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Hybrid Method for Image Segmentation

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***Abstract*—In this research work we have studied Clustering k-means algorithm and Lattice Boltzmann Method. Image segmentation has proved its applicability in various areas like satellite figure processing, medical image processing and many more. In the present development the researchers tries to develop hybrid image segmentation techniques to generates efficient segmentation. Due to the progress of the parallel programming, the lattice Boltzmann method (LBM) has attracted much attention as a fast alternative approach for solving partial differential equations. This idea leads to provide color image segmentation using single channel segments of multichannel images. Though this method is widely adopted but doesn't provide complete true segmentation of multichannel i.e. color images because a color image contains three different channels for Red, green and blue components. Hence segmenting a color image, by having only single channel segments information, will definitely loose important segment regions of color images. To overcome this problem this paper work starts with the development of Enhanced Level Set Segmentation for single channel Images Using k-means Clustering algorithm and Lattice Boltzmann Method. Data clustering is one of the important data mining methods. It is a procedure of discovery classes of a data set with most similarity in the same class and most dissimilarity between different classes .In this paper we study on hard clustering K-Means algorithm that is mostly based on Euclidean distance measure [26].Hard clustering methods are based on traditional set theory, and require that an object either does or does not belong to a bunch. Hard clustering means partitioning the data into a specified number of mutually exclusive subsets. [27].**

For the study of the proposed segmentation scheme three segmentation parameters have been utilized, they are Probabilistic Rand Index (PRI), Variation of Information (VOI) and Global Consistency Error (GCE).

Keywords— K-means, image segmentation, intensity in - homogeneity, lattice Boltzmann method (LBM), level set equation (LSE), partial differential equation (PDE).

I. INTRODUCTION

In computer vision, image segmentation [38]–[40] is a major and nontrivial task which aims to partition a given image into several regions or to detect an object of interest from the background. This task is more challenging that most of the actual imaging devices produce images corrupted by intensity in-homogeneity. The level set method (LSM) is a part of the whole family of active contour methods (ACMs). The key idea that started the level set fanfare was the Hamilton –Jacobi approach, i.e., a time -dependent equation for a moving surface. This was first completed in the seminal work of Osher and Sethian [1]. in 2-D space, the LSM represents a closed curve in the plane as the zero level set of a 3-D function Ø. For example, Starting with a curve around the object to be detected, the curve travels toward its inner normal and has to stop on the boundary of the object. Two approaches are usually used to stop the evolving curve on the boundary of the desired object; the first one uses an edge indicator depending on the gradient of the image like in classical snakes and ACMs [2]–[5], [21], [31], and the second one uses some regional attributes to stop the evolving curve on the actual boundary [22], [23], [32] where the authors extend the representative region-based level set from scalar to tensors by simultaneously taking into account the pixel's gray level and some local statistics such as gradient and orientation. The latter is more robust against noise and can detect objects without edges.

k-means is one of the simplest algorithm which uses unsupervised learning method to solve the known clustering issues . It works with really well with enormous datasets.[27]

Many clustering algorithms have been proposed by researchers. partition clustering and hierarchical clustering are two main approaches to clustering. A number of the clustering algorithms in the literature are *K* -means, *K* -medoid, FCM, PAM, CLARA, CLARANS, BIRCH, CURE, ROCK and CHAELEON. Along with the above mentioned clustering techniques, *K* -means and FCM algorithms are widely used partitioning techniques by the researchers in many real-world applications.

K -means [3] is the most popular classical hard clustering method. Each data point is from only one cluster. It requires the previous knowledge about the number of clusters. This technique is not appropriate for real world data sets in which there are no definite boundaries between the clusters.

In the LSM, the movement of the zero level set is actually driven by the level set equation (LSE), which is a partial differential equation (PDE). For solving the LSE, most classical methods such as the upwind scheme are based on some finite difference, finite volume or finite element approximations and an exp licit computation of the curvature [20]. Unfortunately, these methods cost a lot of CPU time.

Recently, the lattice Boltzmann method (LBM) has been used as an alternative approach for solving LSE [12], [14], [29], [36]. It can better handle the problem of time consuming because the curvature is implicitly computed

and the algorithm is simple and highly parallelizable.
In this paper, the LBM is used to solve the LSE. The proposed method is based on the approach of the LBM PDE solver defined in [14].

II. BACKGROUND

The proposed method uses mainly two techniques belonging to different frameworks: the LSM and the LBM.

