Review of brain MRI image segmentation methods

**M. A. Balafar · A. R. Ramli ·
M. I. Saripan · S. Mashohor**

Abstract   Brain image segmentation is one of the most important parts of clinical diagnostic tools. Brain images mostly contain noise, inhomogeneity and sometimes deviation. Therefore, accurate segmentation of brain images is a very difficult task. However, the process of accurate segmentation of these images is very important and crucial for a correct diagnosis by clinical tools. We presented a review of the methods used in brain segmentation. The review covers imaging modalities, magnetic resonance imaging and methods for noise reduction, inhomogeneity correction and segmentation. We conclude with a discussion on the trend of future research in brain segmentation.

Keywords   Brain · MRI · Segmentation

1 Introduction

The application of image processing techniques has rapidly increased in recent years. Nowadays, capturing and storing of medical images are done digitally (Chang and Teng 2007). However, the interpretation of details of medical images is still time-consuming. This matter is especially observed in regions with abnormal color and shape which should be identified by radiologists for future studies (Chang and Teng 2007). Image segmentation is a key task in many image processes and computer vision applications. The purpose of image segmentation

M. A. Balafar (✉) · A. R. Ramli · M. I. Saripan · S. Mashohor
Department of Computer & Communication Systems, Faculty of Engineering,
University Putra Malaysia, 43400 Serdang, Selangor, Malaysia
e-mail: gs19162@mutiara.upm.edu.my; balafarila@yahoo.com

A. R. Ramli
e-mail: arr@putra.upm.edu.my

M. I. Saripan
e-mail: iqbal@eng.upm.edu.my

S. Mashohor
e-mail: syamsiah@eng.upm.edu.my

is to partition image to different regions based on given criteria for future process (Chang and Teng 2007).

Medical image segmentation is a key task in many medical applications such as surgical planning, post-surgical assessment, abnormality detection, and so on (Zhang et al. 2007). There are lots of methods for automatic and semi-automatic image segmentation, though, most of them fail because of unknown noise, poor image contrast, inhomogeneity and weak boundaries that are usual in medical images. Medical images mostly contain complicated structures and their precise segmentation is necessary for clinical diagnosis (Hall et al. 1992).

One of such is brain image segmentation which is quite complicated and challenging but its accurate segmentation is very important for detecting tumors, edema, and necrotic tissues. Accurate detection of these tissues is very important in diagnostic systems. Also, magnetic resonance imaging (MRI) is an important imaging technique for detecting abnormal changes in different parts of the brain in early stage. MRI imaging is a popular way to obtain an image of brain with high contrast. MRI acquisition parameters can be adjusted to give different grey levels for different tissues and various types of neuropathology (Tian and Fan 2007). MRI images have good contrast in comparison to computerized tomography (CT). Therefore, most of research in medical image segmentation uses MRI images.

The identification of brain structures in magnetic resonance imaging (MRI) is very important in neuroscience and has many applications such as: mapping of functional activation onto brain anatomy, the study of brain development, and the analysis of neuroanatomical variability in normal brains (Han and Fischl 2007). Brain image segmentation is also useful in clinical diagnosis of neurodegenerative and psychiatric disorders, treatment evaluation, and surgical planning (Han and Fischl 2007). There are lots of methods for automatic and semi-automatic image segmentation, though, most of them fail because of unknown noise, poor image contrast, and weak boundaries that are usual in medical images.

1.1 Imaging modalities

The human body consists primarily of water and bones. Moreover, trace elements exist in different parts of human body, such as iodine in the thyroid, tellurium in the liver and iron in blood. Medical imaging techniques use different properties of these elements. The important modalities are x-ray, computed tomography (CT), positron emission tomography (PET), single-photon emission computed tomography (SPECT), ultrasound and magnetic resonance imaging (MRI). The x-ray, invented by Wilhelm in 1895, is based on the measurement of the transmission of x-ray through the body. However, a disadvantage of x-ray is the high level of radiation emitted which can cause diseases such as cancer and eye cataract. In x-ray computer assistance tomography (CT), image is reconstructed from a large number of x-rays. In PET, radio nuclides are injected into patient's body which attach to a specific organ. SPECT is a nuclear medicine tomographic imaging techniques which able to produce true 3D image. It uses gamma rays. Ultrasound measures the reflection of ultrasonic waves transmitted through the body and is the best modality for investigation of soft tissues.

