Image Segmentation Based on Multiscale Initialized Gaussian Mixtures

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Abstract. Image segmentation is a key step for image processing and Gaussian Mixture Models(GMMs) are the common models for segmentation. The EM algorithm is usually used to estimete the parameters of GMMs, which is opt to get stuck at local minimum. In this paper we propose a new initialized shceme, multiscale online learning, for EM to aviod local minima and for GMMs to decide the optimal initial number of components. Experimental results have shown that this scheme can effectively improve the precision of segmentation compared to classical EM algorithm.

Keywords: Image segmentation, clustering, Gaussian mixture models(GMMs), online multiscale learning.

1 Introduction

Image segmentation is a process of partition an image into several non-overlapped regions and a preprocessing step in image processing. There have been many approaches for segmentation and many of them are based on clustering techniques. Among them, Gaussian mixture models(GMMs) are a class of effictive methods[1-4]. In image segmentation, one assumes that data comply with Gaussian mixture distributions with unknown parameters and then determines the optimal parameter values by using EM algorithm. By far, there have existed some extened GMMs for image segmentation and fearture selection. Recently, researchers have extended GMMs by using Markov Random Fields as the spatial constraints of pixels[5-11], such as SVMMs, DCM-SVFMMs. However, the elementary GMMs with EM algorithm still have some drawbakcs in image applications. First, the initial number of clusters must be prespecified. This is not practical in many situations. Second, EM is apt to get stuck into the local minima, which may make the model unable to find all clusters.

To overcome the drawbacks of GMMs and EM algorithm, we propose in this paper a new online learning algorithm for EM initialization and the reduction of conponents

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of GMMs, and it simultaneously avoids EM algorithm get stuck into local minima. Experimental comperisons on standard test image set have shown our algprithm takes advantage over the common EM algorithm in segmentation quality.

2 Multiscale Online Learning(MSOL)

Borrowed from the basic principle of the online competitive learning approach, the online multiscale learning rule for *i*th prototype has the following form[12],

$$P_i^{(k+1)} = P_i^{(k)} + \frac{pr_{ij}^{(k)}}{k}\left(x_j - P_i^{(k)}\right), \tag{1}$$

where $pr_{ij}^{(k)} = G\left(x_j, P_i^{(k)}\right) = \exp\left\{-d^2\left(x_j, P_i^{(k)}\right)/2\sigma_i^2\right\}$. $d(\cdot)$ is commonly Euclidean distance and σ_i^2 is estimated by

$$S^2 = \frac{1}{K-1}\sum_{x\in N(P_i)}\left(x - P_i\right)^2,\ K = \left|N\left(P_i\right)\right|. \tag{2}$$

Suppose that the numbers of sample and prototypes are *n* and *m*, respectively, then the computation complexity of MSOL is approximate $O(mn)$ when $K \ll n$. This is superior to multiscale spectrul clustering algorithm whose computation complexity is $O(n^2)$. Figure 1 demostrates the clustering result on an irregular dataset. MSOL correctly divides the data into two classes.

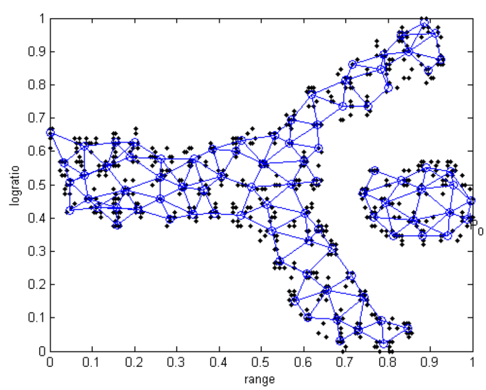


Fig. 1. The cluster result of MSCL on an irregular dataset

3 Gaussian Mixture Models and EM Algorithm

Given sample X and unknown parameter Θ , GMMs have the following form[1-4],

$$G\left(X \mid \Theta\right) = \sum_{i=1}^{M} \alpha_i G_i\left(X \mid \theta_i\right), \tag{3}$$

where $\theta_i = (\mu_i, \Sigma_i)^T$ and

$$G_i(X \mid \theta_i) = \frac{1}{2\pi|\Sigma_i|^{1/2}} \exp\left\{-\frac{1}{2}(X-\mu_i)^{'} \Sigma_i^{-1}(X-\mu_i)\right\}. \tag{4}$$