A. LSM

The LSM is a numerical technique for tracking interfaces and shapes. Using an imp licit representation of active contours, it has the advantage of handling automatically topological changes of the tracked shape. In 2-D image segmentation, the LSM represents a closed curve as the zero level set of φ, called the level set function. The progress of the curve starts from an
random starting contour and evolve itself driven by the LSE which can be seen as a convection–diffusion equation

$$\frac{\partial\theta}{\partial t} + \vec{V} \cdot \nabla\phi = b\Delta\phi \quad \ldots (1)$$

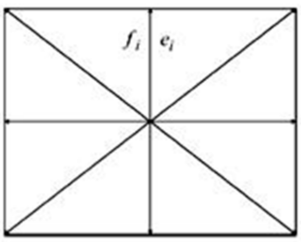
Where ∇∅ and ∆∅ are the gradient and the Laplacian of ∅, respectively. The term ∅ is called artificial viscosity (Sethian suggested replacing it with | ∅| which is better for handling the evolution of lower dimensional interfaces [12]), and k is the curvature of the distance function ∅. The LSE can therefore be written as

$$\frac{\partial\theta}{\partial t} + \vec{V} \cdot \nabla\phi = bk|\Delta\phi|. \quad \ldots (2)$$

Being an alternative method for solving PDE, the LBM has several advantages, such as parallelizability and ease. In this paper, we use the D2Q9 LBM model to resolve the LSE in 2-D space.

B. LBM

The LBM is a numerical framework for modeling Boltzmann particle dynamics on a 2-D or 3-D lattice [13]. It was first designed to solve macroscopic fluid dynamics problems [14]. The method is second order accurate both in time and in Fig. 1. Spatial structure of the D2Q9 LBM lattice. Space, and in the limit of zero time step and lattice spacing, it yields the Navier Stokes equations for an incompressible flu id [15].



The proposed method uses the D2Q9 (2-D with eight links with its neighbors and one link for the cell itself) LBM lattice structure. Fig. 1 shows a typical D2Q9 model. Each link has its velocity vector (,) and the particle distribution (,) that moves along this link, where is the position of the cell, and t is the time. The LBM evolution equation can be written as follows using the Bhatnagar, Gross, and Krook collision model [7].

$$f_i(\vec{r} + \vec{e}_i, t+1) = f_i(\vec{r}, t) + \frac{1}{\tau}\left[f_i^{eq}(\vec{r}, t) - f_i(\vec{r}, t)\right] \quad \ldots(3)$$

where τ represents the relaxation time determining the kinematic viscosity ϑ of the fluid by

$$\vartheta = \frac{1}{3}\left(\tau - \frac{1}{2}\right) \quad \ldots(4)$$

and $f$eq i is the equilibrium particle allocation defined as

$$f_i^{eq}(\rho, \vec{u}) = \rho\left(A_i + B_i(\vec{e}_i \cdot \vec{u}) + C_i(\vec{e}_i \cdot \vec{u})^2 + D_i(\vec{u})^2\right) \quad (5)$$

Where Ai to Di are constant coefficients depending on the geometry of the lattice links and ρ and are the macroscopic flu id density and speed, respectively, computed from the particle distributions as

$$\rho = \sum_i f_i \quad \vec{u} = \frac{1}{\rho}\sum_i f_i \vec{e}_i. \quad \ldots\ldots\ldots.(6)$$

For modeling typical diffusion computations, the equilibrium function can be simplified as follows [14]: $f$eq

$$f_i^{eq}(\rho, \vec{u}) = \rho A_i. \quad \ldots (7)$$

In the case of D2Q9 model, Ai = 4⁄9 for the zero link, Ai = 1/ 9 for the axial links, and Ai = 1⁄36 for the diagonal links. Now, the relaxation time τ is determined by the diffusion coefficient γ defined as

$$\gamma = \frac{2}{9}(2\tau - 1) \quad \ldots (8)$$

As shown in [14], LBM can be used to solve the parabolic diffusion equation which can be recovered by the Chapman– Enskog expansion

$$\frac{\partial\rho}{\partial t} = \gamma\nabla \cdot \nabla\rho. \quad \ldots (9)$$

In this case, the external force can be included as follows:

$$f_i \leftarrow f_i + \frac{2\tau - 1}{2\tau}B_i(\vec{F} \cdot \vec{e}_i) \quad \ldots (10)$$

Moreover, thus, (9) becomes

$$\frac{\partial\rho}{\partial t} = \gamma\nabla \cdot \nabla\rho + F. \quad \ldots (11)$$

Replacing by the signed distance function ∅, the LSE can be formed.

