior information about the general shape and location of objects is available, the algorithm finds a boundary between two regions using the path connection algorithm and changing the threshold value adaptively. However, since the thresholding based segmentation scheme depends on the gray-level information of an image, segmentation result obtained from this scheme provides disconnected segmented regions rather than a connected one.

Better results can be obtained by statistical segmentation schemes like Markov Random Field (MRF) model [14]. MRF, a well known statistical model, provides a convenient way to model contextual features of an image such as image gray values, edge,

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entropy, color, texture, etc. This is achieved through characterizing mutual influences among such entities using conditional probability distributions. MRFs and the Maximum a'posterior probability (MAP) criterion together give rise to the MAP-MRF framework [15]. An early work on brain MRI segmentation using MRF model is found to be effective [16]. The authors have considered Simulated Annealing (SA) and Iterated Conditional Mode (ICM) schemes for getting a good solution from the given conditional priors. A statistical degenerate version of MRF model termed as Hidden Markov Random Field (HMRF) is also used for segmentation by Zhang et al. [4]. Advantage of such a method is derived by the way the spatial information is encoded through the conditional probability distributions. Wu and Chung [17] have proposed a modified version of the MRF model called compound MRF model and used it for brain MRI segmentation. Here the authors have combined the label information with the boundary information to preserve the blurred boundary of the MRIs in segmentation. A popular variant of MRF model i.e., conditional random field [18] is also used in medical MRI segmentation [19]. Here the pixel labels and the original pixel values are modeled in probabilistic framework to segment the MRI into different classes. It may be noted that MRF based segmentation scheme inherently depends on the assumption that the prior probability of MRF follows Gibb's distribution and the likelihood estimation follows Gaussian distribution. It is also true that any real life image rarely follows any statistical distribution; hence the accuracy of segmentation relies on statistical distribution assumptions.

Watershed algorithm [20] is another approach of segmentation using gray level morphological operation. An intuitive idea is to partition the image into a number of regions or basins separated by dams, called watershed lines [21]. It is proved [1] that the MRI segmentation using watershed approach provides good accuracy in complex situations [22,23]. One of the main problems in watershed segmentation is that it gives over-segmented results. To overcome such disadvantages, many modifications of the watershed algorithm were proposed in the literature. A hybrid algorithm that combines the morphological watershed segments and edges of the image are used to segment and identify the contents of MRIs [24]. A probabilistic watershed model is studied by Grau et al. [22] found to give good results in noisy scene also. It is also observed that an inclusion of prior shape in watershed segmentation improves the accuracy of medical image segmentation. Recently, Li et al. [25] also studied a combined problem of intensity inhomogeneity estimation and MRI segmentation where the intensity inhomogeneity is iteratively optimized by using efficient matrix computations. The energy function defined here is composed of two multiplicative components of an MRI. This approach is popularly called multiplicative intrinsic component optimization (MICO).

Region growing based segmentation, is another approach of segmentation found to be popular in this regard. A popular work on region growing based medical image segmentation is proposed by Pohle and Toennies [10] where pixels with less gradient values are selected as seed points for starting the segmentation. A 3D region growing algorithm has been proposed for MRI segmentation by Justice et al. [26]. A texture feature based region growing technique is proposed by Wu et al. [27]. The authors have proposed an automatic segmentation of organs in abdominal MRI, where different textural features are fused; region growing is made on the combined textural feature space to get better segmentation accuracy.

It is observed that region growing approach of spatial segmentation is simple, less complex and robust to noise. However, it is found that selection of seed points for region growing scheme and preservation of accurate shape of an object in an image are very difficult. In this regard several modification of the conventional region growing is also made. Deng and Manjunath [28] have proposed an unsupervised segmentation technique using color quantization followed by region growing. Selection of seed point and boundary preservation is accomplished by considering multi-scale joint image generation (JSEG) scheme. To enhance the accuracy of segmentation, Kim and Park [29] proposed a new edge based region growing scheme which considered the following three popular edge features: local contrast, region ratio and edge potentials. A Bayesian analysis based edge preserving region-growing technique is proposed by Pan and Lu [30], where multislices Gaussian and anisotropic filters are used to remove the irrelevant details in the images.

From the above discussions we may conclude that research on MRI segmentation is one of the challenging tasks in computer vision. It may be observed from the state-of-the-art techniques that a single method of MRI segmentation is found to be not good for segmenting different regions from all MRIs and all methods are not promising to segment a particular region from an MRI. Hence, here it is required to mention that an efficient segmentation scheme is required to be developed so as to segment different abnormalities from an MRI. To the best of the authors' knowledge, in the literature of MRI and scene image segmentation, there is no method available that takes the advantages of the Fourier transform based features with singular value decomposition for seed point selection in region growing segmentation.

It is also true that region growing based segmentation scheme is also quite popular and found to be efficient for MRI segmentation. To alleviate some of the existing problems in region growing technique, in this article, we have proposed an edge preserving segmentation technique by fusing multiple binary levels to segment an MRI. The process starts with selection of suitable seed points. The seed points are obtained by taking the phase components of the Fourier transform of MRI followed by singular value decomposition (SVD) technique to generate a singular value diagonal matrix. A thresholding procedure is adhered to this diagonal matrix to identify the smooth and edgy regions in the image. To get rid of over-segmentation problem due to edgy seed points, we consider some (confident) pixels from different smooth areas as the seeds for region growing. By considering each seed point we perform a binary segmentation of the MRI and hence with all seed points we get an equal number of binary images. Then all the binary images are fused together using statistical fusion process to segment the image.

To evaluate the proposed scheme we have conducted experiments on three different kinds of MRIs for identifying different abnormalities. This includes: prostatic carcinoma detection, tuberculous granulomas identification and intracranial neoplasm or brain tumor detection. It is observed that the proposed scheme effectively segments these abnormalities from the MRIs with noise, surface reflections and smooth segments. To validate the proposed scheme, results obtained by it are compared with those of seven existing schemes: Bayes-theory based Region-Growing (BRG) [30], adaptive region-growing (ARG) [10], compound MRF (CMRF) [17], improved watershed transformation (IWT) [22], mean-shift [31], level set [32] and MICO [25] techniques. The effectiveness of the proposed scheme is evaluated by six performance evaluation measures: accuracy, sensitivity, specificity, precision, f-measure and G-mean [33].

The organization of this paper is as follows. Section 2 presents the block diagram and an overview of the proposed algorithm for medical image segmentation in detail. A short introduction to Fourier transform for image and singular value decomposition is provided in Sections 3 and 4, respectively. Section 5 describes the proposed MRI segmentation technique with seed point selection, region growing and image fusion techniques. Results and discussion with evaluation of the proposed algorithm are provided in Section 6. Finally, Section 7 draws conclusions.