A robust modified Gaussian mixture model with rough set for image segmentation

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\textbf{A B S T R A C T}

Accurate image segmentation is an essential step in image processing, where Gaussian mixture models with spatial constraint play an important role and have been proven effective for image segmentation. Nevertheless, most methods suffer from one or more challenges such as limited robustness to outliers, over-smoothness for segmentations, sensitive to initializations and manually setting parameters. To address these issues and further improve the accuracy for image segmentation, in this paper, a robust modified Gaussian mixture model combining with rough set theory is proposed for image segmentation. Firstly, to make the Gaussian mixture models more robust to noise, a new spatial weight factor is constructed to replace the conditional probability of an image pixel with the calculation of the probabilities of pixels in its immediate neighborhood. Secondly, to further reduce the over-smoothness for segmentations, a novel prior factor is proposed by incorporating the spatial information amongst neighborhood pixels. Finally, each Gaussian component is characterized by three automatically determined rough regions, and accordingly the posterior probability of each pixel is estimated with respect to the region it locates. We compare our algorithm to state-of-the-art segmentation approaches in both synthetic and real images to demonstrate the superior performance of the proposed algorithm.

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1. Introduction

As one of the classical problems in image processing, image segmentation has been extensively studied, which can be treated as a classification problem [1–4] for the target image. The process of image segmentation techniques generally involves grouping or clustering pixels/voxels based on their intensity and spatial locations. During last decades, various image segmentation algorithms have been proposed, which can be generally categorized as supervised, semi-supervised and unsupervised models. As supervised models, many deep learning based segmentation algorithms have showed superior performances [5,6], where a deep neural network is generally trained end-to-end, pixels-to-pixels on semantic/instance segmentation. In semi-supervised models, the user is allowed to provide a few seeds to represent the label information [7,8], or the user can set an initial contour to let the model drive the corresponding contour to the boundaries of the objects [9–11]. However, in many practical applications, the supervised information is very hard to obtain, where the unsupervised models can play a major role in image segmentation. Various unsupervised models have been widely studied and applied to image segmentation, such as low-rank representation based algorithms [12,13] where the low-rank constraint is helpful to suppressing the effects of data noise and corruptions [14], and fuzzy clustering technologies [15–17] in which the membership function can handle the overlapped clusters efficiently. However, automated unsupervised segmentation algorithm is still a very challenging research topic due to the overlapping intensities, low contrast, and noise contained in the target images.

A number of model-based techniques [18,19] have been proposed during the last decades. Among the model-based techniques, the standard Gaussian mixture model (GMM) [20,21] has been widely utilized because it is very simple and the involved parameters can be efficiently estimated with the expectation maximization (EM) algorithm [22]. 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.

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To address these drawbacks, mixture models with Markov random fields (MRF) or hidden Markov random field (HMRF) have been frequently employed, which can be generally categorized into two groups. In the first group [23,24], the prior distribution is calculated on a pixel-by-pixel basis, depending on each pixel’s label and its neighboring pixels. The other group of mixture models utilizes HMRF to model the joint prior distribution of pixel labels [25–28]. Displaros et al. [26] introduced a pseudo-likelihood quantity to incorporate the spatial smoothness constrains into the model, and thus proposed a generative GMM. Nikou et al. [27] proposed a spatial constraint which can adaptively select the spatial directions. To improve the efficiency of MRF-EM based algorithms, Nguyen and Wu [28] 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 have been widely studied [29]. 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 [32]. Nguyen et al. [32–34] 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 without considering any spatial information.

For most GMM-based segmentation approaches, the corresponding objective functions are non-convex, and hence may be trapped by local optima. Thus, most GMM-based algorithms depend on the initializations. A common approach to deal with this problem is using the results of other algorithms such as k-means for initialization, which, however, is often not satisfactory because there is no mechanism that can measure how different these multiple initializations are from each other. Consequently, this approach may not explore the solution space effectively using multiple independent runs [35]. To deal with above problems, the population-based stochastic search algorithms are increasingly researched, where different potential solutions are allowed to interact with each other [36]. Genetic algorithm (GA) [37], differential evolution (DE) [38], and particles warm optimization (PSO) [39] have been the most common population-based stochastic search algorithms used for the parameter estimation of GMMs. Even though these approaches have been shown to perform better than non-stochastic alternatives such as k-means and fuzzy c-means, the interaction mechanism of the stochastic search algorithms has also limited the use of these methods due to some inherent assumptions in the candidate solution parametrization [35].

