Auxiliary Recognition of Alzheimer's Disease Based on Gaussian Probability Brain Image Segmentation Model

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Abstract. Alzheimer's disease is an important disease that threatens the health of the elderly after cardiovascular disease, cerebrovascular disease and cancer. Early diagnosis and early intervention have an inestimable effect on disease control and treatment. Especially for China, which is facing the problem of population aging, early detection and early treatment are particularly important. According to the neuroimaging study of disease, by studying the degree of local brain loss in patients with Alzheimer's disease, the disease information of the disease manifested in the brain structure is revealed, such as the decrease of the volume of the hippocampus and the thickness of the medial frontal temporal cortex. Thin and so on. In this paper, the local Gaussian probability image segmentation model is used to segment and extract the brain nuclear magnetic image, and the image segmentation of the hippocampus structure is extracted. The local Gaussian probability algorithm of image segmentation extraction algorithm is designed and optimized. The maximal posterior probability principle and Bayes' rule are introduced to optimize the algorithm by grayscale processing of local image. Therefore, the Gaussian probability model is used to obtain the local mean and standard deviation as a function of spatial variation. Therefore, the probability model is more suitable for image segmentation with uneven gray scale than the probability model based on global hypothesis. Finally, experiments are carried out to verify the correctness of the theory and the robustness of Gaussian probability brain image segmentation.

Keywords: Alzheimer's disease · Nuclear magnetic resonance · Local Gaussian probability · Hippocampus · Image segmentation

1 Introduction

Symptoms of the disease: Alzheimer's disease (AD) is a chronic degenerative disease of the acquired nervous system. The early course of the disease is slow and only shows short-term memory impairment, but as the disease progresses, the subject will appear subjective. Abnormal behaviors such as memory loss, language barriers, time and spatial orientation disorders, poor judgment, emotional changes, and decreased self-care ability [1].

Status of disease development: Alzheimer's disease is not only a cardiovascular disease, cerebrovascular disease and tumor, but also an important disease that threatens

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the health of the elderly. Since Dr. Alzheimer first reported a 51-year-old female case in the early 20th century (1906), Alzheimer's disease has been in the medical history for nearly 110 years. The discovery of this disease has opened up a new world for human understanding of dementia. There are about 7 million new cases each year, with an average of 1 case every 4 s (one stroke every 7 s), and the number of global dementia cases has doubled in about 20 years. According to epidemiological survey data, as of 2013, about 62% of dementia cases worldwide are concentrated in developing countries. By 2050, 71% of patients will be concentrated in developing countries, and the fastest progress in aging is China, India, and South Asia and the Western Pacific [2]. The current status of Alzheimer's disease is serious, but so far there is no effective way to cure or control the progression of the disease. Early diagnosis and early intervention have an inestimable effect on disease control and treatment. Especially for China, which is facing the problem of population aging, early detection and early treatment are particularly important.

2 Current Status of Disease Diagnosis

First, the biomarker diagnosis, and the emergence of the biomarker, to some extent, predicts the possibility of Alzheimer's disease. Currently, clinically used biomarkers based on cerebrospinal fluid extraction, and mainly include: protein (divided into T-tau, P-tau, P-tau231, P-tau181). Although the use of cerebrospinal fluid can achieve diagnostic purposes to a certain extent, it is generally not easily accepted by patients because it is often a traumatic procedure [3].

Second, genetic diagnosis. In the pathogenesis hypothesis of AD, genetic factors are considered as a risk factor for the onset (such as APOE4) or pathogenic factors (such as Presenilin-1, PS-1), and gradually become an active research area. Ten genetic loci related to AD have been identified, and more are being discovered [3].

Third, neuroimaging research [4]. Because neuroimaging techniques can assess the brain from a functional metabolic or structural perspective, the brains of AD patients can be studied early in the absence of morphological changes. Neuroimaging has gradually shown its unique advantages in the early prediction of AD and its intervention. There are mainly magnetic resonance imaging (MRI) studies, through the study of the extent of local brain damage in patients with Alzheimer's disease, revealing the disease information of the disease in the brain structure, such as the volume reduction of the hippocampus The thickness of the medial frontal temporal cortex is thinner. In the functional study of the brain, there is mainly functional magnetic resonance imaging (fMRI), which can display the activation site and extent of the brain region, so that it can further reflect the fusion of function and structure, which can be used as a primary diagnostic tool for clinical use; There are also studies of brain structure networks, such as MRI imaging techniques based on structure and DTI. By constructing a network of brain structures, the resulting structural network computing models are analyzed to study the network trends of the patient's brain. These neuroimaging studies have laid a solid foundation for the early prevention and detection of AD and the continuous improvement of clinical assistant diagnosis.

