A Self-adaptive Vector Quantization Algorithm for MR Image Segmentation

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Abstract. We present a new fully automatic algorithm for MR image segmentation. The MR image data is first interpolated for an adequate local feature vector on each voxel. Then, a two-level segmentation scheme is applied. One is a data-oriented low level segmentation, which is based on a modified self-adaptive on-line vector quantization technique. The other is a goal-directed high level processing, which depends on anatomical knowledge. The presented algorithm is robust, efficient, and self-adaptive. Experimental results on brain MR images are presented.*

1. Introduction

Magnetic Resonance (MR) imaging technique has been widely used in the study of neural disorders. Tissue classification and segmentation are the key steps toward quantifying the shape and volume of different types of tissues, which are used for three-dimensional display and feature analysis to facilitate diagnosis and therapy. In general, MR images possess the following characteristics: (1) spatial intensity non-uniformity, (2) partial-volume effect, (3) high image contrast, and (4) low spatial resolution. These characteristics require that automatic segmentation methods must be adaptive and robust. There exist several classes of methods for MR image segmentation, such as thresholding, clustering analysis, and statistical model [1,2]. Each has its advantages and limitations. In this paper, we focus on developing an adaptive algorithm and consider the above mentioned image characteristics. An interpolation is first performed for an adequate local feature vector on each voxel. This interpolation can mitigate the effects due to partial volume and low resolution, preserving the high contrast. Then, a modified self-adaptive on-line vector quantization algorithm is applied for the low level segmentation, which is data-oriented. The non-uniformity effect is automatically included in the self-adaptive process. Meanwhile, anatomical knowledge is adopted for a goal-directed high level processing to extract regions of interest (ROIs). This two-level algorithm models the local statistics, analyzes group features and classifies each voxel by thresholding in the feature space. It demonstrates the efficiency in experiments.

2. Methods

A. *Low level segmentation*

The main idea of low level segmentation is to classify voxels based on their local intensity vectors rather than their intensities only. A first-order Lagrange interpolation procedure [3] is applied first for an adequate local feature vector on each voxel. Then, a feature extraction algorithm [4] is used to analyze the local features. Finally, the feature vectors are classified by a modified self-adaptive on-line vector quantization algorithm.

The implementation is summarized as follows.

(1). Feature extraction [4]: The principal component analysis (PCA) is applied to the local intensity vector series of the MR image in order to determine the dimension of the feature vector and the Karhunen-Loéve (K-L) transformation matrix. Then, the feature vector series are generated by the K-L transformation from the local intensity vector series.

(2). Classification of feature vectors: Let K be the possible maximum class number. T is a threshold to be set adaptive to each MR image. Let dist(x,y) be the Euclidean distance between vector x and y. The algorithm scans from the first voxel to the last one in the image. At the beginning, there is one class and its representative vector is the feature vector of the first voxel. For each next voxel, the Euclidean distance, dist(•,•), between its feature vector and representative vectors of existed classes is calculated. If dist(•,•) < T, the representative vector of the current class will be modified. If not, a new class will be generated subject to the constraint of the maximum class number K. After a scan, the representative vectors of all classes are generated. Then, voxels are classified based on a nearest neighbor rule. Obviously, the segmentation results will depend on K and T. K is determined by anatomical knowledge, whereas the optimal value of T is set to the maximum component variance of the feature vector series.

B. *High level processing*

For a certain clinical application, the number of possible types of tissue can be assumed based on anatomical knowledge. This number provides a good estimation to the value of K.

In the study of neural disorders, we will focus on the brain tissues. There are many papers to discuss extracting the region of brain tissues [5]. When K is set to 2, our algorithm automatically classifies the brain tissues in a class and the non-brain tissues, e.g. skull and scalp, in another class. Further segmentation will be performed only on the brain tissues.

3. Results

Fig. 1 depicts a slice of a T2-weighted 256x256 MR image (left, Tr=2,500 ms and Te=80 ms) and the extracted brain region based on the high level processing (right). The low level segmentation algorithm was then applied to the extracted region. Fig. 2 shows the three extracted classes of the low-level segmentation (left: white matter; middle: gray matter; right: cerebrospinal fluid). The computing time is approximately 15 seconds for 100 slices on a PC/266Mhz pentium II.

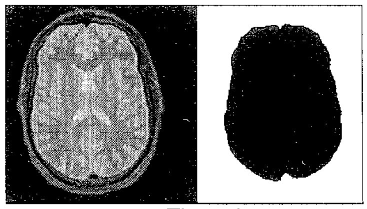

Figure 1

Figure 2

4. Conclusions

A two level fully automatic MR image segmentation scheme was developed. It is self-adaptive with a combination of anatomical knowledge. The segmentation scheme has demonstrated robust and efficient performance. Moreover, the implementation time of the algorithm is much less than those methods based on Markov Random Field [2].

References

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