III. PROPOSED METHODOLOGY

A. K Means

In this paper we use K –means technique for data clustering. The K –means algorithm is described as follows: Let $X = \{x_1, x_2, \ldots, x_n\}$ be the set of data points and $v = \{v_1, v_2, \ldots, v_c\}$ be the set of cluster centers.[26]

Step 1. Select the number of cluster centers.

Step 2. Randomly initialize the c cluster centroid vector.

Step 3. Compute the distance of each object in the data set from each of the cluster centroids.

Step 4. Assign the data point to the cluster center whose distance from the cluster center is Smallest of all the cluster centers.

Step 5. i) Recalculate the new cluster center using

$$v_i = \frac{\sum_{i=1}^{c_i} x_i}{c_i}$$

Where c_i represent the number of data points in the i –th cluster.

ii) Recalculate the distance among each data point and fresh obtained cluster centers.

Step 6 . If the stopping criterion has been met then stop otherwise go to step 4.

Distance measures

Clustering techniques are based on measuring similarity between data vectors by calculating the distance between each pair. There is no common distance measure which can be best suited for all clustering applications.[26]

The following points are a few significant characteristics of distance measure:

- i Distance is always positive.
- ii Distance from point *a* to itself is always zero.
- iii Distance from point *a* to point *b* cannot be greater than the sum of the distance from *a* to some other point *c* and distance from *c* to *b*.
- iv Distance from *a* to *b* is always the identical as from *b* to *a*.

B. LSE

As done in [10], to obtain the LSE, we minimize E(U, V, B, Y, Ø) with respect to f. For permanent U, V, and B, we use the gradient

$$\frac{\partial \phi}{\partial t} = -\frac{\partial E}{\partial \phi} \quad \ldots(12)$$

Where ∂E/∂f is the Gateaux derivative [11] of E. We obtain the following LSE:

$$\begin{aligned}\frac{\partial \phi}{\partial t} = \delta(\phi)\Big(U_1^p(x,y)\,\|Y(x,y)-B(x,y)-v_1\|^2 \\ -U_2^p(x,y)\,\|Y(x,y)-B(x,y)-v_2\|^2\Big) \\ +\nu\delta(\phi)\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)\end{aligned}$$

$$\begin{aligned}\text{s.t. } U_1(x,y)+U_2(x,y)=1\ \forall x,y \\ 0 \le U_k(x,y) \le 1\ \forall k,x,y.\end{aligned}$$

…(13)

However, for solving the minimization problem of E(U, V, B, Y, Ø), we should also compute the first derivatives of E(U, V, B, Y, Ø) with respect to u*ki* , v*k*, and ß*i* and set them equal to zero. We thus obtain three necessary conditions

$$U_k^*(x,y) = \frac{1}{\sum_{l=1}^{c}\left(\frac{\|Y(x,y)-B(x,y)-v_k\|}{\|Y(x,y)-B(x,y)-v_l\|}\right)^{\frac{2}{(p-1)}}} \quad \ldots(14)$$

$$v_k^* = \frac{\int_\Omega U_k^p(x,y)\,(Y(x,y)-B(x,y))\,dxdy}{\int_\Omega U_k^p(x,y)dxdy} \quad \ldots(15)$$

$$B^*(x,y) = Y(x,y) - \frac{\sum_{k=1}^{c} U_k^p(x,y)v_k}{\sum_{k=1}^{c} U_k^p(x,y)}. \quad \ldots(16)$$

C. Lattice Boltzmann Solver for LSE

By using the gradient projection method of Rosen [17], we can replace d(Ø) by |∇ Ø | in the proposed LSE, and as Ø is a distance function, we have |∇ Ø | =1[16], [20] and will stay at each step since an adaptive approach is not used and the distant field is valid in the whole domain [25]. Thus, the proposed LSE becomes

$$\begin{aligned}\frac{\partial \phi}{\partial t} = U_1^p(x,y)\,\|Y(x,y)-B(x,y)-v_1\|^2 \\ - U_2^p(x,y)\,\|Y(x,y)-B(x,y)-v_2\|^2 + \nu\mathrm{div}(\nabla\phi) \\ \text{s.t. } U_1(x,y)+U_2(x,y)=1\ \forall x,y \\ 0 \le U_k(x,y) \le 1\ \forall k,x,y.\end{aligned} \quad (17)$$