1.2 MR imaging (MRI)

MR imaging (MRI), invented in 1970, is a popular method in medical imaging. MRI scanning is relatively safe and unlike other medical imaging modalities, can be used as often as necessary. Moreover, it can be adapted to image brain. Clinical MRI is based on the hydrogen

nucleus due to their abundance in the human body and their magnetic resonance sensitivity. For image formation, a large static magnetic field is used to perturb magnetic moments of proton that exist in the hydrogen nucleus from their equilibrium and observing how perturbed moments relaxes back to their equilibrium. Naturally, the protons are oriented randomly. But in existence of a static magnetic field, they line up with the field and the net magnetization of protons tends toward the direction of the field. In existence of enough energy, it is possible to make the net magnetization zero. In the relaxation process an induced electronic signal is recorded. The strength and duration of the signal depend on three quantities:

1. ρ (proton density)
2. spin-lattice relaxation time: the time which describes how fast the net magnetization takes to relax back to its equilibrium (T1).
3. spin-spin relaxation time: with this time, magnetization components decrease to zero (T2).

In scanning of a person's body, by using different parameters setting, it is possible to obtain three different images of the same body: T1-weighted, T2-weighted, and ρ-weighted.

2 Literature review

Segmentation is the partitioning of an image to several segments. The main difficulties in segmentation are:

- Noise
- The bias field (the presence of smoothly varying intensities inside tissues)
- The partial-volume effect (a voxel contributes in multiple tissue types)

This review is organized as follows: In Sect. 2.1, existing De-noising algorithms are reviewed. In Sect. 2.2, current approaches in inhomogeneity correction are summarized. Finally, in Sect. 2.3, existing segmentation algorithms are reviewed.

2.1 Existing de-noising methods

It is difficult to remove noise from MRI images and state-of-art methods in removing the noise are substantial. Methods vary from standard filters to more advanced filters, from general methods to specific MRI de-noising methods such as linear filtering methods, nonlinear filtering methods, anisotropic nonlinear diffusion filtering, a Markov random field (MRF) models, wavelet models, non-local means models (NL-means) and analytically correction schemes.

These methods have advantages and disadvantages. None of the methods is better than others in terms of computation cost, de-noising, quality of de-noising and boundary preserving. Therefore, de-noising is still an open issue and de-noising methods need improvement. Linear filters are conceptually simple. They update value of a pixel by (weighted) average of its neighborhood. These filters reduce noise but degrade image details and the edges of the image; therefore, restored image looks blurred. In contrast to linear filters, nonlinear filters have better performance in edge preserving but degrade fine structure; therefore, the resolution of the image is reduced.

2.1.1 Anisotropic nonlinear diffusion

This is a modification of the linear diffusion methods (Perona and Malik 1990; Smolka 2008; Kim et al. 2008; Gallea et al. 2008). It is more powerful in reducing noise in flat regions and reducing the diffusivity at the edges of image. Perona and Malik (1990) introduced anisotropic diffusion process. The equation is

$$I_t(x, y, t) = \nabla \cdot C(|\nabla I(x, y, t)|)\nabla I(x, y, t), \tag{1}$$

where $I(x, y, t)$ is intensity of input image, and t is the iteration number. $C(\nabla I(x, y, t))$ is a monotonically decreasing diffusion function of the image gradient magnitude. The gradient magnitude in boundary of a region is higher than its interior, and the diffusion function is monotonically decreasing, so the diffusion process happens in regions' interiors faster.

These models can use prior knowledge and extends to high dimensionality but they are not robust in very noisy images. You et al. (1996) modified the equation in the way that diffusion happens in points where its gradient magnitude is more than average gradient magnitude in neighbour points.

Lions et al. (1992) used $\nabla|G\sigma * u|$ as input of C(.) which smoothens image using Gaussian filter. Ren and He (2007) proposed the following modified equation:

$$X(\sigma) = 1/(1 + K) \tag{2}$$

where parameter K is the average difference of gradient magnitude and maximum gradient magnitude in the neighbour of each pixel.

2.1.2 A Markov random field method (MRF)

This method incorporates spatial correlation information to preserve fine detail (An and An 1984), in other words, instead of smoothing of both signals and noise, spatial regularization of the noise estimation is performed. In MRF method, the value of pixel is updated by iterated conditional modes and simulated annealing with maximizing a posterior estimate. Usually, it is computationally expensive.

2.1.3 Wavelet-based methods

These methods are performed in the frequency domain and attempt to distinguish signal from noise in the frequency domain and preserve the signal in the de-noising process. After applying this method on MRI image, the wavelet and scaling coefficients are biased. To solve this problem, the wavelet is applied on squared MRI image (which is non-central chi-square distributed) (Nowak 1999). The scaling coefficients still are biased, but, it isn't dependent on signal and easily can be removed (Edelstein et al. 1986). These methods do not preserve fine detail, especially in low SNR images (Tisdall and Atkins 2005).

