Brain MR image segmentation using NAMS in pseudo-color

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ABSTRACT

Image segmentation plays a crucial role in various biomedical applications. In general, the segmentation of brain Magnetic Resonance (MR) images is mainly used to represent the image with several homogeneous regions instead of pixels for surgical analyzing and planning. This paper proposes a new approach for segmenting MR brain images by using pseudo-color based segmentation with Non-symmetry and Anti-packing Model with Squares (NAMS). First of all, the NAMS model is presented. The model can represent the image with sub-patterns to keep the image content and largely reduce the data redundancy. Second, the key idea is proposed that convert the original gray-scale brain MR image into a pseudo-colored image and then segment the pseudo-colored image with NAMS model. The pseudo-colored image can enhance the color contrast in different tissues in brain MR images, which can improve the precision of segmentation as well as directly visual perceptual distinction. Experimental results indicate that compared with other brain MR image segmentation methods, the proposed NAMS based pseudo-color segmentation method performs more excellent in not only segmenting precisely but also saving storage.

1. Introduction

Medical image segmentation is an important fundamental field in medical image processing. Brain Magnetic Resonance (MR) image segmentation is one of the most significant research and diagnosis. Automated segmentation of brain MR images can largely reduce the time consuming rather than manual image segmentation [1]. The research can be applied in many areas of clinical tasks such as surgical planning, computer integrated surgery, and so on [2,3]. Generally, the aim of brain MR image segmentation is to sort different major consisted tissue type like White Matter (WM), Grey Matter (GM), Cerebrospinal Fluid (CSF) and other pathological tissues like tumor [4]. So a Brain MR image is usually divided into several homogeneous regions according to certain criteria, like the similarity and the connectivity between pixels [5,6].

In recent years, there are many segmentation algorithms for human brain MR images [7-9]. One of the most widely used methods is the Fuzzy C means (FCM) clustering segmentation which is applied for brain tissue segmentation [10]. The segmentation process of the method may be complex because of its iteration [11]. Used a semi-supervised classification method to segment brain tissue. Experts labeled some slices to classes such as GM, WM, and CSF. Then other slices can be segmented by Gaussian Mixture Model (GMM) with the labeled data and statistic information [12]. Proposed an unsupervised method to segment tissue in brain MR images, in which Bayesian-based adaptive mean shift, Fuzzy C means clustering and a priori spatial tissue probability maps are combined to segment the image. However, the computational cost was relatively high [13]. Proposed a method that combines semi-supervised and unsupervised classification techniques for segmenting brain MR images. This method can segment brain MR images fully automatically and achieve high efficiency. However, these segmentation methods for human brain MR images usually divide pixels by the degree of similarity of gray value in image, but the effect is not ideal for the low brightness or the edge blur brain MR images.

In this paper, a new brain MR image segmentation method using Non-symmetry and Anti-packing Model...
with Squares (NAMS) based on pseudo-color is proposed. The gray brain MR image is converted into a pseudo-color image in the method to enhance the color contrast. Then the pseudo-color brain MR image is segmented by NAMS algorithm, which can largely reduce the data redundancy and adhere to the edge of tissue precisely in the meantime.

The main contributions of this paper are as follows:

Firstly, a pseudo-color brain image is generated from the input brain MR image before segmentation. Different from the traditional MR image segmentation methods that segment the input gray image, the pseudo-color images can enhance color contrast and segmenting performance particularly in precise segmentation of brain tissues.

Secondly, NAMS algorithm is presented to segment the image. Since the segmenting strategy of the anti-packing method is asymmetrical and greedy principle is used, the NAMS algorithm can preserve the characteristics and adhere to the edge of brain tissues. Besides, it is convenient to record the homogeneous block and improve the computing efficiency since the divided blocks are squares or isolate pixels in the algorithm.

Thirdly, through several measure metrics and multiple sets of experiments using the Internet Brain Segmentation Repository (IBSR), which is made by the Center for Morphometric Analysis, Massachusetts General Hospital (http://www.cma.mgh.harvard.edu/ibsr). The advantages of the proposed method are presented clearly by statistics as well as visual perception.

The rest of the paper is organized as follows: In section 2, the pseudo-color convention is introduced. Then, the details of the NAMS algorithm to segment brain MR images are presented in section 3. The experimental results of the proposed method and other comparison methods are showed in section 4. Finally, section 5 is the conclusion.

2. Pseudo-color convention

Pseudo-color convention is a method of image processing, namely, changing gray images into color images. Generally, human’s color sensitive cells can only recognize dozens of gray scales. Compared to low sensitivity to gray scale, human’s vision can distinguish thousands of color brightness and hues [14]. Since human eyes to color image is far more sensitive than to gray image, converting gray image into color image can improve the human visual perception to the image details and achieve the goal of image enhancement.

The process of pseudo-color technology is to map a gray image into a color image with corresponding colors according to certain relationship. The mapping method is only to change the gray value to a color value by one to one correspondence between input and output pixels, and not change the pixels’ spatial position.

