NOISE INSENSITIVE CONTRAST ENHANCED ADAPTIVE GLOBAL MAXIMUM CLUSTERING BASED MULTIPLE REGION SEGMENTATION

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***Abstract*—**

Multiple region image segmentation aims to partition a given image into several meaningful regions based on certain attributes such as intensity, texture, color, etc. A multiple-region segmentation problem is unstable because detection of number of regions is done manually. This is one of the most challenging and important problems in computer vision. This project present a region based method for joint clustering of multiple image segmentations. This proposes new method of segmenting an image into several sets of pixels with similar intensity values. To solve this problem use an Adaptive Global Maximum Clustering method this automatically finds the number of regions using image histogram. The proposed method is able to find the reasonable number of distinct regions not only for clean images but also for noisy ones. This method is made up of two procedures. First, develop the adaptive global maximum clustering. In this method use image histogram and automatically obtain the number of significant local maxima of the histogram which indicates the number of different regions in the image. Second, derive a simple and fast calculation to segment an image into distinct multiple regions.

***Index Terms* — Adaptive global maximum clustering, image histogram, multiple region segmentation**

I. INTRODUCTION

Image segmentation is the process of partitioning or subdividing an image into its constituent regions or objects. The set of pixels with the same label forms a region. The image is classified into several regions by traits such as intensity, shape, or texture so that the pixels in one region have a similar trait. This project describes a new method of segmenting an image into several sets of pixels with similar intensity values called regions.A multiple region problem is unstable because the result considerably depends on the number of regions given a priori. Therefore, one of the most important tasks in solving the problem is automatically finding the number of regions. The proposed method is able to find the reasonable number of distinct regions not only for clean images but also for noisy ones.

In existing approach, various models have been proposed to solve the image segmentation problem i.e., the Mum-ford–Shah minimal partition model[1], Chan -Vese model[2], Song-Chan model[5]etc. Chan and Vese applied the level set framework to effectively minimize the Mumford–Shah functional, and thus, they could automatically manage topological changes of the set of zero level. The proposed system provides a new method of segmenting an image into several sets of pixels with similar intensity values called regions.

In chan and vese model[2], proposes a new model for active contours to detect objects in a given image, based on techniques of curve evolution, Mumford-Shah functional for segmentation and level sets. This model can detect objects whose boundaries are not necessarily defined by gradient. The basic idea in active contour models is to evolve a curve, subject to constraints from a given image, in order to detect objects in that image. However,it is inevitable that the computational cost is high because their minimization problem results in solving a nonlinear parabolic partial differential equation. Chan and Vese expanded their two-phase active contours model to multiphase level set framework in[6],[7].

II. PAST WORK

Song and Chan also proposed a fast method to solve the Chan–Vese model [3] and calculated the energy in directly to decide the sign of , which is the level set function that determines inside or outside contours. They do not need to compute the corresponding Euler–Lagrange equation and use the full energy including the length term. They therefore can remove noise in the given image very fast. However, those methods split the given image into only two regions and they would not work well for the multiphase segmentation. In order to segment the image into more than three regions, Chan and Vese expanded their two-phase active contours model to a multiphase level set framework in [6] and [7]. However, these methods require level set functions and phases to detect regions. To reduce the storage, Lie et al. [8] exploited the PCLSM for problem. The noticeable feature of the PCLSM is to use only one piecewise constant function to recognize all the regions.

In the multiple-region segmentation problem, if the number of regions to be classified is given a priori, we could obtain the almost desirable result. However, in real applications, we do not know the number beforehand. In addition, the result is very sensitive to the given number. Although we experiment with the same image, the results would be dissimilar if different numbers are given. For the dynamic programming approach, it is required to divide the original problem into sub problems, and then obtain the original solution from the solutions of the sub problems.. In [16], a phase balancing model, which is a model to automatically find the number of distinct phases of an image without a histogram.

Optimal piecewise constant function splits the image into only two distinct regions of which each intensity has the optimal value . Gibou and Fedkiw suggested a fast algorithm to solve the Chan–Vese model for images without noise. If there is no noise in the given image, the first term related to the length of contours is no longer important, and thus, we can ignore that term.

III. PROPOSED METHOD

The proposed system provides a new method of segmenting an image into several sets of pixels with similar intensity values called regions. A multiple-region segmentation problem is unstable because the result considerably depends on the number of regions given a priori. Therefore, one of the most important tasks in solving the problem is automatically finding the number of regions. The proposed method is able to find the reasonable number of distinct regions not only for clean images but also for noisy ones. This method is made up of two procedures. First, develop the adaptive global maximum clustering. This procedure deals with an image histogram and automatically obtains the number of significant local maxima of the histogram. This number indicates the number of different regions in the image. Second derives a simple and fast calculation to segment an image composed of distinct multiple regions. Then, it split an image into multiple regions according to the previous procedure.

