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GPU -based Fuzzy C Means Clustering Model For Brain MR Image

Che-Lun Hung, Yuan-Huai Wu, Yaw-Ling Lin, Yu-Chen Hu, Jieh-Shan Yeh, Chia-Chen Lin

Abstract—**In the computer aided medical image process, image segmentation is always required as a preprocess stage. Fuzzy c-means (FCM) clustering algorithm has been commonly used in many medical image segmentations, particularly in the analysis of magnetic resonance (MR) brain image. However, all of these FCM methods are computation consuming that is difficult to be used in real time application. In the paper, we proposed a Parallel FCM algorithm based on graphic process units (GPUs) to accelerate computation speed of time-consuming FCM applications. The experimental results show that the proposed algorithm can reduce the computational cost dramatically.**

Keywords—**Fuzzy C-Means, Magnetic Resonanace, Brain, White Matter, GPU, Parallel Processing**

I. Introduction

In the past decades, medical image has been commonly used to facilitate the clinic diagnosis. Various imaging techniques such as X-rays, Ultrasounds, Computed Tomography scans (CT) or Magnetic Resonance Images (MRIs) have been used to sense the irregularities in human body. The physicians identify the tumors, tissues, and the anatomical structures according to all of these images. To detect abnormality in brain the brain MRI is useful medical imaging tool. In general, the brain MRI can be classified into three significant regions, such as matter (WM), grey matter (GM) and cerebrospinal fluid spaces (CSF).

Many image-processing technologies [1, 2] have been used to copy with medical images; especially image segmentation technologies. The image segmentation is the process to split image data to a serial of non-overlapping homogeneous region [3]. It has been used to analyze medical images for facilitating diagnosis and therapy [3, 4]. In addition, it can be used to reconstruct image, where it is useful to identify the abnormality in the brain. For the brain MRI, the image segmentation techniques are essential for clinic diagnosis, as they are used to classify WM, GM and CSF regions from observed image. The physicians can determine abnormality in the patient brain from these regions.

Clustering algorithm is one of the segmentation techniques. Clustering is the process of classifying data into group of similarity [5]. Some of clustering algorithms have been commonly adopted in computer, engineering and mathematics field [6]. Similarly, the clustering algorithms have been broadening to medical fields.

Che-Lun Hung, Yuan-Huai Wu, Yaw-Ling Lin, Yu-Chen Hu, Jieh-Shan Yeh, Chia-Chen Lin

Providence University
Taiwan

Clustering algorithms, such as K-means (KM) clustering [6], Moving K-means (MKM) [7] and Fuzzy C-means [8], have been proposed to make the analysis of the brain MRI easier. Fuzzy C-means (FCM) algorithm has been proved to achieve the better segmentation efficiency over the other clustering approaches. But the drawback of these clustering algorithms is the huge computational time required for convergence.

In recent years, many high performance hardware and software technologies have been released, such as Intel and AMD multi-core systems, graphic processing units (GPU), OpenMP, OpenCL, CUDA and Hadoop. In these new technologies, the development of GPU is rapidly growing, and it has been used to accelerate computation-consuming applications. The GPU devices consist of up to hundreds cores per-chip, and it can issue the thousands of threads to fully utilize its computational power. GPU is not only adopted to develop graphic application but also utilized to solve general computing problem. The General-Purpose computing on Graphics Processing Units (GPGPU) such as Open Computing Language (OpenCL) [9] and compute unified device architecture (CUDA) [10], has successfully made supercomputing available to variety of applications. Nvidia G80 archirtecture introduced the single-instruction multiple-thread (SIMT) execution model that allows multiple independent threads to simultaneously execute a same instruction. The first GPU-based medical image segmentation technique was introduced to computing level set segmentation as a sequence of graphics operators of image blending [11]. The curvature regularization based on GPU has been proposed to enable the segmentation of 3D images to favor smooth isosurfaces [12]. Jenog et al. [13] proposed a multiphase level set segmentation approach implemented in CUDA for reconstruction of complex neural processes. GPU-based watershed [14] and region growing algorithms [15] adopt the pixel/voxel information to retrieve the target objects/regions without statistical information of the target objects/regions. Narayanaswamy et al. [16] proposed a robust statistical segmentation based on GPU that utilized adaptive region growing process for confocal microscope images. Walters et al. [17] proposed a GPU-based segmentation method for liver image by using Markov random fields (MRF). Ailling et al. [18] proposed a GPU implementation of image segmentation algorithm based on self-organizing map SOM network for segmenting the human brain MRI images.