2.1.4 Analytical correction method

This method attempts to estimate noise and subsequently noise-free signal from observed image. In this method, maximum likelihood estimation (MLE) (Sijbers et al. 1998) is used to estimate noise-free signal by considering different hypothesis for noise. Usually, signal is considered constant in small areas and neighborhood smoothing is used to estimate noise free image. Neighborhood smoothing can degrade the edges of image.

2.1.5 Non-local (NL)

This method takes advantage of the redundancy in the image and preserves the edges of image. It is very useful in de-noising of movies and videos which contain high degree of redundancy but it is computationally expensive. This method was proposed by Buades et al. (2005). It is assumed that there is redundancy in the image. In other words, for each pixel, there are samples with neighborhood similar to the neighborhood of the pixel. In this method, the value of the pixel is updated to the weighted average of these samples. This method successfully reduces noise and in mean time preserves the geometrical edges of the image with textured or periodic case (Andersen et al. 2002), due to large redundancy in these two kinds of images. In MRI images, there may be non-repeated details due to noise, complicated structures, blur in acquisition and the partial volume effect originating from the low sensor resolution. Such details can be eliminated by this method.

2.2 Inhomogeneity correction

Generally, intensity inhomogeneity is considered as a smooth spatially varying function which alters intensity inside originally homogeneous regions. It is considered multiplicative or additive. Usually in MR images, noise is considered independent of inhomogeneity and image models as multiplicative of image and inhomogeneity plus noise. Inhomogeneity correction methods are categorized in two groups: prospective methods and retrospective methods.

2.2.1 Prospective methods

These methods consider inhomogeneity as an error of the imaging process that can be corrected by estimating inhomogeneity field of MRI acquisition system. These methods are listed here:

1. Phantom Based: Inhomogeneity field can be estimated by taking the image of a uniform phantom, then, scaling and smoothing the image (Vovk et al. 2007).
2. Multi-coil: Surface and body are two common types of coils; usually, surface type has good (signal to noise ratio SNR) but high inhomogeneity, while body type has low inhomogeneity but poor SNR. It is proposed to combine both types to have an image with good SNR and less inhomogeneity (Andersen et al. 2002).
3. Special Sequences: This group is related to specific hardware designs. The spatial distribution of the flip angle for certain pulse sequences is estimated to obtain inhomogeneity field (Likar et al. 2001).

2.2.2 Retrospective methods

These methods don't assume any information about acquisition methods and are more general; therefore, they can correct both MR scanner-induced and patient-induced inhomogeneity. These methods are listed here:

1. Surface Fitting Methods: These methods use image features which have information about inhomogeneity. A parametric surface is fitted to the features. The result surface represents an inhomogeneity field (Buades et al. 2005).

2. Segmentation Based: After segmentation, inhomogeneity correction is very simple. Therefore these methods merge these two steps to benefit from each other. Maximum-likelihood (ML), maximum a posterior probability (MAP) Based: The ML or MAP is used to estimate probability distribution of inhomogeneity (Andersen et al. 2002). Fuzzy C-Means (FCM): Inhomogeneity is considered as a function of location and objective function of FCM is updated via multiplication of centre of clusters by the function. Non-parametric segmentation: These methods iteratively minimize class error within class scatter which is due to inhomogeneity.

3. Histogram Based Methods: These methods use a histogram of image usually without using a priori knowledge about image.

4. High-frequency Maximization: Iteratively, inhomogeneity is estimated by maximizing the high frequency information of distribution of tissue intensity Vovk et al. (2007).

5. Information Minimization: These methods assume inhomogeneity as extra information in the image and estimate inhomogeneity field using minimizing information (Likar et al. 2001).

6. Histogram Matching: The image is divided to sub volumes. Constant inhomogeneity is assumed for sub volumes. The histogram model is fitted to histogram of sub volume to estimate inhomogeneity of sub volumes. After elimination of outliers from these inhomogeneity estimates, they are interpolated to produce the global inhomogeneity field.

7. Filtering Methods: Filtering methods consider inhomogeneity as a low-frequency artifact which can be separated from image by low-pass filtering. For most of medical images this assumption is not correct. Two most important filtering inhomogeneity correction methods are (a) homomorphic filtering and (b) homomorphic un-sharp masking. (a) Homomorphic Filtering: The image background is usually altered; then, log-transformed of input image is subtracted by log-transformed of its low-pass filtered via homomorphic filter (Buades et al. 2005). (b) Homomorphic Un-sharp Mask: The corrected image is obtained by dividing the low-pass filtered image by a constant to preserve mean or median intensity. When homomorphic filtering is performed a streak artifact is produce on boundary between tissues. Guillemaud proposed a method to eliminate this artifact on boundary between backgrounds and object (Ardizzone et al. 2005).

