Image Segmentation using Gaussian Mixture Adaptive Fuzzy C-mean Clustering

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Summary
This paper presents a new approach for image segmentation by applying Gaussian mixture. This segmentation process includes a new mechanism for clustering the elements of high-resolution images in order to improve precision and reduce computation time. The system applies fuzzy C-means clustering to the image segmentation after optimized by Gaussian Algorithm. The algorithm considers the centroid placement which should be located as far as possible from each other to with stand against the pressure distribution, as identical to the number of centroids amongst the data distribution. This algorithm is able to optimize the fuzzy C-means clustering for image segmentation in aspects of precision and computation time. It designates the initial centroids' positions by calculating the probability distance metric between each data point and all previous centroids, and then selects data points which have the maximum distance as new initial centroids. This algorithm distributes all initial centroids according to the maximum probability distance metric. This paper evaluates the proposed approach for image segmentation by comparing with fuzzy c-mean clustering and Gaussian Mixture Model algorithm and involving RGB, HSV, HSL and CIELAB color spaces. The experimental results clarify the effectiveness of our approach to improve the segmentation quality in aspects of precision and computational time.
Key words:
Gaussian mixture model, fuzzy c-mean clustering ,image segmentation

1. Introduction

Image segmentation is defined as the process of dividing an image into different regions such that each region is homogenous. F or intensity images (i.e. those represented by point-wise intensity levels) segmentation, there exists three popular approaches: histogram threshold techniques [5], edge-based methods [6] and region-based techniques [3]. Recently , with the progress on the theory of Gaussian mixture ture model has also become popular [7]. One of the powerful algorithms is fuzzy c mean clustering. It is widely a used algorithm for image segmentation widely applied for image segmentation .the author proposed a color image segmentation method based on fuzzy c mean clustering estimation. The observed color image is considered as a mixture of multi variant densities and the mixture parameters are estimated using the EM algorithm. The segmentation is completed by clustering each pixel into a component according to the fuzzy clustering estimation. Experiment results show this method is useful and stable in color image segmentation. However, a main drawback of this method is that the number of Gaussian mixture components is assumed known as prior, so it cannot be considered as totally unsupervised image segmentation method.

Another problem in using EM algorithm in image segmentation is that the problem of mixture parameter initialization. This will greatly affect the segmentation result. A commonly used solution is initialization by randomly sampling in the mixture data [8]. Although this method can result in segmentation result when the selected number is large, but the computation time is also heavily increased. When the selected number is small, it is high likely that some small regions may not be sampled, so the segmentation result is coarse. Many researches used Gaussian Mixture Model with its variant Expectation Maximization[9].This paper proposes a new approach for image segmentation that utilizes Gaussian mixture model and optimize the fuzzy clustering[10].

2. Basic theory of fuzzy c means clustering:

The goal of clustering is to create new groups of data from large data set. Where that is very useful and needed in many applications (i.e. data management in space, cellular communications, wireless sensors network ... etc.). Fuzzy C-Means (FCM) clustering algorithm minimizes the cost function.FCM algorithm divide data for different size cluster by using fuzzy system depend on many criteria like distances between one data point and another's, choosing center point and membership function that mean we don't have accurate data cluster size. This paper is adding a new development to the FCM algorithm to get equal size clustering method. The modification is an addition to FCM and not internal modification of the algorithm. FCM choosing cluster size and central point depend on fuzzy model but this paper solve this problem by using fuzzy model to define central point of cluster then use Euclidean function and distance value for cluster size[11][1].

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3. THE FCM ALGORITHM

Let R be the set of real s, R_p the set of p tuples of real s, R+ the set of nonnegative reals, and W_{cn} the set of real c x n matrices. R_p Will be called feature space, and elements x ϵ R_p feature vectors; feature vector x =(xI, x2,……….. , x_p) is composed of p real numbers.

Definition: Let X be a subset of R_p.Every function u: X [0, 1] is said to assign to each x ϵ X its grade of membership in the fuzzy set u. The function u is called a fuzzy subset of X .Note that there are infinitely many fuzzy sets associated with the set X. It is desired to "partition" X by means of fuzzy sets. This is accomplished by defining several fuzzy sets on X such that for each x E X, the sum of the fuzzy memberships of x in the fuzzy subsets is one.

