Robust generative asymmetric GMM for brain MR image segmentation

Zexuan Ji\textsuperscript{a,}\textsuperscript{*}, Yong Xia\textsuperscript{b,c,*}, Yuhui Zheng\textsuperscript{d}

\textsuperscript{a} School of Computer Science and Engineering, Nanjing University of Science and Technology, Nanjing, 210094, China
\textsuperscript{b} Shannxi Key Lab of Speech and Image Information Processing (SMIP), School of Computer Science, Northwestern Polytechnical University, Xi’an, 710072, China
\textsuperscript{c} Centre for Multidisciplinary Convergence Computing (CMCC), School of Computer Science, Northwestern Polytechnical University, Xi’an, 710072, China
\textsuperscript{d} School of Computer and Software, Nanjing University of Information Science and Technology, Nanjing, 210044, China

\begin{abstract}
\textbf{Background and objectives}: Accurate segmentation of brain tissues from magnetic resonance (MR) images based on the unsupervised statistical models such as Gaussian mixture model (GMM) has been widely studied during last decades. However, most GMM based segmentation methods suffer from limited accuracy due to the influences of noise and intensity inhomogeneity in brain MR images. To further improve the accuracy for brain MR image segmentation, this paper presents a Robust Generative Asymmetric Gaussian Mixture Model (RGAGMM) for simultaneous brain MR image segmentation and intensity inhomogeneity correction.

\textbf{Method}: First, we develop an asymmetric distribution to fit the data shapes, and thus construct a spatial constrained asymmetric model. Then, we incorporate two pseudo-likelihood quantities and bias field estimation into the model’s log-likelihood, aiming to exploit the neighboring priors of within-cluster and between-cluster and to alleviate the impact of intensity inhomogeneity, respectively. Finally, an expectation maximization algorithm is derived to iteratively maximize the approximation of the data log-likelihood function to overcome the intensity inhomogeneity in the image and segment the brain MR images simultaneously.

\textbf{Results}: To demonstrate the performances of the proposed algorithm, we first applied the proposed algorithm to a synthetic brain MR image to show the intermediate illustrations and the estimated distribution of the proposed algorithm. The next group of experiments is carried out in clinical 3T-weighted brain MR images which contain quite serious intensity inhomogeneity and noise. Then we quantitatively compare our algorithm to state-of-the-art segmentation approaches by using Dice coefficient (DC) on benchmark images obtained from IBSR and BrainWeb with different level of noise and intensity inhomogeneity. The comparison results on various brain MR images demonstrate the superior performances of the proposed algorithm in dealing with the noise and intensity inhomogeneity.

\textbf{Conclusion}: In this paper, the RGAGMM algorithm is proposed which can simply and efficiently incorporate spatial constraints into an EM framework to simultaneously segment brain MR images and estimate the intensity inhomogeneity. The proposed algorithm is flexible to fit the data shapes, and can simultaneously overcome the influence of noise and intensity inhomogeneity, and hence is capable of improving over 5% segmentation accuracy comparing with several state-of-the-art algorithms.

\end{abstract}

\section{Introduction}

As one of the classical problems in image processing, image segmentation has been extensively studied, which can be treated as a classification problem \cite{1-4} for the target image. Magnetic resonance (MR) imaging has been widely used in medical diagnosis because of the multi-spectral, high contrast and high spatial resolution characteristics. Automated segmentation of brain tissues into the gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) is an essential step in quantitative brain image analysis. However, MR images generally suffer from the intensity inhomogeneity \cite{5}, and contain a smoothly varying bias field, which makes the intensities of the same tissue vary across pixel/voxel locations. Hence, simultaneous bias field estimation and brain MR image segmentation algorithms have been widely developed during the last decades \cite{6-11}. Among them, the statistical model-based \cite{12-22} algorithm is the one of the most popular models.

Gaussian mixture models (GMM) \cite{12} has been widely utilized in image segmentation because it is simple and easy to be im-

\textsuperscript{*} Corresponding authors.
\textit{E-mail addresses}: jizexuan@njust.edu.cn (Z. Ji), yxia@nwpu.edu.cn (Y. Xia).

\url{http://dx.doi.org/10.1016/j.cmpb.2017.08.017}
\url{0169-2607/© 2017 Elsevier B.V. All rights reserved.}
plemented, where the expectation maximization (EM) algorithm [23] is generally utilized to efficiently estimate the involved parameters. Wells et al. [13] proposed an adaptive segmentation framework based on the EM algorithm to simultaneously correct intensity inhomogeneity and segment brain MR images. Leemput et al. [14] furthered this work by utilizing a digital brain atlas to provide the prior probability maps of brain tissues. However, due to the Gaussian assumption of each type of tissue pixels and the lack of using spatial information, GMM suffers from less flexibility to fit the shape of data and the sensitivity to noise.

To address these drawbacks, mixture models with Markov random fields (MRF) or hidden MRF (HMRF) have been frequently employed, which can be generally categorized into two groups. In the first group [24–26], the prior distribution is calculated on a pixel-by-pixel basis, depending on each pixel’s label and its neighboring pixels [27]. The other group of mixture models utilizes MRF to model the joint prior distribution of pixel labels [27–29]. Diplaros et al. [27] introduced a pseudo-likelihood quantity to incorporate the spatial smoothness constrains into the model, and thus proposed a generative GMM. Nikou et al. [28] proposed a spatial constraint which can adaptively select the spatial directions. To improve the efficiency of MRF-EM based algorithms, Nguyen and Wu [29] proposed a fast and robust spatially constrained GMM by introducing a spatial factor into the prior distribution. Although these algorithms can reduce the impact of noise, most MRF or HMRF-based algorithms are still not robust enough with respect to different types and levels of noise and have high computational complexity.