2.3 Image segmentation methods

Many image techniques have been used for image segmentation, like thresholding, the region growing, statistical models, active control models and clustering. The distribution of intensities in medical images is usually very complex, and therefore, determining a threshold is difficult and thresholding methods fail. Mostly, thresholding method is combined with other methods (Suzuki and Toriwaki 1991). The region growing method extends thresholding by combining it with connectivity. This method needs seed for each region and has the same problem of thresholding for determining suitable threshold for homogeneity (Robb 2000). Fuzzy c-means (FCM) and statistical methods are popular methods in medical image segmentation due to few advantages.

FCM only considers intensity of image and in noisy images, intensity is not trustful. As a result, this algorithm does not produce a good result in noisy and in homogeneity images (Hall et al. 1992). Many algorithms are introduced to make FCM robust against noise and in homogeneity but most of them still are not flawless (Hall et al. 1992; Lions et al. 1992; Acton and Mukherjee 2000; Zhang and Chen 2004; Dave 1991; Tolias and Panas 1998).

The probabilistic classification is sensitive to accurate estimation of the probability density function (PDF) (Song et al. 2007). There are two approaches to obtain the parameters

of the PDF, Parametric approach and nonparametric approach. Nonparametric approaches obtain the parameters of the PDF from data without any assumptions, so these approaches are accurate but expensive (Chang and Teng 2007). In parametric approaches, a function is assumed to be a PDF function. It is easy to implement but sometimes lacks accuracy and does not match real data distribution (Song et al. 2007).

2.3.1 FCM

FCM is a clustering algorithm introduced by Bezdek based on minimizing an object function as follows (Pohle and Toennies 2001)

$$J_q = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^q d(x_i, \theta_j) \tag{3}$$

where q controls the fuzziness degree of clustering, u is fuzzy membership of data x_i to cluster with centre θ_j, and d is distance between data x_i and centre of the cluster j, θ_j. The u has the following conditions

$$u_{ij} \in [0, 1], \sum_{j=1}^{n} u_{ij} = 1 \& 0 < \sum_{j=1}^{n} u_{ij} < n \tag{4}$$

The membership function and centre of each cluster are obtained as follow

$$u_{ij} = 1 \Big/ \sum_{k=1}^{m} (d(x_i, \theta_j)/d(x_i, \theta_k))^{(2/q-1)} \tag{5}$$

$$\theta_j = \sum_{i=1}^{N} u_{ij}^q x_i \Big/ \sum_{i=1}^{N} u_{ij}^q \tag{6}$$

FCM optimize object function by continual update of the membership function and centers of clusters until optimization between iteration is more than a threshold.

FCM widely is used for medical image segmentation (Balafar 2008; Balafar et al. 2008a,b,c,d,e).

2.3.2 Gauss mixture vector

Gaussian mixture model is probability density to estimate distribution in each class. Gaussian mixture model for class j is a probability density having the following form (Dokur 2008);

$$p(x|j) = \sum_{l=1}^{L} p_l * G_l(x) \tag{7}$$

where L is the number of Gaussian components, x data, p_l is the priori probability of Gaussian component l, and G_l is the probability density function of Gaussian component l; all in class j

$$G_l(x) = \frac{1}{(2\pi)^{\frac{d}{2}} |\sum_l|^{\frac{1}{2}}} e^{-\frac{1}{2}(x-m_l)^t \sum_l^{-1} (x-m_l)} \tag{8}$$

where m_l is the mean of training data in component l, $\sum_l$ is the covariance matrix of training data in Gaussian component l, and d is the dimension of x.

Usually, the expectation-maximization (EM) (Diplaros et al. 2007; Wang 2007; Adalsteinsson and Sethian 1995; Sethian 1996) and Lioyd clustering algorithm are used to obtain parameters of Gaussian mixture. EM steps are demonstrated in the following steps:

1. Initialization: Mean and covariance matrix are initialized using *k*-means (Diplaros et al. 2007) and prior probability is initialized uniformly.
2. E-step: Calculate membership probability of each training data.
3. M-step: Computes mean and variance of each Gaussian component using membership probability obtained in E-step. EM steps are repeated until convergence (Wang 2007). Gauss mixture vector of each class is obtained by EM and training data for that class.

Lloyd clustering algorithm steps for finding Gaussian mixture parameters can be found in Adalsteinsson and Sethian (1995) and Sethian (1996).

2.3.3 LVQ

Learning vector quantization (LVQ) is a supervised competitive learning. LVQ obtains decision boundaries in input space based on training data. LVQ defines class boundaries prototypes, a nearest-neighbor rule and a winner-takes-it-all paradigm. LVQ has three layers: input layer, competitive layer and output layer. Each target class has several patterns. The competitive layer learns to classify input data in a way similar to Self-Organization Map (SOM) and the output layer maps competitive layer classes (patterns) to target classes. The learning means adjusting weights of neurons based on training data. The winner neuron is specified based on the Euclidean distance, then the weight of the winner neuron is adjusted (Tian and Fan 2007). There are several algorithms to learn LVQ networks. LVQ1 (Tian and Fan 2007) is one of them. The LVQ1 selects a set of best matching neurons in competitive layer based on correct target class of each data; adjust weight of selected set to move closer or away from input data if the classification is correct or wrong, respectively.