3 Disease Image Detection Principle

Plane measurement using MR1 plane measurement method to measure the brain structure of patients with Alzheimer's disease, compared with three-dimensional volume measurement, it is simpler, more convenient, faster, and more widely used clinically. DeLeon et al. [5]. performed MRI scans of cadaveric specimens from patients with Alzheimer's disease. The change in the width of the lateral ventricle can reflect the extent of hippocampal atrophy to some extent, and can simultaneously understand the extent of atrophy of the medial temporal lobe and the entire lobe. Tanabe et al. used MRI to measure the brain parenchyma, gray matter, cerebral sulcus, etc., and found that all indicators between the dementia group and the normal elderly control group have a large overlap, so the dementia can be suggested according to the sulcus measurement results, but Patients with Alzheimer's disease and normal elderly cannot be accurately identified. In view of this, it may be more appropriate to select the hippocampal structure and lateral ventricle width as an identification index. Therefore, it is more inclined to use MRI three-dimensional measurement method to study brain structural changes in patients with Alzheimer's disease. In some brain regions of patients with Alzheimer's disease, the intensity of functional magnetic resonance imaging scan signals increases and the range expands when they receive cognitive activation. Functional magnetic resonance imaging studies have found that patients with mild cognitive impairment developing Alzheimer's disease have a greater range of cerebral palsy signal strength in the right hippocampus during the memory phase of the memory test, which may be Al Pathological compensatory response in patients with Alzheimer's disease. In a cognitive activation test of patients with Alzheimer's disease, Johnson et al. found that the greater the degree of atrophy of the left frontal hippocampus, the greater the area activated and the stronger the signal. In this regard, he believes that in patients with memory problems, some of the remaining normal nerve tissue can replace the tissue that has already developed lesions, and thus the signal intensity of the activated brain region increases and the range expands.

4 Image Processing Methods Introduced

According to the requirements of the specific brain magnetic imaging technology analysis task, the Gaussian probability image segmentation model is used to segment the brain image. The purpose of segmentation is to divide or extract the original image into the hippocampus of the important disease analysis site of Alzheimer's disease. structure. By analyzing and comparing changes in hippocampal structure, it provides a basis for the diagnosis of Alzheimer's disease.

Brain image segmentation is mainly divided into the following steps:

(1) Image preprocessing, that is, image restoration. The image contains noise due to factors such as equipment. Removing noise without losing tissue information facilitates subsequent image processing;
(2) Tick off brain tissue. It is to remove non-brain tissue in the brain image, such as brain shell, fat and other tissues. Since the non-brain tissue and the background part

contain a large proportion in the brain image. Therefore, the removal of non-brain tissue and background parts can improve the processing accuracy of subsequent processes;

(3) Go to the offset field. Due to the influence of the imaging mechanism, the image will contain an offset field, resulting in uneven image gray scale, which makes the segmentation result inaccurate. Accurate offset field recovery model can greatly improve the accuracy of subsequent image processing;

(4) Split the effective area. The region of interest is segmented using an active contour model or the like to analyze the image. This paper attempts to integrate each problem into a unified image segmentation framework, which makes it highly intelligent.

The main work and research results and algorithm steps of this paper are as follows:

In order to make full use of the information of the local image, we first consider the grayscale distribution of the image in the neighborhood of each pixel.

For each point x in image domain Ω, there is a neighborhood of radius $\rho : \mathcal{O}_x \triangleq \{y : |x - y| \leq \rho\}$.

Suppose the image consists of $\{\Omega_i\}_{i=1}^N$, satisfying the number of categories of $\Omega = \cup_{i=1}^N \Omega_i, \Omega_i \cap \Omega_j = \emptyset$ in which the N image is. For O_x, $\{\Omega_i\}_{i=1}^N$ will divide the neighborhood O_x into $\{\Omega_i \cap \mathcal{O}_x\}_{i=1}^N$. For example, as shown, the figure (Fig. 1) has three parts: Ω_1, Ω_2, and Ω_3. These three parts divide x's neighborhood O_x into three sub-parts $\Omega_1 \cap \mathcal{O}_x$, $\Omega_2 \cap \mathcal{O}_x$ and $\Omega_3 \cap \mathcal{O}_x$

