Segmentation by fusion of histogram-based K-means

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Abstract

The image processing is one of the most advanced domains of research. The image occupies a special place in many areas of daily life (manuscript, satellite images, advertising, industry, etc.). In this article we present a segmentation method based on EM, histogram and k-Means Clustering Algorithm Initialization. In a first time, we present the functioning of the used methods. Secondly, we present the segmentation algorithm and results.

Keywords :*segmentation, EM, Kmeans, Gaussian mixtures, histogram.*

1. Introduction

The segmentation is a process of dividing an image into regions or objects. It's the first step in the field of image analysis. The image processing displays images and alters them to make it look "better".

The basic idea of image segmentation is to group individual pixels (dots in the image) together into regions if they are similar. Similar mean they are the same intensity (shade of gray), form a texture, line up in a row, create a shape, etc. There are many techniques available for image segmentation, and they vary in complexity, power, and area of application.[1]

In this context we propose in this paper a new method for segmentation of images; this method is based on the EM algorithm initialized by the Kmeans algorithm and histogram.

2. Gaussian Mixture Models and EM Algorithm

2.1 Gaussian Mixture Models

Mixture Models are a type of density model which comprise a number of component functions, usually Gaussian. These component functions are combined to provide a multimodal density. They can be employed to the model colours of an object in order to perform tasks such as real-time colour-based tracking and segmentation.

Consider a mixture model with M > 1:

$$p(x\backslash\theta) = \sum_{m=1}^{M} \alpha_m p(x\backslash\theta_m), \forall x \in R^n$$

Where: $\alpha_1, \dots, \alpha_M$: are the mixing proportions,
θ_m: is the set of parameters defining the math component.
$\vartheta \equiv \{\theta_1, \dots, \theta_M, \alpha_1, \dots, \alpha_M\}$: is the complete set of parameters needed to specify the mixture.

Being probabilities, the α_m must satisfy

$$\alpha_m \geq 0, m = 1, \dots, M, \sum_{m=1}^{M} \alpha_m = 1$$

For the Gaussian mixtures, each component density $p(x\backslash\theta_m)$ is a normal probability distribution:

$$p(x\backslash\theta_m) = \frac{1}{(2\pi)^{\frac{n}{2}} \det(\Sigma_m)^{\frac{1}{2}}} * \exp\{-\frac{1}{2}(x-\mu_m)^T \sum\nolimits_m^{-1} (x-\mu_m)\}$$

Here we encapsulate these parameters into a parameter vector, writing the parameters of each component as $\theta_m = (\mu_m, \Sigma_m)$, to get $\vartheta \equiv \{\theta_1, \dots, \theta_M, \alpha_1, \dots, \alpha_M\}$ then, the first formula can be rewritten as:

$$p(x\backslash\theta) = \sum_{m=1}^{M} \alpha_m N(x\backslash\mu_m, \Sigma_m)$$

Where $N(x\backslash\mu_m, \Sigma_m)$ is a Gaussian distribution with mean μ_m and covariance Σ_m. [2]

2.2 EM Algorithm

Expectation Maximization (EM) is one of the most common algorithms used for density estimation of data points in an unsupervised setting. The algorithm relies on finding the maximum likelihood estimates of parameters. When the data model depends on certain latent variables, in EM, alternating steps of Expectation (E) and

Maximization (M) are performed iteratively till the results converge. [3]

The **E** step computes an expectation of the likelihood by including the latent variables as if they were observed.

The M step (maximization), which computes the maximum likelihood estimates of the parameters by maximizing the expected likelihood found on the last E step.

The parameters found on the M step are then used to begin another E step, and the process is repeated until convergence.

2.3 EM Algorithm andGaussian Mixture Models

The commonly used approach for determining the parameters ɵ of a Gaussian mixture model from a given dataset is to use the maximum-likelihood estimation. The EM algorithm is a general iterative technique for computing maximum-likelihood when the observed data can be regarded as incomplete. The usual EM algorithm consists of an E-step and an M-step. Suppose that ɵ (t) denotes the estimation of ɵ obtained after the (t) th iteration of the algorithm. Then at the (t+1) th iteration, the E-step computers the expected complete data log-likelihood function

$$Q\left(\vartheta,\vartheta^{(t)}\right)=\sum_{k=1}^{K}\sum_{m=1}^{M}\{\log\,\alpha_m\,p(x_k\backslash\theta_m)\}P(m\backslash x_k;\,\vartheta^{(t)})$$

Where$P(m\ \backslash x_k;\ \vartheta^{(t)})$ is a posterior probability and is computed as:

$$P(m\backslash x_k;\vartheta^{(t)})=\frac{\alpha_m^{(t)}p\left(x_k\backslash\theta_m^{(t)}\right)}{\sum_{l=1}^{M}\alpha_l^{(t)}p\left(x_k\backslash\theta_l^{(t)}\right)}$$

The M-step finds the (t+1) the estimation $\vartheta^{(t+1)}$of ϑ by maximizing $Q\left(\vartheta,\vartheta^{(t)}\right)$

$$\alpha_m^{(t+1)}=\frac{1}{K}\sum_{k=1}^{K}P(m\backslash x_k;\vartheta^{(t)})$$

$$\mu_m^{(t+1)}=\frac{\sum_{k=1}^{K}x_kP(m\backslash x_k;\vartheta^{(t)})}{\sum_{k=1}^{K}P(m\backslash x_k;\vartheta^{(t)})}$$

$$\sum_m^{2(t+1)}=\frac{\sum_{k=1}^{K}P\left(m\backslash x_k;\vartheta^{(t)}\right)\left(x_k-\mu_m^{(t+1)}\right)\left(x_k-\mu_m^{(t+1)}\right)^T}{\sum_{k=1}^{K}P(m\backslash x_k;\vartheta^{(t)})}$$

EM algorithm is dependent on initialization. In our method, we initialize the mixture parameters by K-means megre with histogram.