The LVQ1 has two main steps (Tian and Fan 2007): First finding a set of the most similar neuron to the input data, determined by a similarity factor like Euclidean distance, second, updating weight of those neurons based on input. In other words, the weight of selected neurons either moves closer to the input if classification is correct or moves far from the input if classification is incorrect.

2.3.4 SOM

Self-organizing maps (SOM) is an unsupervised clustering network which was introduced by Kohonen in 1982. It is one of the popular networks in the neural network field. It maps inputs which can be high dimensional to one or two dimensional discrete lattice of neuron units (Tian and Fan 2007). It organizes input data into several patterns according to a similarity factor like Euclidean distance. Each pattern assigns to a neuron. Each neuron has a weight that depends to pattern assigned to that neuron. The network learns regularities and correlation in its input and adjusts its future response according to that Tian and Fan (2007). It learns to classify input data according to their grouping in input space and neighboring neuron learn neighboring in input space. Thus SOM learns both the distribution and the topology of input data. In other words, the network map preserve topological relationships in inputs and neighbor inputs mapped to neighbor neuron in map (Tian and Fan 2007). It consists of two layers. The first layer is the input layer and the number of neurons in this layer is equal to dimension of input. The second layer is the competitive layer and each neuron in

this layer corresponds to one class (pattern). The number of neurons in this layer depends to the number of clusters. The neurons in competitive layer are arranged in regular geometric structure like mesh. A weight vector is assigned to each connection from input layer to a neuron in competitive layer.

In learning phase winner neuron, neuron in competitive layer with least difference from input data, is found then winner neuron in its neighborhood neurons changed towards input data. Neighborhood size decreases in each iteration.

The SOM has two main steps (Tian and Fan 2007). First, finding the winning neuron, the most similar neuron to input by a similarity factor like Euclidean distance, second, updating weight of winning neuron and its neighbor pixels based on input. In other words, the weight of the winning neuron and its neighbor pixels are changed towards the input.

2.3.5 Watersheds

Watershed is a gradient-based segmentation technique. Different gradient values are considered as different heights. Making a hole in each local minimum and immerse in water, the water will rise until local maximums. When two body of water meet, a dam is built between them. The water rises until all points in the map are immersed. The image is segmented by the dams. The dams are called watersheds and the segmented regions are called catchments basins (Adalsteinsson and Sethian 1995; Li et al. 2007). Its fast implementation method is proposed by Vincent and Soille (1991) and Sethian (1996). The over segmentation problem still exists in this method (Adalsteinsson and Sethian 1995; Li et al. 2007). The average grey level of each region is considered the grey level of pixels in the region.

2.3.6 The region growing

The region growing starts with a seed. During the region growing, pixels in the neighbor of seed are added to region based on homogeneity criteria. Therefore, a connected region forms during the region growing process.

2.3.7 Active control model

The active control model is based on a curve, $X(s) = [x(s), y(s)]$, defined in the image domain where s in range of [0,1] is an arc length. It deforms in a way that minimizes an energy function. This energy function has the following form

$$E = \int \frac{1}{2}(\alpha|X'(s)|^2 + \beta|X''(s)|^2) + E_{ext}(X(s))ds \tag{9}$$

The first term on the right side is called the internal energy and is used to control the tension and rigidity of the deforming curve. The last term is the external energy that is used to guide the deforming curve toward the target.

Yoon et al. (2004) used Gaussian Gradient Force to compute external force. Advantages of this method are insensitiveness to contour initialization, boundary concavities, saving computation time, and high accuracy (Yoon et al. 2004).

2.3.8 Double region based active control

In Wang (2007), region based segmentation for two regions is formulated as follows

$$E(\Phi, p_1, p_2) = -\int_\Omega H(\Phi) \log p_1 dx - \int_\Omega (1 - H(\Phi)) \log p_2 dx + v \int_\Omega |\nabla H(\Phi)| d_x \quad (10)$$

where Φ is Level Set Function that is $\Phi > 0$ for first region and $\Phi < 0$ for second region and H is Heaviside function for separating two regions that is, 0 for second region and 1 for first region. In Caselles et al. (1997), P_1 and P_2 are determined by nonparametric Parzen density estimates (Ren and He 2007), which are computed by means of smoothed histograms of the regions (Rousson et al. 2003).