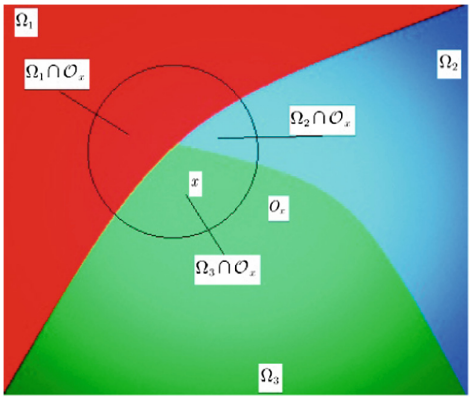


Fig. 1. Example of $\Omega_i \cap \mathcal{O}_x$. The green circle represents the neighborhood O_x of the current point x. The image consists of three parts: $\Omega_1, \Omega_2, \Omega_3$; these three parts divide the neighborhood x of O_x into three sub-parts: $\Omega_1 \cap \mathcal{O}_x$, $\Omega_2 \cap \mathcal{O}_x$ and $\Omega_3 \cap \mathcal{O}_x$. (Color figure online)

According to the maximum a posteriori probability (MAP) [6], we will focus on how to optimally segment this neighborhood O_x. We define $p(y \in \Omega_i \cap \mathcal{O}_x | I(y))$ as the posterior probability that the subpart y at a given $I(y)$ belongs to $\Omega_i \cap \mathcal{O}_x$.

According to the Bayes rule, we can get

$$p(y \in \Omega_i \cap \mathcal{O}_x | I(y)) = \frac{p(I(y)|y \in \Omega_i \cap \mathcal{O}_x) p(y \in \Omega_i \cap \mathcal{O}_x)}{p(I(y))} \tag{4.1}$$

Where $p(I(y)|y \in \Omega_i \cap \mathcal{O}_x)$ is the probability that the gray value $I(y)$ belongs to $\Omega_i \cap \mathcal{O}_x$, and is abbreviated as $p_{i,x}(I(y))$ for convenience; $p(y \in \Omega_i \cap \mathcal{O}_x)$ is the prior probability that y belongs to $\Omega_i \cap \mathcal{O}_x$, and $p(I(y))$ is the prior probability of gray value $I(y)$. Since $p(I(y))$ is independent of region $\Omega_i \cap \mathcal{O}_x$, $p(I(y))$ is treated as a fixed value.

Assuming that the probability of the prior probability $p(y \in \Omega_i \cap \mathcal{O}_x)$ is equal in each region, i.e.

$$p(y \in \Omega_i \cap \mathcal{O}_x) = \frac{1}{N}$$

then the prior probability $p(y \in \Omega_i \cap \mathcal{O}_x)$ can also be omitted. At the same time, we assume that the distribution of each pixel in each region is independent of each other, and by maximizing the posterior probability (the MAP) we can get:

$$\prod_{i=1}^{N} \prod_{y \in \Omega_i \cap \mathcal{O}_x} p_{i,x}(I(y)) \tag{4.2}$$

By doing an log transformation on Eq. (4.2), we can transform the maximized posterior probability to minimize the following energy ε_x^{LGDF}:

$$\mathcal{E}_x^{LGDF} = \sum_{i=1}^{N} \int_{\Omega_i \cap \mathcal{O}_x} -\log p_{i,x}(I(y))dy \tag{4.3}$$

For the construction of probability $p_{i,x}(I(y))$ in Eq. (4.3), there is a large amount of literature to draw on, such as the Gaussian probability model based on variance with a fixed value proposed by Chan and Vese, or the proposed full Gaussian probability model, and the proposed Parzen-based window [7]. Nonparametric probability model. However, these probabilistic models are all built on the global space, and these probabilities do not change with the spatial position within each region. Therefore, these global-based probability models are not able to overcome the gray-scale inhomogeneities that often exist in images. In this section, we will use a local Gaussian probability model:

$$p_{i,x}(I(y)) = \frac{1}{\sqrt{2\pi}\sigma_i(x)} \exp\left(-\frac{(u_i(x) - I(y))^2}{2\sigma_i(x)^2}\right) \tag{4.4}$$

The probability model is defined at each point on the image and varies with the position of the space, where $u_i(x)$ and $\sigma_i(x)$ are local mean and standard deviation, respectively [8]. Since the local mean and standard deviation are functions that vary with spatial variation, the probability model is more suitable for dealing with gray-scale inhomogeneity than the probability model based on global hypothesis.

We further add the window function in Eq. (4.4) to get the following energy:

$$\mathcal{E}_x^{LGDF} = \sum_{i=1}^{N} \int_{\Omega_i \cap O_x} -\omega(x - y) \log p_{i,x}(I(y))dy \tag{4.5}$$

Where $\omega(x-y)$ is a non-negative window function that satisfies $\omega(x-y)=0$, when $|x-y|>\rho$; $\int \omega(x-y)dy=1$.

Mainly reflected in the following two aspects: (1) we introduce a local energy in the form of a Gaussian nucleus, (2) our energy is a double integral form, and ordinary energy is a one-fold integral.