Given a gray image \( I \), the three components of generated pseudo-color image are \( C_r \), \( C_g \), \( C_b \) respectively. The three transform functions of the pseudo-color convention are \( f_r \), \( f_g \), \( f_b \). The mapping relationship is as follows:

\[
\begin{align*}
C_r &= I \cdot f_r \\
C_g &= I \cdot f_g \\
C_b &= I \cdot f_b
\end{align*}
\] (1)

Then, superimposing three color components \( C_r \), \( C_g \), \( C_b \) can ultimately display and form pseudo-color image.

The key point in the process of converting gray image to pseudo-color image is how to decide the transform functions \( f_r \), \( f_g \), \( f_b \). The most frequently-used method currently is linear conversion method or typical pseudo-color coding method. The relevantly mature typical pseudo-color coding method in [15] is used in the proposed paper to decide the transform functions.

Suppose \( l(x, y) \) is one of the pixels in the gray image \( I \), and the value of \( l(x, y) \) is \( v \). The mathematical expression forms of transform functions \( f_r \), \( f_g \), \( f_b \) are as follows:

\[
\begin{align*}
f_r(l(x, y)) &= \begin{cases} 0 & 0 \leq v < 96 \\ 255(v - 96)/32 & 96 \leq v < 128 \\ 255 & 128 \leq v \leq 255 \end{cases} \\
f_g(l(x, y)) &= \begin{cases} 0 & 0 \leq v < 32 \\ 255(v - 32)/32 & 32 \leq v < 64 \\ 255 & 64 \leq v < 128 \\ 255(v - 192)/64 & 128 \leq v < 192 \\ 255 & 192 \leq v \leq 255 \end{cases} \\
f_b(l(x, y)) &= \begin{cases} 0 & 0 \leq v < 32 \\ 255v/32 & 32 \leq v < 64 \\ 255 & 64 \leq v \leq 128 \\ 255(v - 96)/32 & 128 \leq v < 192 \\ 255 & 192 \leq v \leq 255 \end{cases}
\end{align*}
\] (2)

Figure 1 shows the results of the generated pseudo-color images for the brain MR images. The brain MR images are from IBSR dataset, which includes a three dimensional T1-weighted MRI brain data set for 20 normal subjects and expert manual segmentation [16]. In pseudo-color images, the color contrasts among different brain tissues are enhanced and this can improve the efficiency of segmentation.
3. NAMS based segmentation

3.1. Idea of NAMS

NAMS algorithm is an anti-packing problem based on the Non-symmetry and Anti-packing Model (NAM) [17–19]. In image pattern, the idea of the NAMS can be described as follows: give an image (packed pattern) and some squares (defined sub-patterns) of different sizes, and then represent the image (packed pattern) using the combination of the squares (sub-patterns) [20,21].

Given an image \( I \), the representation image is \( I' \). Then, \( I' \) can be obtained by NAMS. The transforming procedure is as follows:

\[
I' = \bigcup_{j=1}^{n} s_j(\text{arv}_j, l_j)
\]

where \( S = \{s_1, s_2, \ldots, s_n\} \) is a set of packed squares; \( n \) is the number of the squares; \( s_j(1 \leq j \leq n) \) is one of the squares; \( \text{arv} \) is the average value of all the pixels of the square, and \( l \) is the length of the square. Specially, there will be some isolated pixels not belonged to any squares. The length of the isolate pixels is record as zero. The data structure of NAMS algorithm is showed in Table 1, in which \( sp(x_n, y_n) \) is the axis of the start point of the square \( s_n \).

In NAMS algorithm, to record a homogeneous region, that is the square in the proposed algorithm, only need to store the start point, length and average value of the square. This can largely reduce the data amount since in most other method every pixel is necessary to store.

Figure 2 illustrates the square generated rule of the NAMS by taking a binary image (in Figure 2(a)) for example. Search each pixel to form squares by raster scanning order, mark out a square with a length of 1 (in Figure 2(b)). Then the square grows at length of 2 (in Figure 2(c)). If the larger square is successful to grow up, it will be marked, and the smaller one is changed to be unmarked, as it is illustrated in Figure 2(d). The greed principle is adopted in the process of square growing. The square will keep enlarging until it cannot grow into a larger one. There will be some isolated points left, since not every pixel in the image can be used to construct squares.

The NAMS algorithm can merge the homogeneous pixels into one region, and at the same time preserve the characteristics of image context and adhere to the edge, since anti-packing method is asymmetrically splitting and greed principle is adopted in the splitting process. On the other hand, it can also reduce the data amount of the homogeneous regions to be recorded.

3.2. Algorithm of NAMS based segmentation

For a given brain MR image \( I \), an encoding queue set \( S = \{s_1, s_2, \ldots, s_n\} \), where \( s_1, s_2, \ldots, s_n \) denote the sub-patterns of the square and \( n \) is the total numbers of the squares. The following steps present the procedure of the proposed NAMS based segmentation algorithm:

- Step 1. Convert the input brain MR image \( I \) to a pseudo-color image \( I_p \) using the transforming method in chapter 2.
- Step 2. Set all the pixels in image \( I_p \) unmarked.