Definition: Given a finite set X CR_p , X ={xI, x2,…,x} and an integer c, 2 < c < n, a fuzzy c partition of X can be represented by a matrix U ϵ W_{cn}whose entries satisfy the following conditions.

1) Row i of U, say u_i = (u 1, u2,.. , u_{in}) exhibits the Ith membership function (or ith fuzzy subset) of X.

2) Column j of U, say u_j =(u_1, u_2,.., u_i) exhibits the values of the c membership functions of the jth datum in X.

3) u_{ik} shall be interpreted as u_i (x_k), the value of the membership function of the ith fuzzy subset for the kth datum.

4) The sum of the membership values for each X_k is one (column sum u_{ik} = 1 v_k).

5) No fuzzy subset is empty (row sum $\sum$ u_{ik} > 0 v_k).

6) No fuzzy subset is all of X (row sum $\sum$ u_{ik} < n v_k).

m_f will denote the set of fuzzy c partitions of X. The special subset m_{cc} and m_{fc} of fuzzy c partitions of X wherein every u_{ik} is 0 or 1 is the discrete set of "hard," i.e., non-fuzzy c partitions of X. M, is the solution space for conventional clustering algorithms. The fuzzy c-means algorithm uses iterative optimization to approximate minima of an objective function which is a member of a family of fuzzy c-means functional s using a particular inner product norm metric as a similarity measure on R_p X R_p. The distinction between family members is the result of the application of a weighting exponent m to the membership values used in the definition of the functional. The FCM algorithm, via iterative optimization of j_m , produces a fuzzy c partition of the data set X ={x,…….,xn }. The basic steps of the algorithm are given as follows (cf. [4] for the derivation).

Fix the number of clusters c, 2 c c < n where n =number of data items. Fix m,1 < m < ∞. Choose any inner product induced norm metric e.g.,

$\|$ x-$\upsilon\|_a^2$= $(x-\upsilon)^t$A$(x-\upsilon)$ (1)

A ϵ W_p positive definite.

2) initialize the fuzzy c partition U^0,

3) at step b, b =0, 1, 2, … ,

4) calculate the c cluster centers {v(b)} with U(b) and the formula for the ith cluster center:

$\mathsf{U}_{il} = \frac{\sum_{k=1}^{n}(\mathsf{U}_{ik})^m x_{kl}}{\sum_{k=1}^{n}(\mathsf{U}_{ik})^m}$ L=1,2,…..,p.(2)

5) Update U(b): calculate the memberships in U(b+1) as follows. For k = 1 to n,

a) calculate I_k and I_{k+1}:

$$I_k = \{i|1 \le i \le c, d_{ik} = \|x_k - u_i\| = 0\}$$

b) for data item k, compute new membership values:

$$\tilde{I}_k = \{1,2,\dots,c\} - I_k;$$

i) if I_k =ϕ

$\mathsf{U}_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{2/m-1}}$ (3)

ii) else U_{ik} = 0 for all i ϵ I_k and $\sum$ i ϵ I_k U_{ik} = 1;

next k.

6) Compare Mb) and U(b +1) in a convenient matrix norm; if (U(b) - U(b + l)) < ε , stop; otherwise, step =b + 1, and go to step(4).

Use of the FCM algorithm requires determination of several parameters, i.e., c, , m, the inner product norm and a matrix norm. In addition, the set U° of initial cluster centers must be defined. Although no theoretical basis for choosing a good value of m is available, 1.1 <m c 5 is typically reported as the most useful range of values. Further details of computing protocols, empirical examples, and computational subtleties are summarized elsewhere, cf. [4]. The point of attack below is to reduce the computational burden imposed by iterative looping between (1) and (2) when c, p, and n are large. It is this task to which we now turn[2,3,11].