In image segmentation, GMMs use a combination of Gaussian functions with unknown parameters to approximate the unknown distribution. The optimal values of parameters are computed via maximal likelihood estimation and EM algorithm proposed by A. P. Dempster et al in 1977. The genral iterative formulas of EM algorithm for parameter estimation are presented as follows[3],

$$w_i^{j(k)} = \frac{\alpha_i^{(k)} G\left(x_j \mid \theta_i^{(k)}\right)}{\sum_{i=1}^{M} \alpha_l^{(k)} G\left(x_j \mid \theta_l^{(k)}\right)},$$

$$\alpha_i = \frac{1}{N}\sum_{i=1}^{N} w_i^{j(k)}, \tag{5}$$

$$\mu_i = \frac{1}{N\alpha_i^{(k)}}\sum_{i=1}^{N} w_i^{j(k)} x_j, \tag{6}$$

$$\Sigma_i = \frac{1}{N\alpha_i^{(k)}}\sum_{i=1}^{N} w_i^{j(k)} (x_j-\mu_i)(x_j-\mu_i)^T. \tag{7}$$

To make sure the number of components, two schemes are frequently used in image segmentation. First scheme is to preset the number of components, in which K-means algorithm is usually used to initialize the EM, and second is to decide it by online learning way. First scheme can not satisfy the reqirements of online analysis and thus adopted in real time environments. On the other hand, most of online learning algorithms is oriented to single scale of data and may produce more components for the cluster with larger scattering degree. To settle this problem and decrease the number of components in GMMs, this paper presents a new algorithm based on the multiscale online learning algorithm and GMMs and then apply it to image segmentation.

4 Algorithm

The detail steps of our algorithm is present as follows.

Initialize
① initialize P_0, K, ε, δ, pr for MSOL;
② locate the centers μ_i of components by MSOL;
③ compute the local variance Σ_i of components;
Main loop
④ compute the α_i for each component by (5);
⑤ update μ_i and Σ_i separately by (6) and (7);
⑥ if $\left|Q^{(k+1)} - Q^{(k)}\right| \le \varepsilon$, then stop; else goto ④.

This algorithm has the approximate linear complexity and suit to large scale data analysis.

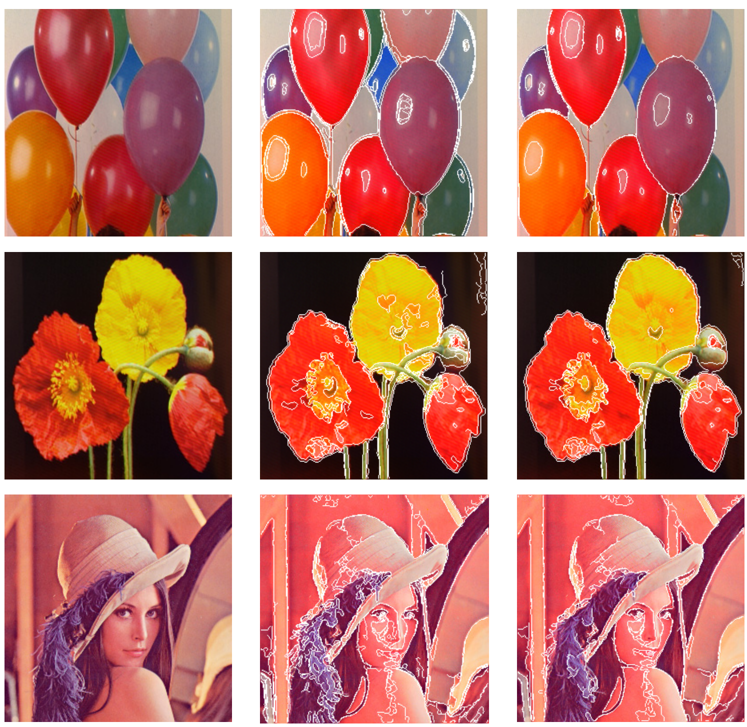
5 Experiments on Image Segmentation

We ran our algorithm on standard test image sets and compared the results with GMMs+EM model. The image sets can be freely obtained from web and have been widely applied to many segmentation problems. We select the figures with 256×256 pixels and the segmentation results of our algorithm and GMMs+EM are shown in Figure 2. From these figures we can know that k-means can not adaptively decide the number of clusters and thus may induce to loss clusters, such as the blue balloon in the figure of pallon. Moreover our algorithm can clearly show the detail parts in original figures.

pallon (k=3)

carnev (k=5)

lena (k=5)



Origin Our approach GMM+EM

Fig. 2. The result comparisons of our approach and GMMs+EM

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