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Brain tissue classification method for clinical decision-support systems

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ABSTRACT

Studies have shown that the degree of atrophy for the brain tissue volumes could provide an indicator of disease progression for patients with age-related dementia. In this paper, the proposed method for joint tissue segmentation and removal of non-brain tissues during post-processing is carried out in magnetic resonance imaging (MRI) by integrating the models of Threshold Segmentation and Post-processing Pipeline (TS–PP), based on greyscale histograms. In the approach, we employ the coefficient of variance statistically to determine the dual thresholds in the intensities of grey matter and white matter, and then use them to obtain preliminary thresholded masks, which consist of some non-brain tissues on skull. Different from other popular methods relied on pre-processing steps to be performed first for removal of non-brain tissues before segmentation, the TS–PP selects thresholds by the coefficient of variance for segmentation first, and then performs two groups of operations during post-processing, iterative contour refinement and morphological reconstruction, in order to minimize non-brain tissues on skull. In the validation, the TS–PP is implemented using 20 simulated T1-weighted MRI datasets and a real-time OASIS data. The experimental results demonstrate the robustness of the approach, compared to some existing segmentation methods building upon the pre-processing steps. In comparison, the proposed hybrid model TS–PP achieves an improved performance in tissue classification in MRI.

1. Introduction

Brain tissue segmentation in magnetic resonance imaging (MRI) refers to the partitioning of an image into disjoint regions with respect to a chosen property such as texture and colour (Tohka, 2014; Pepe et al., 2013). Clinical studies have shown that the degree of atrophy for the volume of brain tissues, e.g., grey matter (GM), could provide an indicator of disease progression and, potentially, treatment outcomes for patients with age-related dementia (Weiner et al., 2013; Duchesne et al., 2008). There is a crucial need for robust computational methods for image segmentation and tissue classification in clinical centres. As the brain tissue segmentation and classification are crucial early steps in clinical diagnosis, it has become one of the important areas of research in assess patients with neurodegenerative disease and brain tumour in developmental neuroscience. A robust method which could offer quantitative measurements to achieve accurate segmentation results, however, remains challenging (Weiner et al., 2013; Kloppel et al., 2008).

In the image segmentation, many popular methods relied on the pre-processing steps using deformable models (Huang et al., 2009; Jack et al., 2010; Yushkevich et al., 2006), the watershed transform algorithms (Beare, 2006; Duyn, 2012; Segonne et al., 2004), the thresholding method (Otsu, 1979; Genovese et al., 2002) and the graph cut optimization (Pepe et al., 2013; Yang et al., 2005; El-Zehiry and Elmaghraby, 2007). In the segmentation, the watershed transform algorithms were performed on the intensity inverted image by selecting the basin to represent the brain; this may fail to remove dura, skull and various non-brain structures in brain tissue segmentation in the neck/eye area (Tohka, 2014; Huang et al., 2009). For deformable models, one popular category of segmentation methods is based on image geometric information using a minimization of an energy functional (Yushkevich et al., 2006; Chung et al., 2003; Jack et al., 2010) and a hybrid geometric–statistical feature (Pepe et al., 2013; Huang et al., 2009) to regularize deformable model convergence.

Some methods mentioned above required various image pre-processing steps to be performed before the brain tissue segmentation could take place, where the pre-processing steps included intensity non-uniformity correction and brain extraction or skull stripping. With the pre-processing steps for removal of non-brain tissues, constructing a good model in MRI is strenuous and requires sufficient samples to avoid the tissue underestimation in the subsequent segmentation process; it may also lead to inappropriate removal of brain tissue, and therefore the subsequent tissue segmentation would be more problematic. A review of some methods with the image pre-processing steps can be found in the work (Tohka, 2014; Duyn, 2012; Liew and Hong, 2006).

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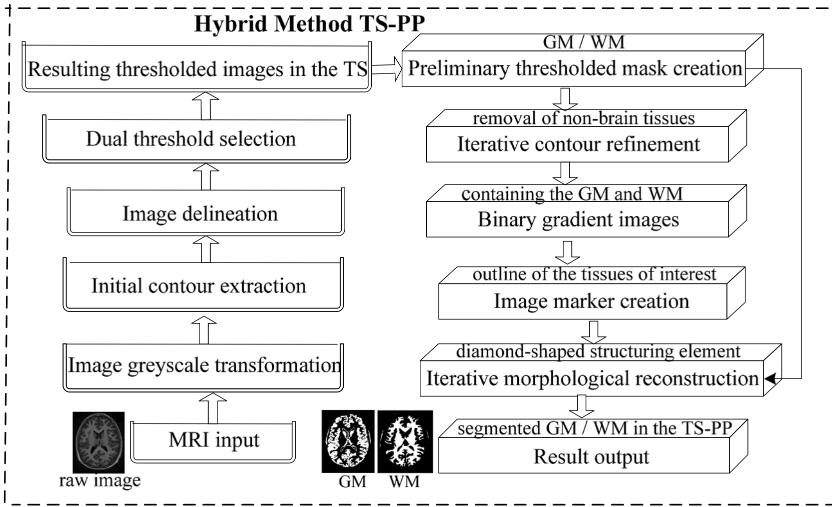

Fig. 1. Proposed approach.