4. Noise removal:

An adaptive noise removal filtering using the Wiener filter is applied for noise removal of images. The Wiener filter can be considered as one of the most fundamental noise reduction approaches and widely used for solution for image restoration problems. In our system, we use 3x3 neighborhoods of filtering size[4].

5. Color Space Transformation:

Our image segmentation system pre-proceeds the image by transforming the color space from RGB to HSL and CIELAB color systems. HSL is well-known as an improved color space of HSV because it represents brightness much better than saturation. Beside, since the hue component in the HSL color space integrates all chromatic information, it is more powerful and successful for segmentation of color images than the primary colors. The CIELAB color system has the advantage of being approximately perceptually uniform, and it is better than the RGB color system based on the assumption of three statistically independent color attributes. The CIELAB color space is also widely-used for image restoration and segmentation. Considering the advantages of each color system of HSL and CIELAB, in our system we utilize both of them as hybrid color systems for image segmentation [4].

6. Data Normalization:

Because of different ranges of data points in HSL and CIELAB color spaces, we need to normalize the datasets. In our system, Softmax algorithm is used for the data normalization. The Softmax can reach softly toward its maximum and minimum value, but never getting there. The transformation using Softmax is more or less linear in the middle range, and has a smooth nonlinearity at both ends. The output range is between 0 and 1. A function in principle used to obtain the needed S-curve is the logistic function.

f(xi) = $\frac{1}{1+e^{-x_i}}$ (3)

The logistic function produces the needed S-curve but not over the needed range of values, and there is also no way to select the range of linear response. In order to resolve this problem, {x} should be first transformed linearly to vary around the mean x in the following way:

$x_i{}' = \frac{x_i}{\lambda({}^{\sigma}x/_{2\pi})}$ (3)

Where:

x is the mean value of variable x

σ_x is the standard deviation of variable x

λ is the linear response measured in standard deviation. It describes in terms of how many normally distributed standard deviations of the variables are to have a linear response. In our case, we set λ=10 in order to make smoother for normalizing the datasets [4].

7. Gaussian Mixture Models and EM Algorithm:

7.1 Gaussian Mixture Models:

Consider a mixture model with M > 1 components in <n for n > 1:

$p(x|\theta) = \sum_{m=1}^{m} \alpha_m p(x|\theta_m), \forall x \in R_n$ [4]

Where $\{\alpha_1 \ldots.. \alpha_m\}$ are the mixing proportions, each θ_m is the set of parameters defining the mth component , and θ_m={ $\theta_1, \theta_2, \ldots\ldots, \theta_n$ } is the complete set of parameters needed to specify the mixture. Being probabilities, the α_m must satisfy.

$$\alpha_n > 0, m = 1,2,3, \ldots, m, \sum_{m=1}^{m} \alpha_m = 1$$

F or the Gaussian mixtures, each component density p(x| θ_m) is a normal probability distribution

P(x|θ_m)=$\frac{1}{(2\pi)\det(\sum m)^{1/2}}$*exp{-1/2$(x-\mu_m)^t \sum_m^{-1}(x-\mu_m)$}

(4)

Here we encapsulate these parameters into a parameter vector, writing the parameters of each component as θ_m $\{\alpha_1\alpha_2\alpha_3 \ldots \alpha_n\}$ and to get ($\sum m, \mu_m$) Then, (4) can be rewritten as

$p(x|\theta) = \sum_{m=1}^{m} \alpha_m N(x| \mu_m, \sum m), \forall x \in R_n$ (5)

Where $N(x| \mu_m, \sum m)$ is a Gaussian distribution with μ_m mean and covariance $\sum m$[12].

7.2 EM algorithm:

The commonly used approach for determining the parameters θ of a Gaussian mixture model from a given dataset is to use the fuzzy c mean clustering estimation. The EM algorithm is a general iterative technique for computing fuzzy c mean clustering when the observed data can be regarded as incomplete. The usual EM algorithm consists of an E-step and an M-step. Suppose that θ(t) denotes the estimation of θ_t 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-c mean function

$U_{ij} = \frac{1}{\sum_{i=1}^{c}\left(\frac{\|x_i - c_j\|}{\|x_i - c_\lambda\|}\right)^{\frac{2}{n-l}}}$ (6)

U_{ij} is the main clustering function x_i is the input image c centroid and c_j and c_λ number of clustering.

$$U_{ij} = \begin{bmatrix} X & - & Z \\ - & - & - \\ A & - & C \end{bmatrix}$$

{x-z} clusters and {A-C} data.