Chan and Vese (2001) introduced other method for using region information

$$F(c_1 + c_2 + C) = \mu \cdot Length(C) + v \cdot Area(inside(C)) + \lambda_1 \int_{inside(C)} |u_0(x, y) - c_1|^2 dxdy$$

$$+ \lambda_2 \int_{outside(C)} |u_0(x, y) - c_2|^2 dxdy \quad (11)$$

where $\mu, v >= 0$ and $\lambda_1, \lambda_2 > 0$ are fixed parameters.

Where c_1 and c_2 are the average intensities of the inside and outside evolving curve. This model can not detect edges far from evolving curve for solving that Ren and He (2007) replaced Dirac with gradient of level set. Jijun Ren and Mingyi He, incorporate an edge detection function in order to eliminate area and length effect in edges. Shaojun et al., Liu and Li (2006) used edge and intensity information for active control evolution. Probability distribution of intensity in the image and separately in and out of region are considered as Gaussian mixture model. They used an offset for reliability of probability of intensity.

2.3.9 Multi region based active control

Zhu and Yuille introduced the following function for segmentation of Multi Region Images

$$E(\Omega_i, \Gamma_i, p_i, N) = \sum_{i=1}^{N} \left(-\int_{\Omega_i} \log p_i dx + \frac{v}{2} \int_{\Gamma_i} ds + e \right) \quad (12)$$

The first term maximizes the probability that pixel x is assigned to a correct region when each region is modeled by a probability density of p_i, The second term minimizes the total length of boundaries, and the third term penalizes each region according to a limitation on the number of regions.

For using level set in more than two region, idea of assigning a Level Set for each region is introduced (Zhao et al. 1996) and adopted for segmentation in Paragios and Deriche (1999).

In this model there are two difficulties: joined region and pixel assigned to none of the region. In Zhao et al. (1996), a new constraint is introduced for handling these two difficulties. In Paragios and Deriche (1999), Gaussian Mixture Model is used to estimate the number of regions. In Caselles et al. (1997), the following equation is introduced for multi region

segmentation:

$$e_k := \log p_k + \frac{\nu}{2} div\left(\frac{\nabla \Phi_k}{|\nabla \Phi_k|}\right) \tag{13}$$

$$\partial_t \Phi_i = H'(\Phi_i)\left(e_i - \max_{H'(\Phi_j)_{i \neq i} > 0}(e_j, e_i - 1)\right) \tag{14}$$

The term $ei - 1$ ensures that if there is no any region in vicinity, means there is a vacuum. means the region is extended to vacuum by constant speed.

The authors used an algorithm to estimate the number of regions and initialize the evolving contour.

2.3.10 Atlas-based segmentation

Using data obtained from different subjects, an atlas as a common anatomy for the image (brain) is constructed. Some techniques for atlas construction can be found in Rohlfing et al. (2004). In segmentation, an atlas is used as prior information. When there is not enough contrast between tissues, the atlas-based methods is the best choice. An atlas brings a common anatomical map of the brain prior to segmentation. Therefore, the method uses knowledge about the structure of the brain. The disadvantages of atlas-based methods is the time necessary for atlas construction from different subjects which need complex rigid registration. To take advantage of atlas in segmentation of an image, first, the image should be registered to the atlas. Some techniques for image registration can be found in Mäkelä et al. (2002).

2.3.11 A Markov random field models

A Markov random field (MRF) model is a statistical model which is used to model spatial relations that exist in the neighbor of pixels (Li 1994). Different image segmentation methods use MRF to take advantage of neighborhood information in the segmentation process. For example, in medical images, most neighborhood pixels have the same class. Segmentation method can use MRF to model this fact. By using neighborhood information, influence of noise in segmentation is decreased.

2.3.12 Segmentation for brain with anatomical deviations

Segmentation of the brain with anatomical deviation is a challenging job. Brain tumor is one of the reasons for deviation. The tumor can have different shape, size, location and intensities. The tumor not only changes the part of brain which tumor exists but also sometimes it influences shape and intensities of other structures of the brain. Therefore the existence of deviation makes use of prior information about intensity and spatial distribution challenging. On the other hand, in clinical applications, segmentation of the brain with anatomical deviation is very important. For example, segmentation of the tumor, its surrounding edema and other structures of the brain is very important for treatment and surgical planning. Some methods for brain tumor segmentation can be found in Clark et al. (1998) and Kaus et al. (1999). Another example for brain with anatomical deviation is the brain of a newborn. The brain of a newborn change dynamically from birth until the age of one. Some methods for segmentation for brain of a newborn can be found in Matsuzawa et al. (2001) and Warfield et al. (2000).

