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Brain extraction based on locally linear representation-based classification

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ABSTRACT

Brain extraction is an important procedure in brain image analysis. Although numerous brain extraction methods have been presented, enhancing brain extraction methods remains challenging because brain MRI images exhibit complex characteristics, such as anatomical variability and intensity differences across different sequences and scanners. To address this problem, we present a Locally Linear Representation-based Classification (LLRC) method for brain extraction. A novel classification framework is derived by introducing the locally linear representation to the classical classification model. Under this classification framework, a common label fusion approach can be considered as a special case and thoroughly interpreted. Locality is important to calculate fusion weights for LLRC; this factor is also considered to determine that Local Anchor Embedding is more applicable in solving locally linear coefficients compared with other linear representation approaches. Moreover, LLRC supplies a way to learn the optimal classification scores of the training samples in the dictionary to obtain accurate classification. The International Consortium for Brain Mapping and the Alzheimer's Disease Neuroimaging Initiative databases were used to build a training dataset containing 70 scans. To evaluate the proposed method, we used four publicly available datasets (IBSR1, IBSR2, LPBA40, and ADNI3T, with a total of 241 scans). Experimental results demonstrate that the proposed method outperforms the four common brain extraction methods (BET, BSE, GCUT, and ROBEX), and is comparable to the performance of BEaST, while being more accurate on some datasets compared with BEaST.

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Introduction

Brain extraction, also known as skull stripping, aims to remove non-brain tissues (e.g., scalp, skull, and dura); this procedure is an important step in brain image analysis. Stripped MRI brain images provide several advantages in terms of several factors, such as brain tissue classification (Shattuck et al., 2001), registration (Shen and Davatzikos, 2004), and cortical surface reconstruction (Dale et al., 1999). Accurate brain extraction is also important for cortical thickness estimation; on the one hand, cortical thickness may be overestimated if the dura is not removed (van der Kouwe et al., 2008). On the other hand, cortical thickness may be underestimated if the cortical surface is unintentionally removed. The manual delineation of the brain is time consuming and suffers from inter-operator variations. For these reasons, semi-automated and automated brain extraction methods are more preferred than manual delineation.

Anatomical changes in the brain caused by diseases or old age present a major challenge when designing a brain extraction method. For instance, the brains of older individuals usually exhibit atrophy with higher rates of brain tissue loss compared with those of younger individuals. Diseases such as Alzheimer's disease (AD) and mild cognitive impairment (MCI) lead to the loss of brain tissue. Image variations also present another challenge because of various acquisition sequences and scanner types. Most existing brain extraction methods often need to be tuned to work on a certain type of study or a certain population. Hence, a reliable and robust method that is capable of working on a variety of brain morphologies and acquisition sequences would be highly desired in neuroimaging studies.

To extract the brain, researchers developed numerous algorithms, such as morphology operations (Chiverton et al., 2007; Lemieux et al., 1999; Mikheev et al., 2008; Park and Lee, 2009; Ward, 1999), atlas matching (Ashburner and Friston, 2000), histogram analysis

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[2] Data used in the preparation of this article were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (www.loni.ucla.edu/ADNI). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. Complete listing of ADNI investigators is available at http://adni.loni.ucla.edu/wp-content/uploads/how_to_apply/ADNI_Authorship_List.pdf.

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(Shan et al., 2002), watershed (Hahn and Peitgen, 2000), graph cuts (Sadananthan et al., 2010), level sets (Baillard et al., 2001; Zhuang et al., 2006), deformable models (Smith, 2002), label fusion (Eskildsen et al., 2012; Leung et al., 2011), and hybrid approaches (Carass et al., 2011; Iglesias et al., 2011; Rehm et al., 2004; Rex et al., 2004; Segonne et al., 2004; Shattuck et al., 2001; Shi et al., 2012). Each of these methods provides advantages and disadvantages. For instance, morphology operations are fast and can be easily adjusted; however, this method fails to determine the optimum morphology size necessary to separate brain tissues from non-brain tissues (Park and Lee, 2009). Histogram (Shan et al., 2002) and watershed (Hahn and Peitgen, 2000) methods are simple and consistently producing complete boundaries. However, these two methods are sensitive to noise, which is a common problem encountered in intensity-based methods. Brain extraction methods based on deformable surfaces can achieve a smooth closed surface. However, these methods assume that the brain surface is smooth with low curvature; this characteristic is often not observed on the brain boundary, particularly in basal regions (Hahn and Peitgen, 2000). In meta-algorithm (Rex et al., 2004; Shi et al., 2012), several existing brain extraction methods are combined to compensate for the weaknesses of each method. However, the model should be specifically designed through meta-algorithm to gain optimum performance when new data are sufficiently different from previous training datasets (Rex et al., 2004).

