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MRI brain tumor segmentation based on texture features and kernel sparse coding

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ABSTRACT

An automatic brain tumor segmentation method based on texture feature and kernel sparse coding from FLAIR (fluid attenuated inversion recovery) contrast-enhanced MRIs (magnetic resonance imaging) is presented in this paper. First, the MRIs are pre-processed to reduce noise, enhance contrast and correct the intensity non-uniformity. Then sparse coding is performed on the first order and second order statistical eigenvector extracted from original MRIs which is a patch of 3×3 around the voxel. The kernel dictionary learning is used to extract the non-linear features to construct two adaptive dictionaries for healthy and pathologically tissues respectively. A kernel-clustering algorithm based on dictionary learning is developed to code the voxels, then the linear discrimination method is used to classify the target pixels. In the end, the flood-fill operation is used to improve the segmentation quality. The results demonstrate that the method based on kernel sparse coding has better capacity and higher segmentation accuracy with low computation cost.

1. Introduction

Brain tumor segmentation is used to separate the abnormal mass of tissue (which may be solid or fluid-filled) from normal brain tissues. It plays an important roles in the diagnosis of disease, treatment planning and surgical navigation. Therefore it is necessary to design efficient and robust brain tumor segmentation algorithm. Compared with CT (computed tomography) technology, MRI technology contains the features of non-invasive, harmless to human body and high resolution and soft tissue structure and other advantages. Thus MRIs are widely used in brain tumor image segmentation. However brain tumor segmentation is still a challenging subject due to the complex structure of brain tumors, blurred boundary of imaging, difficult to distinguish normal and non-normal tissue. According to the degree of human intervention [1,2], brain tumor segmentation methods can be divided into three categories: manual segmentation, semi-automatic segmentation, automatic segmentation. In practice, brain tumor segmentation often relies on experienced physicians to manually label tumor, which is not only time-consuming and too dependent on the physician's subjective experience. To improve brain tumor segmentation efficiency and accuracy, many researches based on MRI images of semi-automatic and fully automated brain tumor segmentation have been carried out. In recent years, automatic brain tumor segmentation has attracted much attention and many effective methods have been proposed. In the early work, segmentation are often based on threshold segmentation algorithms [3,4], region-based segmentation algorithms [5,6], and algorithms based on edge detection [7]. The threshold segmentation method based on single threshold and multi-threshold is simple and efficient. The size of the threshold is often assessed by local or global statistics, such as the mean of the grayscale [8]. Due to the high complexity of the brain structure and the blurred boundaries between normal and abnormal brain tissue, a threshold-based approach is often used to locate brain tumors [9,10]. The segmentation method based on region combines disjoint regions by studying the properties of the pixels in the image and combining adjacent pixels with the same properties according to the preset similarity criterion [11]. Experiments show that the region growing method is another efficient segmentation method and is widely used in MRI brain segmentation [12–14]. In general, it is difficult to obtain good segmentation results using the segmentation method of a single algorithm [15,16]. The current segmentation methods are usually the classification or clustering methods at the pixel level [17]. Goetzd et al. [18] extracted 54 features under each pixel of each modality and built 216-dimensional eigenvectors, then trained the data using extreme random tree classifier. Pinto et al. [19] proposed an automatic segmentation algorithm of keratinocytes based

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on the appearance and context features. Extremely random forest classifiers (Extra-Trees) were used to train the classification data in this method. Ahmed et al. [20] modified the objective function of the standard fuzzy c-means algorithm for base-domain evaluation. Pixel-based classification or clustering algorithms are used for the segmentation of two-dimensional images. Some scholars attempt to extend the algorithm to the segmentation of 3D MRI data by reconstructing the existing algorithms, such as, the knowledge-based fuzzy clustering algorithm uses the 3D connectivity region to construct the shape of the tumor [21,22], the conditional random field fusing spatial information to the clustering and classification steps [23,24], and the deformation model-based approach integrates the priori Tumor shape information as well as regional and borderline information [25]. Many of the above methods are used to manually extract features, the quality of the features to a large extent, become the bottleneck of the system. Another feasible method is to sparsely code and learn an ultra-complete dictionary from the original data or a large number of low-level features extracted, and express the data efficiently through the sparse linear combination of dictionary atoms [26]. Thiagarajan et al. [27] propose sparse coding-based approaches for MRI segmentation of tumor regions using k-lines clustering method. Salman et al. [17] used K-SVD algorithm to classify brain tumors based on the dictionary learning method of topological and texture features. Youyong et al. [28] proposed a sparse coding denoising method based on 3D diffusion tensor imaging, which used the redundant information between adjacent slices to learn an adaptive dictionary and validated it under simulated and real data. Muhammad et al. [29] used sparse coding to detect not only the presence of tumors, but also the types of tumors into eight categories. Tong et al. [30] proposed a fixed discriminative dictionary learning for segmentation (F-DDLS) strategy for segmentation strategy, and achieved online segmentation online learning through sparse coding and dictionary learning technology.