In many practical applications, it is not good enough to fit different shapes of observed data by only utilizing one statistical distribution for each component of a mixture model. Recently, the mixture of mixture models and asymmetric mixture model has been widely studied. Zhang et al. [30] modified the GMM by constructing the conditional probability of each pixel with the probabilities of pixels in its immediate neighborhood. Browne et al. [31] combined a multivariate Gaussian distribution and a multivariate uniform distribution as the component density, which allows for the bursts of probability, locally higher tails or both [31]. Nguyen and coworkers [22,32,33] proposed various bounded asymmetric mixture models (AMM) by modeling each component of a mixture model with multivariate bounded Gaussian/Student’s-t distribution. However, AMMs are still sensitive to the noise.

In this paper, we propose a novel robust generative asymmetric GMM for brain MR image segmentation. We first modify the asymmetric distribution by incorporating the spatial information into the asymmetric mixture model. Then we extend the work by Diplaros et al. [27] and similarly introduce two pseudo-likelihood quantities to couple neighboring priors of within- and between-cluster based on the Kullback–Leibler (KL) divergence [34], respectively. Meanwhile, an asymmetric weight factor is constructed to further reflect the damping extent of the neighbors. Next, we integrate the bias field estimation model into the log-likelihood function to estimate and correct the intensity inhomogeneity. Finally, an EM algorithm is derived to estimate parameters of the proposed model by iteratively maximizing the approximation of the data log-likelihood function. The proposed algorithm has been evaluated against state-of-the-art segmentation algorithms on various brain MR images. The partial pilot data has been presented in our previous work which proposed a spatially constrained asymmetric Gaussian mixture for image segmentation [35]. All the notations and symbols used in this paper have been summarized in Table 1.

2. Background

Let an image with N pixels be denoted by $X = \{x_i, i = 1, 2, ..., N\}$, where $x_i \in \mathbb{R}^D$ is the observation at the $i$th pixel. Suppose there are $K$ target regions in the image, and the density function of a finite mixture model is given by

$$f(x_i|\Pi, \Theta) = \sum_{k=1}^{K} \pi_k p(x_i|\Omega_k). \quad (1)$$

where $\Omega_k$ is the class labels of the $k$th region, and $\Pi = \{\pi_k\}_{k=1}^{K}$ is mixture parameters, which satisfies the constraints $0 \leq \pi_k \leq 1$ and $\sum_{k=1}^{K} \pi_k = 1$.

In GMM [12], $p(x_i|\Omega_k)$ is the Gaussian distribution

$$\Phi(x_i|\theta_k) = \frac{1}{(2\pi)^{D/2} |\Sigma_k|^{1/2}} \exp \left\{ -\frac{1}{2} (x_i - \mu_k)^T \Sigma_k^{-1} (x_i - \mu_k) \right\},$$

where $\mu_k$ is the mean, $\Sigma_k$ is the covariance matrix, $|\Sigma_k|$ is the determinant of $\Sigma_k$, and $\theta_k = \{\mu_k, \Sigma_k\}$ is the assembly of statistical parameters. Fig. 1(a) [10] shows the generative model for GMM, where $z_i$ is hidden random variable that indicates the belonging of each pixel $x_i$.

In AMM [22,32,33], an asymmetric distribution $p(x_i|\Omega_k)$ is defined to model the label $\Omega_k$ as:

$$p(x_i|\Omega_k) = \sum_{l=1}^{L} \psi_{kl} p(x_i|\Omega_{kl}),$$

where $L$ is the number of multivariate distribution $p(x_i|\Omega_{kl})$ and $\psi_{kl}$ is the prior probability of within-cluster which satisfies the constraints $0 \leq \psi_{kl} \leq 1$ and $\sum_{k=1}^{K} \psi_{kl} = 1$. Fig. 1(b) shows the probabilistic graphical model for AMM.

To overcome the influence of noise, the spatial information generally incorporated by utilizing the MRF distribution among prior values

$$p(\Pi) \propto \exp \{-U(\Pi)\},$$

where $U(\Pi)$ is the energy function to smooth the priors and is generally utilized to incorporate spatial correlations into the segmentation process. Based on the type of energy $U(\Pi)$, we can obtain different models [23]. Based on the Bayes’ rule, the posterior probability density function can be written as

$$p(\Pi, \Theta|X) \propto p(X|\Pi, \Theta) p(\Pi).$$

The graphical model for MRF–GMM algorithm is shown in Fig. 1(c).

3. Theory

Motivated by the BAMM algorithm [32], we construct a novel asymmetric Gaussian mixture model to fit data shapes and make use of the spatial information, where the density function $f(x_i|\Pi, \Psi, \Theta)$ for each pixel $x_i$ is defined as

$$f(x_i|\Pi, \Psi, \Theta) = \sum_{k=1}^{K} \pi_k \left( \sum_{l=1}^{L} \psi_{kl} \Phi(x_i|\mu_{kl}, \Sigma_{kl}) \right). \quad (2)$$
دریافت فوری

پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات

امکان دانلود نسخه تمام متن مقالات انگلیسی
امکان دانلود نسخه ترجمه شده مقالات
پذیرش سفارش ترجمه تخصصی
امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
امکان دانلود رایگان ۲ صفحه اول هر مقاله
امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
دانلود فوری مقاله پس از پرداخت آنلاین

ISI Articles
مرجع مقالات تخصصی ایران