Replacing ρ by the signed distance function Ø, (11) becomes

$$\frac{\partial \phi}{\partial t} = \gamma\mathrm{div}(\nabla\phi) + F. \quad (18)$$

By set the external force

$$F = \lambda\Big(U_1^p(x,y)\,\|Y(x,y)-B(x,y)-v_1\|^2 - U_2^p(x,y)\,\|Y(x,y)-B(x,y)-v_2\|^2\Big) \quad (19)$$

Where λ is a positive parameter; we can see that (17) is only a variation formula of (18) and, thus, can be solved by the LBM with the above-defined FEF. The choice of parameter p is at great importance for the segmentation result. Different values for p will generate different outcome, as following.

i If p>2, then the exponent 2/(p - 1) in (14) decreases the membership value of the pixels that are closed to the centroid. The segmentation result will therefore be wrong since it is intuitively better that the membership value be high for those pixels who are closed to the centroid.

ii If p →∞, all the membership values tend to 1/c. This implies that the

$$\text{FEF} \to \lambda\left(\left(\frac{1}{c}\right)^p \|Y(x,y) - B(x,y) - v_1\|^2 - \left(\frac{1}{c}\right)^p \|Y(x,y) - B(x,y) - v_2\|^2\right) \to 0.$$

There is, therefore, no link with the image data in the LSM process. Therefore, segmentation is impossible.

iii If p → 1, the exponent 2/(p - 1) increases the membership values of the pixels who are closed to the centroid. As p → 1, the membership tends to one for the closest pixels and tends to zero for all the other pixels. This case is equivalent to the use of the k-means objective function instead of the FCM one. The segmentation is therefore rig id, and we lose the advantage of FCM over k -means. For all these reasons, a suitable choice of the parameter p can be the value of two; which is therefore used in all our experiments.

IV. IMPLEMENTATION

When using LBM to resolve the convection–diffusion equation, the particle density is set as $\emptyset$ this is a signed distance function. Since the particle number of the cell cannot be negative, we modify the distance function as $\emptyset' = \emptyset - (\emptyset)$. The contour is those pixels which satisfy $\emptyset' = -(\emptyset)$. The steps of proposed multichannel image segmentation technique using RGB color space are outlined as follows.

- Read the multichannel image for the segmentation as input image.
- Initialize the distance function $\emptyset$ and class cancroids values $v1$ and $v2$. Initializing B with zeros.
- Divide the multichannel image into Red, Green and Blue components.
- Now apply the steps v to xiii for each separately on Red, Green and Blue components.
- Compute further using energy function
- Compute the external force with (19).
- Include the external force based on (10).
- Resolve the convection–diffusion equation with LBM with (3).
- Accumulate the (,) values at each grid point by (6), which generates an updated distance value at each point.
- Find the contour.
- If the segmentation is not done, increase the value of λ And go back to step 5).
- After getting contour for all the three separate channels i.e. Red, Green and Blue Channels) combine the entire.
- Three contours to get contour for all three components. Multichannel segmented image as output of The project work.

k-mean is simplest to implement and to run ,all you need to do is choose “k” and run it a number of times.

Solving LSE by using classical method ,mostly based on finite differences approximations ,costs a lots of computer time particularly when processing high dimensional large scale data .in recent year the LBM is explicitly highly parallizable.

V. EXPECTED RESULT

We applied the partitioning algorithm to gray scale images. the segmentation result as generated on different images by each algorithm for varying value of k is as shown in algorithm.

VI. CONCLUSIONS

This paper presents a level set image segmentation method based on the idea of stopping the evolving contour according to the degree of membership of the active pixel to be inside or outside of this evolving contour for the multichannel images (i.e. color images). It is done with the help of the k-means partition matrix. The LSE is solve by using the powerful, simple, and highly parallelizable LBM which allows the method to be a good candidate for GPU implementation. The method gives promising results. Experimental results on medical and real-world images have demonstrated the good performance of the proposed method in terms of PRI, VOI and GCE. It presents a fast and efficient comprehensive implementation for color image segmentation.

The PRI, VOI, GCE value calculated for different images is found to be in a specific desired range which shows the successful implementation of the method. On the basis of PRI, VOI and GCE it is seen in the plots that developed technique is providing much higher PRI, smaller VOI and GCE as compare to exiting technique which leads to true segmentation capability of the.

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