In this paper, an automatic brain tumor segmentation method based on texture features and sparse kernel coding is proposed for FLAIR sequences MRI images. Sparse coding has been successfully applied to image noise reduction and compression perception. The proposed method uses a dictionary learning method based on clustering algorithm. Firstly, extract the target pixel and the surrounding area and get the first and second order texture features. Then, map the feature from the original feature space to the high-dimensional feature space by using the kernel sparse coding. The proposed method avoids the linear inseparability caused by the high similarity between normal tissue and non-normal tissue in the original image space.

2. Method

2.1. Sparse representation and dictionary learning

2.1.1. Sparse coding

Sparse coding is widely used in the fields of image understanding and signal processing, such as image noise reduction [31,32], compressed sensing [33], image restoration [34,35] and speech signal processing [36]. Sparse coding is a way to find an over-complete set of basis vectors that represent data efficiently through its linear combination:

$$y = D \bullet x + n \tag{1}$$

where $y \in R^m$ are eigenvectors with the size of $m \times 1$, $D \in R_{m\times k}$ is an over-complete set of basis vectors, k is the number of dictionary atoms, $n \in R^m$ is assumed to be noise. The process of dictionary learning can be attributed to the process of solving D. The sparse representation means that the equation $y \approx D \bullet x$ is solved under the condition that y and D are known, and get most of the sparse solutions $x \in R^k$ with zero coefficients. The corresponding cost function can be defined as:

$$\min_x \frac{1}{2}||y - Dx||_2^2 + \lambda||x||_1 \tag{2}$$

where $|| \bullet ||_1$ is an ℓ_1 paradigmand it is equivalent to $\sum_{i=1}^{k}|x[i]|$. This is a convex optimization problem called basis pursuit.

We have eigenvectors as $Y \in m \times n$, where m is the vector dimension, and n is the number of vectors. Eq. (2) can be rewritten as follows:

$$\min_{D,X} \frac{1}{2}||Y - DX||_F^2 + \lambda\sum_{i=1}^{n}||x_i||_1 \tag{3}$$

where $X \in k \times n$, $|| \bullet ||_F$ is *Frobenius* norm constraint.

2.1.2. Kernel sparse coding

Sparse coding is usually a linear model. But not all features are separable in linear space. Therefore, the kernel trick can be used to examine the nonlinear similarity between eigenvector: the data is mapped from the original feature space $\mathbb{R}$ to the high-dimensional nonlinear feature space $\psi(\bullet)$ by using a nonlinear transformation $\psi : y \to \psi\psi(y)$. Then Eq. (1) is modified with a kernel sparse representation:

$$\psi(y) = \psi(D) \bullet x + n \tag{4}$$

And the cost function of Eq. (4) is:

$$\min_{D,X} \frac{1}{2}||\psi(Y) - \psi(D)X||_2^2 + \lambda\sum_{i=1}^{n}||x_i||_1 \tag{5}$$

According to Mercer's theory [37], if $\psi(\bullet)$ is a valid kernel function, then it must also be a symmetrically positive semidefinite function. So we choose radial basis function $K(\cdots)$ as the kernel function of the spatial transform. Then the nonlinear similarity between the two eigenvector, y_i and y_j, can be measured by the inner product, that is $K(y_i, y_j) = \psi(y_i)^T\psi(y_j)$, where the radial basis function is:

$$K(y_i, y_j) = \exp(-\gamma||y_i - y_j||_2^2) \tag{6}$$

2.1.3. Dictionary design

Dictionary learning refers to learning an over-complete set of basis vectors that can represent data efficiently. In this section, we describe in detail the kernel dictionary learning method based on clustering algorithm [38,39], with the corresponding constraint as $||X_i||_0 \leq 1$. In kernel space $\psi(\bullet)$, each sample can be represented by a linear combination of over-complete set of basis vectors. The clustering algorithm is divided into two phases, that is, the clustering phase and the clustering updating phase. And the objective function of dictionary learning problem is as follows:

$$\min_X ||\psi(Y) - \psi(D)X||_F^2 \quad \text{subject to} \quad ||x_i|| \leq 1 \tag{7}$$

Suppose that $\psi(Y)$ is the set of n input eigenvectors, where $\psi(Y) = (\psi(y_1), \psi(y_2), \ldots, \psi(y_n)$. We also suppose that $\psi(D)$ is the kernel dictionary of size $m \times K$, where $\psi(D) = (\psi(d_1), \psi(d_2), \ldots, \psi(d_K)$ and $K \ll n$. Each pixel in the image can be represented by a linear combination of atoms representing the basis vectors in the dictionary. In order to calculate the sparse coding of each pixel $X = (x_1, x_2, \ldots, x_n) \in R^{K\times n}$ s.t. $||x_i||_0 \leq 1$, $i = 1, 2, \ldots, n$, we first need to train an over-complete dictionary D.

In the clustering phase, a sample of size K from the set of samples Y is randomly selected as the initialized dictionary D. Here we define a sample set $\{\mathbb{C}_k\}_{k=1}^{K}$ that contains all the kth samples in the set of sample Y, and then calculate the nonlinear similarity $k(y_i$,