$C_j = \frac{\sum_{i=1}^{N} u_{ij}^{N} a X_j}{\sum_{i=1}^{N} u_{ij}^{N}}$ (7)

Where C_j number of input data and m degree of fuzzy set.

$$diff = \sum_{j=1}^{c} \|c_{j.new} - c_{j.old}\|$$

Diff is updating each cluster[13].

The M-step finds the (t+1)th estimation (t+1) of c by iteration of Q(t):

$P\left(m|x_k; \Theta^{(t)}\right) = \frac{\alpha_m^{(t)} P(x_k|\Theta_m^{(t)})}{\sum_{L=1}^{M} \alpha_L^{(t)} P(x_k|\Theta_L^{(t)})}$ (8)

And

$c_m^{(t+1)} = \frac{1}{k}\sum_{k=0}^{K} P(m|x_k; \Theta^{(t)})$ (9)

EM algorithm is highly dependent on initialization. A common approach is using multiple random starts and choosing the final estimate with the highest likelihood.

This will greatly increase the computation burden. In our method, we initialize the mixture parameters by K-means algorithm [14,15]

$$\mu_m^{(t+1)} = \frac{\sum_{k=1}^{k} x_k P(m|x_k;\Theta^{(t)})}{\sum_{k=1}^{k} P(m|x_k;\Theta^{(t)})}$$

$$\Sigma_m^{2(t+1)} = \frac{\sum_{k=1}^{k} P(m|m_k;\Theta^{(t)})\left(x_k-\mu_m^{(t+1)}\right)(x_k-\mu_m^{(t+1)})^T}{\sum_{k=1}^{k} P(m|x_k;\Theta^{(t)})} \quad (10)$$

8. Image segmentation algorithm:

1) [Estimation] Replace $x_k;\Theta^{(t)}$ with its conditional expectation based on the current parameter estimates. Since, the labels may only take values 0 or 1, the expectation is basically equivalent to the posterior probability

$$p(\mathrm{m}|x) = \frac{P(m|x_k;\Theta^{(t)})p(\Theta^{(t)})}{\sum_{k=1}^{k} P(m|x_k;\Theta^{(t)})} \quad (11)$$

Where $\mathrm{P}(\Theta^{(t)})$ denotes the component weight.

2) [Maximization] Then, using the current expectation of the labels as the current labeling of the data, the estimation of the parameters is simple.
3) Go to step until convergence. Each iteration is guaranteed to increase the likelihood of the estimates .The algorithm is stopped when the change of the c mean List less than a predetermined threshold.

9. Experimental result:

In this section, we present the results of the application of algorithm. The performance of this algorithm is compared to the standard version of the FCM. Both techniques are tested on MRI brain synthetic image corrupted by a mixture of Gaussian and impulsive noise, and an MRI cerebral image corrupted by 5% of Gaussian noise. These techniques are experimented in the same conditions (a factor of fuzzy fiction m= 2 and a convergence error = 0.001). The algorithm uses as spatial feature the means μ calculated on an analysis window of size 3x3.

To perform practical applicability of our proposed approach for image segmentation, we made a series of experiments and tested its performance using variance. Variance constraint can express the density of the clusters with the variance within cluster and the variance between clusters . The ideal cluster has minimum variance within cluster to express internal homogeneity and maximum variance between clusters to express external homogeneity [14]. Let X={xi | i=1,…,N} be data set, S={si | i=1,…,k} be clustered X where M ϵ X is Mi={mij | j=1,…,n(si)} as members of si, variance within cluster can be defined as follows .