By developing the AGMC method we are able to find the number of different regions automatically. From the AGMC method, we have not only the number of distinct regions but also subintervals of [1,L] associated with gray levels of distinct regions. The set of subintervals is employed to define an initial for our segmentation model which gives a better segmentation result.

a)Adaptive Global Maximum Clustering:

AGMC can be used to find the number of different regions automatically. It uses an image histogram to get the different regions. In histogram,

- X- axis denotes gray level 'l'.
- Y-axis denotes the number of occurrences of each gray level 'h(l)'.

For consistency, rescaled the range of 'h' as $1 \le h(l) \le 256$.AGMC contains two steps:

- Histogram Extraction.
- Adaptive K-Means clustering.

Histogram Extraction:

To extract the significant local maxima, first search for an interval, including the global maximum of an original histogram, and then fix the interval. This fixed interval is called a cluster. Next remove the cluster, gained from the previous searching process, from the original histogram to find another new cluster. Then search for the new cluster of the reduced histogram and repeat this process until get the desired result. Since the histogram changes every iteration, which is precisely the reduced version of the original histogram, the global maximum also adaptively changes every iteration. Therefore call such a maximum an adaptive global maximum that corresponds to one of the significant local maxima of the original histogram. This whole process is a series of clustering a gray level interval [1,L] into several subintervals.. So this process is called the AGMC process. The goal of this process is,

$$[1,L]= (\cup_{i=1}^{n} I_i) \cup R$$

where each subinterval $I_{i}=[a_i,b_i]$ is a cluster containing the i^{th} adaptive global maximum, which is the global maximum of the i^{th} histogram. R is the domain of the $n+1)^{th}$ histogram.

Adaptive K-Means clustering:

The adaptive K-means clustering algorithm starts with the selection of K elements from the input data set. The K elements form the seeds of clusters and are randomly selected. It is an iterative technique and can be used to partition an image into k-clusters. The algorithm is based on the ability to compute distance between a given element and a cluster. This function is also used to compute distance between two elements. To find a cluster that is a subinterval with an adaptive global maximum at each iteration, we fix k=2 and repetitively implement the standard k-means clustering. The standard k-means clustering method is a process to solve the following minimization problem:

$$\arg\ \min_{I1,..,Ik} \sum_{j=1}^{k} \sum_{x\in Ij} |x - dj|^2$$

where $|x - dj|^2$ is a distance between a data point x and the j^{th} cluster center d_j . The aim of the k-means clustering is to congregate a set of distributed data into k clusters. For an image histogram, the k-means clustering problem is described as

$$\mathrm{argmin}_{I1,..,Ik} \sum_{j=1}^{k} \sum_{l\in Ij} h(l)(l - dj)^2$$

where h is an image histogram, and I_j is a subinterval of gray level. To resolve the above problem fix k=2, setting the initial two centers as starting index of I and ending index of I_1.

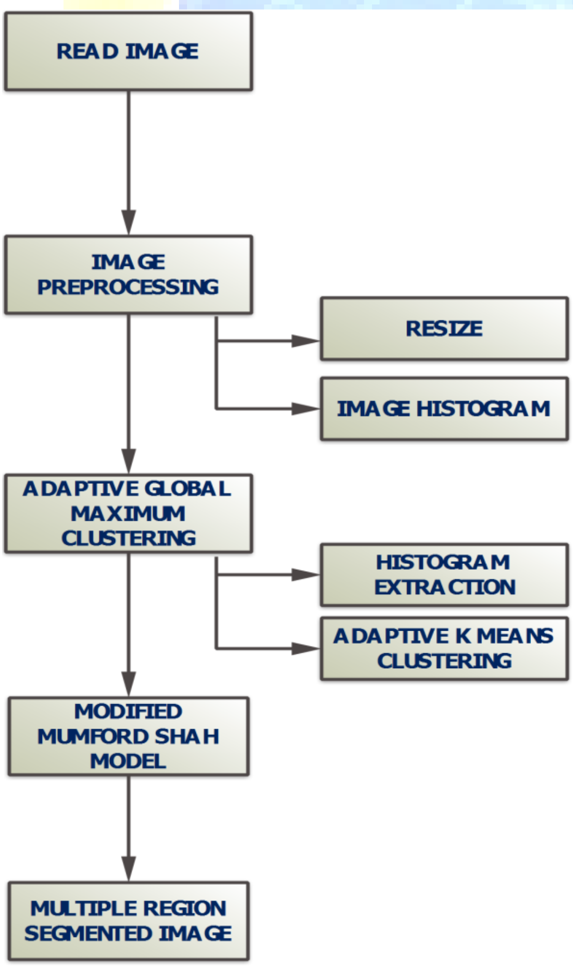

Fig1. Architectural framework

and repeating the k-means clustering. Here, I is the domain of histogram. Note that, the two means clustering is applied to the reduced histograms and the original histogram. Thus, the starting and the ending indexes are changeable, not fixed as 1 and 256. Once implement the two-means clustering, the histogram is divided into two clusters $I_1$and I_2 since k=2 is chosen. Then, we have two maxima, i.e., one is obtained in $I_1$and the other is obtained in I_2 . It is clear that if the maximum value of the histogram in one cluster I_1 is larger than the maximum value of the histogram in the other cluster I_2 , then cluster contains the global maximum of the histogram.

b) Segmentation model:

This module tries to design a simple, fast, and unsupervised multiphase segmentation model by modifying the Mumford–Shah model. Assume that a given 2-D image with or without noise $u_{0:}\Omega\rightarrow R$ consists of n distinct regions, i.e., $\Omega=\bigcup_{i=1}^{n}\Omega i$, where the underlying structure of u_0 is constant in each Ωi. From the AGMC procedure, we automatically get the number of n distinct regions and the n clusters. Compute d_i for each cluster D_i and naturally define an initial $\emptyset$ as follows:

$$\emptyset(x,y) = \begin{cases} 1, if\ u_0(x,y) \leq \frac{d1+d2}{2} \\ i\ \ , if\ \frac{d_{i-1}+d_i}{2} < u_0(x,y) \leq \frac{d_i+d_{i+1}}{2}, \\ n\ , if\ \frac{d_{n-1}+d_n}{2} < u_0(x,y) \end{cases}$$

Where $2 \leq i \leq$ n-1.

If we ignore noise in the segmentation process, which implies that consider noise a part of intensities, we can figure out the simplified version of piecewise constant Mumford–Shah functional as

$$inf_{ci}\ \ \sum_{i=1}^{n}\int_{\Omega i}|ci-u0|^2$$

Then find a unique piecewise constant function of which each constant region represents a different region. Define,

$$\Psi i(\emptyset) = H(\emptyset - i) - H\big(\emptyset(i+1)\big),$$

$1 \leq i \leq n$ where H(∅)is equal to 1 if $\emptyset \geq 0$ and equal to 0 if $\emptyset < 0$..

The exact border between clusters of the histogram is not required in the AGMC process because the border can be adjusted through the segmentation procedure.

IV. NUMERICAL RESULTS

We show the efficiency of our method that gives reasonable results without the prefixed number of distinct regions in an image by comparison with other methods. It can automatically find the number of different regions and the meaningful clusters that have an important role in defining initial of our segmentation procedure. Another advantage of our method is that the reasonable number of regions can be obtained from noisy images and clean images. For a noisy image, we smooth the image and then use the histogram of the smooth image rather than the histogram of the noisy one. This helps to easily find adaptive global maximum clusters. Although the intensities of every pixel were slightly changed by smoothing the image, it does not extremely affect the segmentation result.

The exact locations of the adaptive global maxima are not crucial because we ultimately need not the exact indexes of maxima but clusters, which are subintervals of [1, 256], containing the indexes of maxima. In all our experiments, the range of the histogram was scaled from 1 to 256 for convenience. Although we know only the approximate locations of clusters, we could acquire enough good results because the desired locations will be found through the segmentation procedure. Moreover, we can utilize the histogram of the smooth image for the clean image as well. Then, it makes one remove unnecessary parts to search for maxima.

Therefore, for both clean and noisy images, we can use the histogram of the smooth images in the AGMC procedure to gain the number of distinct regions. The original noisy or clean images are utilized in the segmentation procedure with the number and the clusters obtained from the AGMC procedure. Now, we compare our method with the multilevel thresholding method and the phase balancing model. In the multilevel thresholding method [18], the cost function of Kittler and Illingworth was particularly selected to find the best number of classes of an image histogram. The assumption is that a histogram is normally distributed with distinct means and variances.

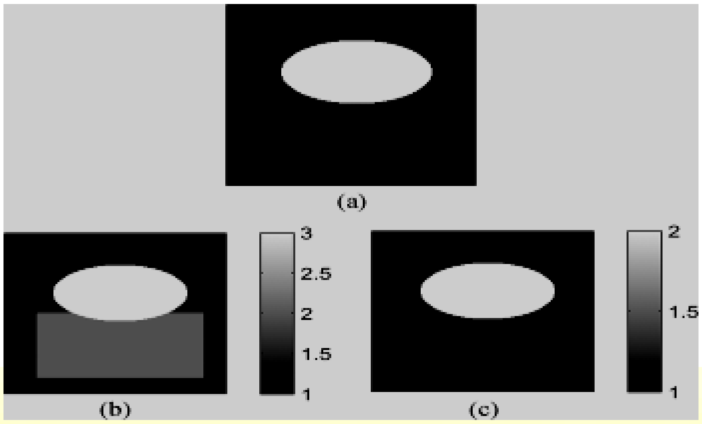

Fig. 2. (a) Original image. (b) Our method with Ω=15. (c) Phase balancing model with μ=1 . Our method splits the image into the correct three regions, but the phase balancing model failed to distinguish between the black and the dark gray regions

V. CONCLUSION

This project developed a new unsupervised multiple-region segmentation method by using the AGMC procedure. This method is composed of two procedures, namely, the segmentation and the AGMC. In the AGMC procedure, can automatically obtain the number of distinct regions and clusters, which are subintervals of gray levels containing adaptive global maxima. It fix k=2 and repeat the k -means clustering under a few rules in this procedure. In the segmentation procedure decomposes the original image into the multiple regions by modifying the Mumford–Shah model according to the number and clusters obtained from the AGMC procedure. In the numerical experiments, presented the efficiency of this method through comparison with other methods.

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