3 Conclusion

Generally, image segmentation has been an active research field for the last several decades. Moreover, it is a most challenging and most active research field in the image processing. Image segmentation is the preliminary stage of almost all image analysing tools. There exist a variety of state-of art methods and good prior knowledge for brain MRI segmentation. But still, brain MRI segmentation is a challenging task and there is a need for future research to improve the accuracy, precision and speed of segmentation methods. Using improved atlas-based methods, parallelization and combining different methods can be the way for making improvement in brain segmentation methods. With increasing knowledge about the relationship between different disorders with anatomical deviation, brain segmentation is used as first stage in tools for detection and analyzing them. For example Alzheimer and Multiple sclerosis (MS) are disorders which can be studied based on deviation in structures of the brain.

References

Acton ST, Mukherjee DP (2000) Scale space classification using area morphology. IEEE Trans Image Process 9(4):623–635
Adalsteinsson D, Sethian JA (1995) A fast level set method for propagating interfaces. J Comput Phys 118: 269–277
An S, An D (1984) Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. IEEE Trans Pattern Anal Mach Intell 6:721–741
Andersen AH et al (2002) Automated segmentation of multispectral brain MR images. J Neurosci Methods 122(1):13–23
Ardizzone E, Pirrone R, Gambino O (2005) Exponential entropy driven HUM on knee MR images. In: 27th annual international conference of the engineering in medicine and biology society, pp 1769–1772
Balafar MA (2008) Medical image segmentation using fuzzy C-mean (FCM) and dominant grey levels of image. In: Visual information engineering conference, pp 314–317
Balafar M et al (2008a) Medical image segmentation using fuzzy C-mean (FCM), Bayesian method and user interaction. In: International conference on wavelet analysis and pattern recognition, pp 68–73
Balafar MA et al (2008b) New multi-scale medical image segmentation based on fuzzy c-mean (FCM). In: IEEE conference on innovative technologies in intelligent systems and industrial applications, pp 66–70
Balafar MA et al (2008c) Medical image segmentation using anisotropic filter, user interaction and fuzzy C-mean (FCM). In: Advanced intelligent computing theories and applications with aspects of contemporary intelligent computing techniques: 4th international conference on intelligent computing, Springer, pp 169–176
Balafar MA et al (2008d) Medical image segmentation using fuzzy C-mean (FCM), learning vector quantization (LVQ) and user interaction. In: Advanced intelligent computing theories and applications with aspects of contemporary intelligent computing techniques: 4th international conference on intelligent computing, Springer, pp 177–184
Balafar MA et al (2008e) MRI segmentation of medical images using FCM with initialized class centers via genetic algorithm. In: International symposium on information technology, pp 1–4
Buades A, Coll B, Morel J (2005) A non-local algorithm for image denoising. In: IEEE computer society conference on computer vision and pattern recognition, pp 60–65
Caselles V, Kimmel R, Sapiro G (1997) Geodesic active contours. Int J Comput Vis 22(1):61–79
Chan TF, Vese LA (2001) Active contours without edges. IEEE Trans Image Process 10(2):266–277
Chang PL, Teng WG (2007) Exploiting the self-organizing map for medical image segmentation. In: Twentieth IEEE international symposium on computer-based medical systems, pp 281–288
Clark MC et al (1998) Automatic tumor segmentation using knowledge-based techniques. IEEE Trans Med Imaging 17(2):187–201
Dave RN (1991) Characterization and detection of noise in clustering. Pattern Recogn Lett 12(11):657–664
Diplaros A, Vlassis N, Gevers T (2007) A spatially constrained generative model and an EM algorithm for image segmentation. IEEE Trans Neural Netw 18(3):798–808

Dokur Z (2008) A unified framework for image compression and segmentation by using an incremental neural network. Expert Syst Appl 34(1):611–619

Edelstein WA et al (1986) The intrinsic signal-to-noise ratio in NMR imaging. Magn Reson Med 3(4): 604–618

Gallea R et al (2008) Noise filtering using edge-driven adaptive anisotropic diffusion. In: 21st IEEE international symposium on computer-based medical systems, pp 29–34

Hall LO, Bensaid AM, Clarke LP, Velthuizen RP, Silbiger MS, Bezdek J (1992) A comparison of neural network and fuzzy clustering techniques in segmenting magnetic resonance images of the brain. IEEE Trans Neural Netw 3:672–682

Han X, Fischl B (2007) Atlas renormalization for improved brain MR image segmentation across scanner platforms. IEEE Trans Med Imaging 26(4):479–486

Kaus MR et al (1999) Segmentation of meningiomas and low grade gliomas in MRI. Lecture Notes in Computer Science, pp 1–10

Kim HS et al (2008) Speckle reducing anisotropic diffusion based on directions of gradient. In: Proceedings of the 2008 international conference on advanced language processing and web information technology, pp 198–203

Li SZ (1994) Markov random field models in computer vision. Lect Notes Comput Sci 801:361–370