$$v_w = \frac{1}{N-k}\sum_{i=1}^{k}\left(n(s_i)-1\right)v_i^2 \quad (14)$$

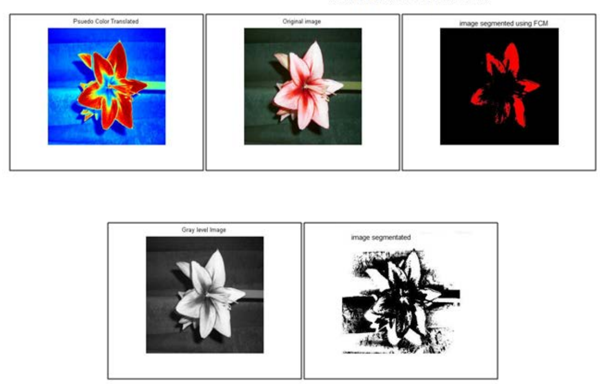
where N is number of data points, k is number of clusters, and
ni is number of members in i-th cluster, while vi is given as:

$$v_i^2 = \frac{1}{n(s_i)-1}\sum_{j=1}^{n(s_i)}\left(\underset{\in s_i}{m_{ij}} - \bar{s}_i\right)^2 \quad (12)$$

where mj is members of i-th clusters.
Variance between clusters then can be defined as follows:

$$v_b = \frac{1}{k-1}\sum_{i=1}^{k} n(s_i)\left(\bar{s}_i - \bar{x}\right) \quad (13)$$

For our experimental study, we use the well known SIMPLI city dataset of Wang et[4] . These images are manually divided into 10 categories which are people, beaches, historian buildings, buses, dinosaurs, elephants, roses, horses, mountains, and foods. We conducted the performance comparison between our approach for image segmentation and two comparing algorithms which are FCM algorithm and Gaussian Mixture Model (GMM) algorithm. For performing the FCM algorithm, we run 10 times of K-means and noticed its average results. For GMM algorithm, we use the spherical model with 50 numbers of iteration.



In order to perform comparisons in several color spaces, we used 4 different color spaces which are RGB, HSV, HSL and CIELAB. We set the comparison parameters up with 4 and 5 numbers of clusters, and with respectively different data normalization algorithms: Z-Score and Soft max (λ=10). Fig. 1 shows the performance comparison of variance within cluster (vw) which expresses the internal homogeneity of image segmentation results. The low vw conveys that the internal homogeneity of the clusters is so high that the variance inside each cluster becomes low. The comparison came from average results of 10 image experiments with 4 and 5 clusters in different color spaces. Fig. 1 shows that our approach for image segmentation using algorithm reached the lowest vw in all color spaces and outperformed the two comparing algorithms in all color spaces.

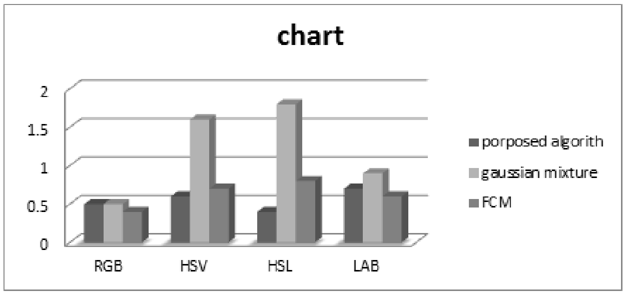


Chart1:show the result of output and compare of them

9. Conclusion:

In this paper, we have presented a new approach for image segmentation using Gaussian mixture and fuzzy c mean clustering algorithm. The system applies c-means clustering after optimized by Gaussian Algorithm. This considers the centroids placement which should be located as far as possible from each other to withstand against the pressure distribution of a roof, as identical to the number of centroids amongst the data distribution. This algorithm is able to optimize the c-means clustering for image segmentation in aspects of precision and computation time. A series of experiments involving four different color spaces with variance constraint and execution time were conducted. The experimental results show that our proposed approach is able to improve the precision and enhance the quality of image segmentation in all color spaces. It also performed the computational time as fast as C-means and kept the high quality of results.

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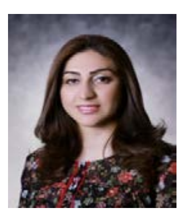

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