![Figure 1. Brain MR images and their corresponding pseudo-color images.](image_url)

![Figure 2.](image_url)
Step 3. Set a threshold $K$ to decide whether the visited pixels belong one square or not.

Step 4. Search the first unmarked pixel of the image $I$ in the order of raster scanning, and set the pixel to be the start point (top and left corner in the experiment) of a new square sub-pattern $s$.

Step 5. Find the biggest square $s$ to make sure that the spatial weighting of every two pixels in the area of the sub-pattern is less than $K$ and mark all the pixels in this sub-pattern belonged to the square.

Step 6. Record the parameters of the marked square, i.e., $s$ (No, $sp$, $l$, value), where No is the serial number of the sub-pattern, $sp$ is the coordinate of the start point of the sub-pattern, $l$ is the length of the square sub-pattern, and value is the average value of all the pixel in the square.

Step 7. Repeat Step 5 and Step 6 until all the pixels are marked in the image $I$. If some isolated pixels do not belong to any squares, set $l=0$, and the start point $sp$ is the pixel itself.

Step 8. Out put the encoding queue $S$.

4. Experiments

In this section, all images used in the experiments are from IBSR dataset which includes a three dimensional T1-weighted MRI brain data set for 20 normal subjects and the corresponding expert manual segmentation. The expert manual segmentation is used as the ground truth to evaluate the proposed algorithm. Figure 3 shows the procedure of one of the brain images segmented. Figure 3(a) is the input image, Figure 3(b) is the generated pseudo image and Figure 3(c) is the NAMS segmentation result. Compared to the gray MR images, the pseudo image has enhanced the color contrast and is better for human visual discrimination. This can reduce the visual fatigue of doctors’ diagnosis.

Figure 4 shows the comparison of the proposed NAMS segmentation algorithm, the classical FCM [10], eSFCM [22], USSFC [13] and the ground truth. Figure 4(a,b) show the original MR image and its ground truth. In Figure 4(c,d), the FCM and eSFCM segmented results have some noises and the edges of different tissues are relatively rough compared to the USSFC (in Figure 4(e)) and NAMS (in Figure 4(f)) segmented result. The proposed algorithm result in Figure 4(f) is closer to the ground truth and it is more convenient to discriminate different tissues for human visual perception. The proposed method segments the brain MR image more efficiently than other methods.

Some evaluation measurements are adopted to assess the results of the classical FCM and our proposed method. Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) are widely used evaluation metrics which can estimate the quality of a segmented image [23]. Besides, Dice coefficient [24] and Hausdorff [25] distance are normally used metrics in segmentation. According to the mentioned metrics, an original brain MR image is referred as a ground truth.

Given the ground truth image $G$ and compared image $X$, both images are $M \times N$ matrixs, MSE between $G$ and $X$ can be defined as:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (G_{ij} - X_{ij})^2$$

(6)

PSNR between $G$ and $T$ can be defined as:

$$PSNR = 10 \log_{10} \frac{255^2}{MSE(G,X)}$$

(7)

Dice coefficient $D$ is as follows:

$$D = \frac{2 |X \cap G|}{|X| + |G|}$$

(8)

Hausdorff distance $d_H$ is as follows:

$$d_H = \max \left\{ \sup_{x \in X} \inf_{y \in G} d(x, y), \sup_{y \in G} \inf_{x \in X} d(x, y) \right\}$$

(9)

where $d(x, y)$ is the Euclidean distance between $x$ and $y$.

Table 2 has figured out the segment quality of proposed method and other compared methods. It is shown that the proposed NAMS method has higher PSNR value than other methods and at the same the
MSE value is the lowest. It indicates that the proposed method can segment the image at higher quality with fewer errors than other methods. Besides, the data measurement unit in NAMS algorithm is square while in other method is pixel. It means that in the image in Figure 4 with size 240 × 245 for example, it can segmented with 8041 squares by NAMS method and we only need to record these squares using the structure in Table 1. On the contrary, in other methods, all the pixels are necessary to be recorded. So the proposed method can get better performance on segmenting brain MR images and reduce the data redundancy.

5. Conclusion

Accurate segmentation of brain MR images and reducing the data amount are both crucial for brain disease diagnosis and pathological study. In this paper, NAMS based in pseudo-color segmentation algorithm has been proposed for brain MR image segmentation. The proposed method has converted the gray brain MR image into pseudo-color, which can enhance the color contrast in segmentation and improve the discrimination of human visual perception. And it also can represent homogeneous area by squares and largely reduce the data redundancy. Experimental results have indicated that the proposed NAMS method can get better performance on segmenting brain MR images and reduce the data redundancy.
high segmentation quality, reduce the data amount, and improve the computing efficiency compared with other segment method. It is a highly effective algorithm for brain MR image segmentation.

Disclosure statement
No potential conflict of interest was reported by the author(s).

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