Li N, Liu M, Li Y (2007) Image segmentation algorithm using watershed transform and level set method. In: IEEE international conference on acoustics, speech and signal processing, pp 613–616

Likar B, Viergever MA, Pernus F (2001) Retrospective correction of MR intensity inhomogeneity by information minimization. IEEE Trans Med Imaging 20(12):1398–1410

Lions PL, Morel JM, Coll T (1992) Image selective smoothing and edge detection by nonlinear diffusion. SIAM J Numer Anal 29(1):182–193

Liu S, Li J (2006) Automatic medical image segmentation using gradient and intensity combined level set method. In: The 28th IEEE EMBS annual international conference, pp 3118–3121

Mäkelä T et al (2002) A review of cardiac image registration methods. IEEE Trans Med Imaging 21(9):1011–1021

Matsuzawa J et al (2001) Age-related volumetric changes of brain gray and white matter in healthy infants and children. Cereb Cortex 11(4):335

Nowak RD (1999) Wavelet-based Rician noise removal for magnetic resonance imaging. IEEE Trans Image Process 8(10):1408–1419

Paragios N, Deriche R (1999) Coupled geodesic active regions for image segmentation. Rapport De Recherche-Institut National De Recherche En Informatique Et En Automatique

Perona P, Malik J (1990) Scale-space and edge detection using anisotropic diffusion. IEEE Trans Pattern Anal Mach Intell 12(7):629–639

Pohle R, Toennies KD (2001) Segmentation of medical images using adaptive region growing. In: Proceedings of SPIE medical imaging, pp 1337–1346

Ren J, He M (2007) A level set method for image segmentation by integrating channel anisotropic diffusion information. In: 2nd IEEE conference on industrial electronics and applications, pp 2554–2557

Robb RA (2000) Biomedical imaging, visualization, and analysis, edited by Wiley-Liss, USA

Rohlfing T et al (2004) Evaluation of atlas selection strategies for atlas-based image segmentation with application to confocal microscopy images of bee brains. NeuroImage 21(4):1428–1442

Rousson M, Brox T, Deriche R (2003) Active unsupervised texture segmentation on a diffusion based feature space. In: IEEE computer society conference on computer vision and pattern recognition, pp 699–704

Sethian JA (1996) A fast marching level set method for monotonically advancing fronts. Proc Natl Acad Sci 93(4):1591–1595

Sijbers J et al (1998) Estimation of the noise in magnitude MR images. Magn Reson Imaging 16(1):87–90

Smolka B (2008) Modified biased anisotropic diffusion processing of noisy color images. In: 9th international conference on signal processing, pp 777–780

Song T et al (2007) A modified probabilistic neural network for partial volume segmentation in brain MR image. IEEE Trans Neural Netw 18(5):1424–1432

Suzuki H, Toriwaki J (1991) Automatic segmentation of head MRI images by knowledge guided thresholding. Comput Med Imaging Graph 15(4):233

Tian D, Fan L (2007) A brain MR images segmentation method based on SOM neural network. In: The 1st international conference on bioinformatics and biomedical engineering, pp 686–689

Tisdall D, Atkins MS (2005) MRI denoising via phase error estimation. In: Proceedings of SPIE pp 646–654

Tolias YA, Panas SM (1998) On applying spatial constraints in fuzzy image clustering using a fuzzy rule-based system. IEEE Signal Process Lett 5(10):245–247

Vincent L, Soille P (1991) Watersheds in digital spaces: an efficient algorithm based on immersion simulations. IEEE Trans Pattern Anal Mach Intell 13(6):583–598

Vovk U, Pernus F, Likar B (2007) A review of methods for correction of intensity inhomogeneity in MRI. IEEE Trans Med Imaging 26(3):405

Wang J (2007) Discriminative Gaussian mixtures for interactive image segmentation. In: IEEE international conference on acoustics, speech and signal processing, pp 386–396

Warfield SK et al (2000) Adaptive, template moderated, spatially varying statistical classification. Med Image Anal 4(1):43–55

Yoon SW et al (2004) Medical endoscopic image segmentation using snakes. IEICE Trans Inf Syst 87(3): 785–789

You YL et al (1996) Behavioral analysis of anisotropic diffusion in image processing. IEEE Trans Image Process 5(11):1539–1553

Zhang DQ, Chen SC (2004) A novel kernelized fuzzy c-means algorithm with application in medical image segmentation. Artif Intell Med 32(1):37–50

Zhang Y et al (2007) A novel medical image segmentation method using dynamic programming. In: International conference on medical information visualisation-bioMedical visualisation, pp 69–74

Zhao HK et al (1996) A variational level set approach to multiphase motion. J Comput Phys 127(1):179–195