Algorithm flow:

Brain MR image segmentation algorithm based on Gaussian probability segmentation model
Initialize the level set function p_1 and p_2
While the algorithm does not converge
according to（4.1），（4.2），Update Ω_i and O_x
according to（4.3），Update level set function p_1
according to（4.4），Update Ω_i and O_x
according to（4.5），Update level set function p_2
end while

5 Experimental and Image Algorithm Experimental Results and Analysis

Image Preprocessing: Image preprocessing is a process before the brain magnetic image is sorted and submitted to the segmentation model for processing [9]. This process is called image preprocessing. In image analysis, the quality of the image directly affects the accuracy of the design and effect of the recognition algorithm. Therefore, before image analysis (feature extraction, segmentation, matching and recognition, etc.), preprocessing is required. The main purpose of image preprocessing is to eliminate irrelevant information in the image, restore useful real information, enhance the detectability of relevant information, and minimize data, thereby improving the reliability of feature extraction, image segmentation, matching and recognition.

The general pre-processing process is (Figs. 2 and 3):

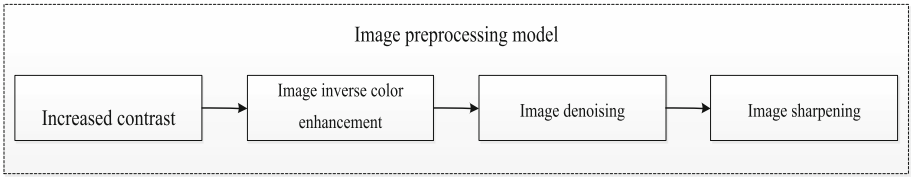
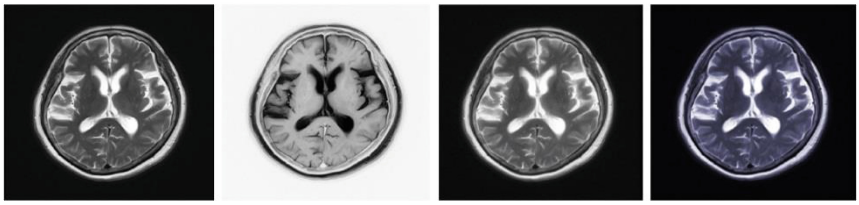


Fig. 2. Image preprocessing model.

Nuclear magnetic image offset field: Due to the existence of the offset field phenomenon in the original nuclear magnetic image, in addition, the boundary between the noise and the tissue in the image is also blurred [10]. The contrast between the gray

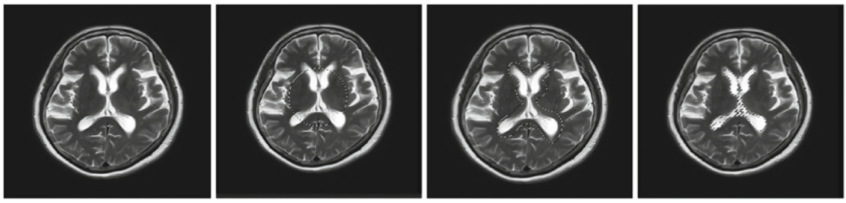


（a） （b） （c） （d）

Fig. 3. Image preprocessing.

matter and the cerebrospinal fluid is lower, as in the vicinity of the ventricles in the image, the gray scale of the gray matter and the gray value of the cerebrospinal fluid are almost equal. Traditional image contrast based segmentation algorithms will find it difficult to get accurate results.

Figure 4(e) is a brain nuclear magnetic image of Alzheimer's disease. In order to show that the method can overcome gray unevenness and low contrast well, we add strong gray unevenness in Fig. 4(e). Sex, as shown in Fig. 4(f). Under the influence of gray scale inhomogeneity, the image contrast of the hippocampus region is very low. Figure 4(g) shows the initial curve, and the image segmentation is rough. The results of the Gaussian partition model are shown in Fig. 4(h). Since the Gaussian probability segmentation model is based on local hypotheses, the Gaussian probability segmentation model can correctly segment the image. On the other hand, the model results can also see that the Fig. 4 can Strongly overcome gray unevenness.



（e） （f） （g） （h）

Fig. 4. Grayscale inhomogeneity and low contrast processing.

6 Summary

We propose a novel regional active contour model based on local Gaussian probability. The model effectively utilizes the local mean and local variance information of the image. Since the local mean and the local variance change with spatial changes, it can well overcome the gradation inequalities in the image, and the noise and Contrast is also better robust. It is worth mentioning that the local mean and local variance of the Gaussian probability model can be strictly derived from the variational principle, unlike other models that are explicitly defined.

The research in this paper has done a brain nuclear magnetic hippocampus segmentation experiment, and the experiment proved that the local Gaussian probability segmentation method is effective.

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