Based on above analysis, we can find that various EM-type mixture models introduce the spatial constrains into the corresponding energy functions. Nevertheless, most methods suffer from one or more challenges listed below, such as limited robustness to outliers, over-smoothness for segmentations, limited segmentation accuracy for image details, and often, sensitive to initializations. To address these issues and further improve the accuracy for image segmentation, in this paper, a robust modified Gaussian mixture model with rough set is proposed for image segmentation. Firstly, motivated by Ref. [30], the conditional probability of an image pixel is replaced by the calculation of the probabilities of pixels in its immediate neighborhood [30]. A new spatial weight factor is constructed by utilizing the intensity information of the original image and controlling the influence of the neighborhood pixels depending on their distance from each other among the neighborhood, which is also free of any balance parameter selection. Secondly, to further overcome the impact of noise and reduce the over-smoothness for segmentations, a novel prior factor is proposed by incorporating the spatial information amongst neighborhood pixels. The proposed prior factor is constructed based on the posterior probabilities and prior probabilities, and takes the spatial direction into account. It plays a role as linear filters for smoothing and restoring images corrupted by noise. During the algorithm procedures, we only need to run the convolution operation on the posterior and prior probabilities with a small amount of predefined filters to adaptively get the satisfied directions with the minimum differences among the intensity values along current direction. Therefore, the proposed prior factor is fast and easy to implement, and can preserve more details. Finally, to improve the robustness to initializations of the algorithm, we introduce the rough set into the GMM-based framework. Rough sets have already been incorporated into the EM algorithm for image segmentation [40], which can deal with the uncertainty, vagueess and incompleteness in data via modeling clusters in terms of the upper and lower approximations [41]. Based on our previous work [42], for each component, we partition an image into three rough regions, including the positive region, boundary region and negative region [43], with two automatically computed thresholds. The posterior probability of a pixel belonging to each sub-region is estimated with respect to the rough region where the pixel lies. Only those pixels in the positive region and boundary region have non-zero posterior probabilities, and are used to determine the mean and covariance of each Gaussian component. The construction of rough regions can be treated as an initialization step in each iteration of the algorithm. The proposed algorithm has been compared to other state-of-the-art segmentation algorithms in both simulated and real images to demonstrate the superior performance of the proposed algorithm.

2. Backgrounds

2.1. Mixture models based on Markov random field

Let the pixels in the neighborhood of the i-th pixel be presented by \( \theta_i \), which is a sample set containing all the neighboring pixels around i-th. Labels are denoted by \( \Omega_1, \Omega_2, \ldots, \Omega_k \), and \( \Omega_k \) is a sample set for all the pixels with label k. To segment an image consisting of N pixels into K labels, GMM assumes that each observation \( x_i \) is considered independent of the label \( \Omega_k, k = 1, 2, \ldots, K \). The corresponding density function is given by

\[
f(x_i|\Pi, \Theta) = \sum_{k=1}^{K} \pi_k \Phi(x_i|\theta_k)
\]

where \( \Pi = \{\pi_k | i = (1, 2, \ldots, N), k = (1, 2, \ldots, K) \} \) is the set of prior distributions modeling the probability that pixel \( x_i \) is in label \( \Omega_k \), which satisfies the constraints 0 \( \leq \pi_k \leq 1 \) and \( \sum_{k=1}^{K} \pi_k = 1 \). \( \Phi(x_i|\theta_k) \) is the Gaussian distribution parameterized by \( \theta_k \), called a component of the mixture. \( \Theta \) is the parameter set for all the components, i.e. \( \Theta = \{\theta_k | k = (1, 2, \ldots, K) \} \). Since the observation \( x_i \) is modeled as statistically independent, the joint conditional density over the whole image can be modeled as

\[
p(X|\Pi, \Theta) = \prod_{i=1}^{N} f(x_i|\Pi, \Theta) = \prod_{i=1}^{N} \sum_{k=1}^{K} \pi_k \Phi(x_i|\theta_k)
\]

To improve the robustness to the noise for GMMs, MRF distribution is applied to incorporate the spatial correlation amongst
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