Label fusion-based segmentation methods have been extensively studied. For instance, in MAPS (Leung et al., 2011), non-rigid registrations of selected atlases to the target image are initially used, and a label fusion technique is then applied to merge the labels from the atlases to create an optimal segmentation in the target image. SuperDyn (Khan et al., 2011) is another popular fusion-based method, in which the spatially local weights for atlases are determined by combining the supervised weight learned from the training set and the dynamic weight obtained from the target–atlas pairing. The main disadvantages of these two methods include (1) their long computational time (19 h for MAPS), and (2) the heavy dependence of the segmentation performance on the registration accuracy. A patch-based label fusion method called BEaST has been proposed (Eskildsen et al., 2012). In BEaST, non-rigid registration is not required but is replaced with rough affine alignment to reduce computational costs. The weights of the fused labels are calculated using non-local means approach (Buades et al., 2005); experimental results show that the patch-based label fusion approach significantly increases the segmentation accuracy. Furthermore, a multi-resolution framework is used in BEaST to improve computational efficiency and robustness. Although label fusion-based methods provide optimum performance for brain extraction, a number of fundamental problems of label fusion, such as the estimation of the labels of test samples by linearly combining the labels of training samples and the mechanism by which fusion weights are calculated remain unclear and require further investigation.

In the current study, a Locally Linear Representation-based Classification (LLRC) method for brain extraction is presented. In LLRC, the locally linear representation is introduced into the classical classification model and a novel classification framework is derived. Under this classification framework, the label fusion approach can be considered a special case and thoroughly interpreted. Locality is important to calculate fusion weights for LLRC; this factor is also considered to determine that Local Anchor Embedding (LAE) (Liu et al., 2010) is more applicable in solving locally linear coefficients compared with other linear representation approaches, such as Sparse Coding (SC) (Wright et al., 2009), non-local means (Buades et al., 2005), and Locality-constrained Linear Coding (LLC) (Wang et al., 2010). Moreover, LLRC supplies a way to learn the optimal classification scores of the training samples in the dictionary to obtain accurate classification. The proposed method was tested on multiple datasets acquired on different scanners. The performance of the proposed brain extraction method was thoroughly evaluated by comparing with other methods, such as brain extraction tool (BET) (Smith, 2002), brain surface extractor (BSE) (Shattuck et al., 2001), GCUT (Sadananthan et al., 2010), ROBEX (Iglesias et al., 2011), and BEaST.

Datasets

Six public datasets (two for training and four for evaluation) were used in our study. The scan parameters of each dataset are listed in Table 1.

The training dataset consisted of 70 T1-weighted scans from two datasets, in which 10 scans were obtained from the International Consortium for Brain Mapping (ICBM) database (age: 18 years to 43 years) (Mazziotta et al., 1995) and 60 scans were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (age: 55 years to 91 years) (Mueller et al., 2005). The ICBM database consisted of healthy subjects. The ADNI database contained cognitive-normal (CN) subjects and subjects with AD and MCI. 20 T1 MRI scans from each class (CN, AD, MCI) were chosen to construct the ADNI training dataset in the present study. All of the scans and their corresponding brain masks in the training dataset were obtained from the websites found in a previous study (Eskildsen et al., 2012). To increase the size of our training dataset, we flipped these 70 scans and their corresponding brain masks along the mid-sagittal plane by utilizing the symmetric properties of the human brain. Thus, our training dataset consisted of a total of 140 scans (original and flipped).

The first test dataset, called IBSR1, was provided by the Internet Brain Segmentation Repository (IBSR)[3] and consisted of 18 T1-weighted scans and their corresponding brain masks obtained from healthy subjects (age: 7 years to 71 years). Some of the scans showed relatively low contrast between the brain and surrounding tissues.

The second test dataset, also provided by IBSR, was named IBSR2 and comprised 20 T1-weighted scans of normal subjects (29.0 ± 4.8 years old) and their corresponding brain masks. This dataset exhibited low resolution in addition to high heterogeneity of several scans; as a result, classifying IBSR2 was challenging.

The third test dataset, namely, LPBA40[4], consisted of 40 T1-weighted scans of normal subjects (29.2 ± 6.30 years old) and their corresponding brain masks.

The fourth test dataset (ADNI3T dataset) consisted of 163 (46 CN, 80 MCI, and 37 AD) T1-weighted MRI scans and their corresponding brain masks from the baseline time point of the ADNI database. The demographics of the subjects are shown in Table 2.

The manual brain extraction protocols of these datasets are given as follows:

For the training dataset, the brain mask includes all cerebral and cerebellar white matter (WM), all cerebral and cerebellar gray matter (GM), cerebral spinal fluid (CSF) in the ventricles (lateral, third and fourth) and cerebellar cistern, CSF in deep sulci and along the surface of the brain and brain stem, and the brainstem (pons, medulla).

For the IBSR1 and IBSR2 test datasets, the brain mask includes all cerebral and cerebellar WM, all cerebral and cerebellar GM, CSF in the ventricles (lateral, third and fourth), CSF in deep sulci and along the surface of the brain and brain stem, and the brainstem (pons, medulla).

The definition of the brain mask of the LPBA40 test dataset is the same as that of the training dataset.

For the ADNI3T test dataset, the brain mask includes GM and WM and excludes internal and external CSF.

[3] http://www.cma.mgh.harvard.edu/ibsr/
[4] http://www.loni.ucla.edu/

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