3. K-means and Histogram-Based Image Segmentation

3.1 K-Means

The k-means algorithm is an algorithm to cluster n objects based on attributes into k partitions or groups, k < n. The K-means algorithm is an iterative technique that is used to partition an image into K clusters.

The basic algorithm is:

1. Pick K cluster centers, either randomly or based on some heuristic;

2. Assign each pixel in the image to the cluster that minimizes the variance between the pixel and the cluster center;

3. Re-compute the cluster centers by averaging all of the pixels in the cluster;

4. Repeat steps 2 and 3 until convergence is attained.

(e.g. no pixels change clusters) [4]

3.2 Histogram-Based Image Segmentation

Histogram-based image segmentation is one of the simplest and most often used segmentation techniques. It uses the histogram to select the gray levels for grouping pixels into regions. In a simple image there are two entities: the background and the object. The background is generally one gray level and occupies most of the image. Therefore, its gray level is a large peak in the histogram. The object or subject of the image is another gray level, and its gray level is another, smaller peak in the histogram. [1]

3. Method

In this article we propose a segmentation method called: segmentation by fusion of histogram-based K-means clusters. Given an image, the idea is shown schematically in figure 1.

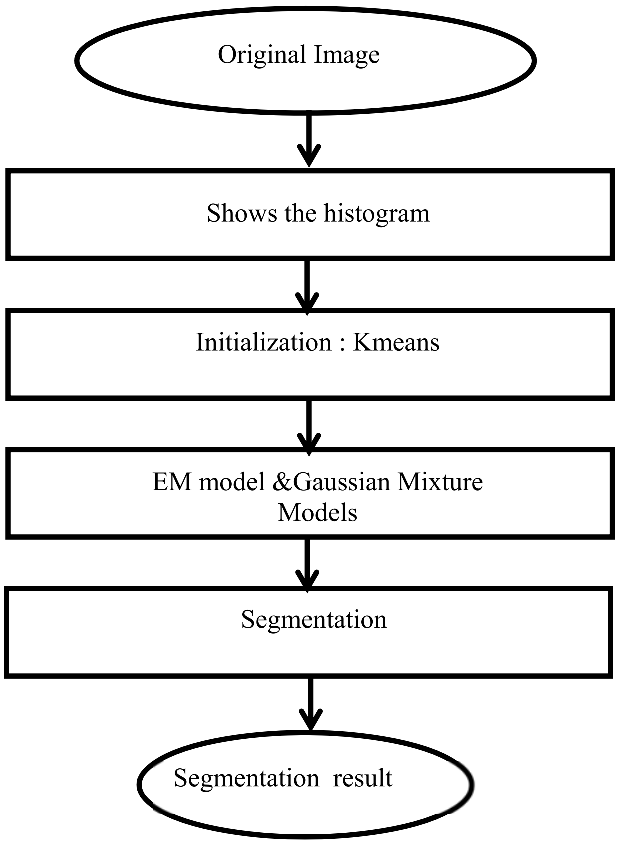

Fig -1: Flowchart of the proposed method

4. Experimental Results

This article is implemented in Matlab 2012a (of both algorithms). The tests were made with a number K of clusters being systematically worth 2,3,4 and 5.We observed that the best results, both from a point of view that a detection as from a point of view calculation time, corresponds, generally corresponds to the detection of 5 clusters. Therefore, we will expose essentially the results for K = 5.

In order, to evaluate the proposed method, we demonstrated our image segmentation algorithm with segmentation by fusion of histogram-based and K-means model by applying it to 5 images namely, Cameraman.tif (2566x255), Lena.png (2566x255), peppere.jpg (2566x255), Flowers.tif (2566x255) and satellite SPOT image representing the Tunisia city.jpg (2566x255).

We also make a comparison between the segmentation by fusion of histogram-based K-means and EM Algorithm initialize by histogram proposed in [5]. The Figure 2 shows the results of segmentation.

Fig. 2: Segmentation results

Compared with the segmentation results using algorithm (Fig.2), we can see the images are segmented more correctly by using our proposed method.

5. Conclusions

In this article we propose an Image Segmentation Method based on Gaussian Mixture Model with EM initialized by K-Means algorithm and histogram. The image was considered as a mixture of K-Component.

The advantage of our method lies by using the K-means algorithm is successfully circumventing the initialization problem of EM algorithm.

Experimental results show the proposed method has better segmentation result than the compared EM initialized by histogram methods.

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