In the brain tissue segmentation, it may be useful to explore new automatic hybrid models using different sources of techniques, for example, post-processing steps, involved in the approach, in order to preserve brain tissues maximally for the final segmentation (Tohka, 2014; Masood and Al-Jumaily, 2014). This study seeks to address the challenge for joint tissue segmentation and post-processing steps for removal of non-brain tissues in MRI. In this paper, based on greyscale histograms, we propose a hybrid method combining the models of threshold segmentation and post-processing pipeline (TS–PP), where the latter is the first method for removal of non-brain tissues using iterative contour refinement and iterative morphological reconstruction for image transformation during post-processing.

The rest of the paper is organized as follows. The proposed TS–PP approach is described in detail in Section 2, including the image greyscale histogram analysis in MRI and the steps for the implementation during post-processing in the approach. In Section 3, we report the experimental results using the 20 simulated T1-weighted MRI datasets and the real-time OASIS data, including comparisons with some published results existing in the literature. A discussion is presented in Section 4 and the conclusion and future work are given in Section 5.

2. Proposed method

Based on greyscale histograms, Fig. 1 presents the proposed hybrid method TS–PP in MRI for selection of thresholds for tissue segmentation, removal of non-brain tissues and morphological reconstruction in transformation during post-processing. In the statistics, the average coefficient of variance (CV) can be employed to measure the degree of spread of intensities (or intensity nonuniformity) to the mean in histograms. In the approach, we first apply the CV to determine the dual thresholds among the intensities of tissues of grey matter (GM) and white matter (WM), and then use them to obtain preliminary thresholded tissue masks. Next, two groups of operations are performed during post-processing, including iterative contour refinement and iterative morphological reconstruction in transformation. In the proposed TS–PP, the operation of iterative contour refinement is to minimize the non-brain tissues on skull, while the iterative morphological reconstruction consists of two images (the marker and the marker, where the latter constrains the transformation) and the diamond-shaped structuring elements (used to define shapes of connectivity) for image reconstruction.

In the implementation, we validate the proposed approach on the 20 simulated T1w MRI datasets from the BrainWeb (Aubert-Broche et al., 2006) and the real-time Open Access Series of Imaging Studies (OASIS) data of MRI scans (http://www.oasis-brains.org). The ground truth from the BrainWeb data is the provided expert-guided manual segmentation label for each of the clinical scans. In the next subsections, we provide descriptions of each technique of the proposed hybrid model TS–PP in detail.

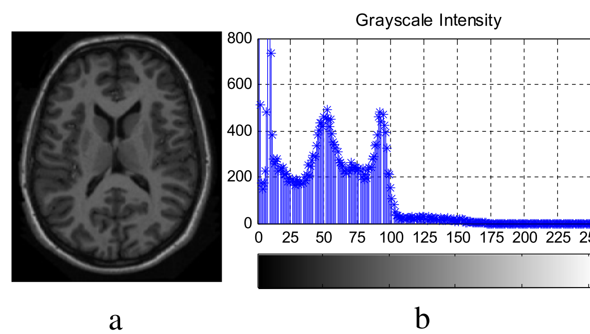

Fig. 2. A sample image of T1w MRI from the OASIS data; (a) raw image, (b) image greyscale histograms.

2.1. *Image greyscale histogram analysis*

Image greyscale histograms provide a rich estimate of a bin region's intensity distribution for image segmentation (Rafael and Wood, 2008). Fig. 2 presents a sample image of MRI scans (selected randomly from the real-time OASIS data) in the greyscale histogram representation. In Fig. 2(b), there are 256 different possible voxel intensities (using 256 bin levels) in the greyscale histograms, and so the greyscale histogram graphically displays 256 numbers showing the distribution of image voxels among those values.

In an image of T1w MRI, the interior of the brain includes GM, separated by white matter (WM) tissue with a lighter colour and cerebrospinal fluid (CSF) with a dark colour (Pepe et al., 2013; West et al., 2012). In this study, we suppose that the data of brain tissues in the histograms could be estimated approximately with three dominant modes, corresponding to the two types of brain tissues (GM and WM) and CSF (Weiner et al., 2013; Chung et al., 2003).

Fig. 2 presents a sample image of T1w MRI from the real-time OASIS data; Fig. 2(a) is the raw image, and Fig. 2(b) is the image greyscale histogram, showing three distinct modes, corresponding to the WM, GM and CSF (from the right to the left), where the CSF with the background are filtered into the left margin of the histogram. The GM intensities reside in the middle while the WM intensities stay in the right margin of the histograms. The objective in this study is to segment the images