FCM is the widely-use and efficient algorithm for image segmentation. In the paper, we proposed a Parallel FCM algorithm based on graphic process units (GPUs) to accelerate computation speed of time-consuming FCM applications. The experimental results shows that the proposed algorithm can obtain the same quality results as original FCM, and it can achieve significant speed up over the original FCM executed on very powerful CPU. The

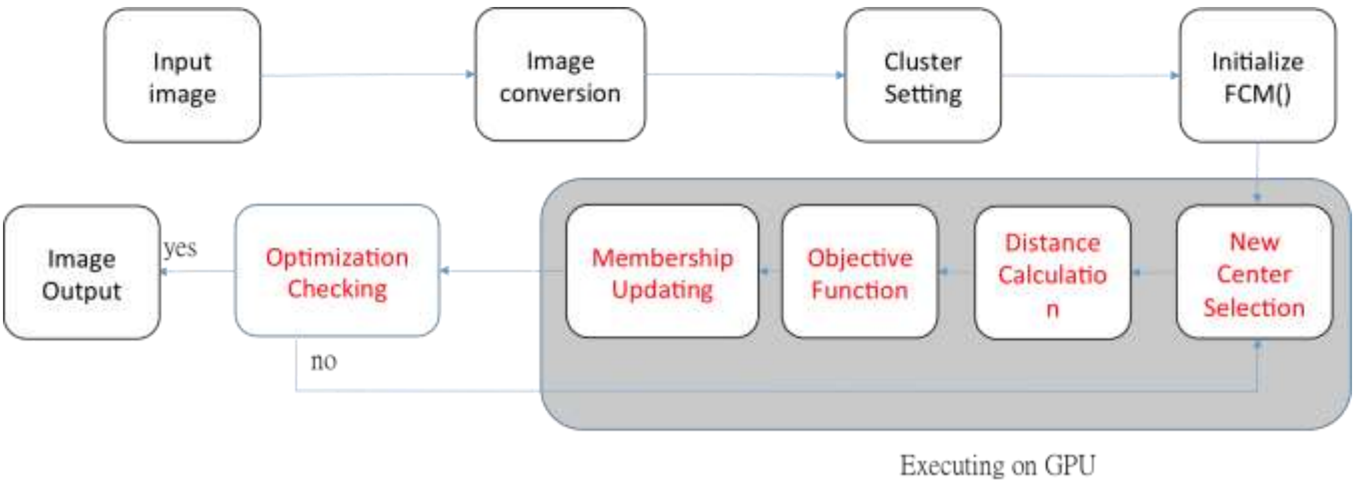


Figure 1. The flowchart of the GPU based FCM algorithm.

Cost/Performance (CP) ratio shows that the proposed algorithm is valuable for analysis of MR brain image.

The remainder of this paper is organized as follows. Section 2 discusses the details of FCM algorithm and the proposed GPU-based FCM algorithm. The experimental results are shown in Section 3. Section 8 provides some final conclusions and directions for future work.

II. Algorithm

A. *Fuzzy C Means algorithm*

Bezdek introducted Fuzzy C-means (FCM) algorithm that allows one piece of data to belong to differenct clusters, and it has been one of the most commonly used clustering algorithm for medical images [8]. FCM clustering is constructed based on minimization of an objective function as K-Means (KM) algorithm [6]. The objective function is shown as following,

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{n} d\left(x_i, q_j\right). \qquad (1)$$

where m is any real number greater than 1, n is number of pixels, and c is the number of cluster, u_{ij} is the degree of membership of x_i to the cluster j with center, x_i is the ith of d-dimensional measured data (image), θ_j is the d-dimension center of the cluster, and $d(x_i, \theta_j)$ is the distance between x_i and the center of the cluster j.

FCM allows more flexibility to copy with multiple cluster by using multiple fuzzy membership grades [8].

B. *GPU-Based FCM Clustering algorithm*

Fig. 1 shows the process diagram of the proposed algorithm. The kernel FCM part (gray box) is re-designed for execution on GPU. It includes following 10 steps:

- Image Conversion

  This step is to cover the original brain MRI to grayscale image. Usually the format of the convered grayscale image is 8-bit. The input image is transferred into a gray-scale image that all the vale of pixels are between 0 and 1

- Cluster Seting

  This step is to set the number of clusters. The cluster number c is determined in FCM. The proper is the key to obtain the good result of FCM algorithm. In general, c is unknown, and c = {1, 2, …, n}. For the segamentation of brain MRI, c is set to 2.

- FCM Initializing

  This step is to select the initial center of cluster. Typically, the performance of FCM depends on the initial cluster center and/or the initial membership matrix. if a initial cluster center that is close to the actual final cluster center, then FCM will converge in short.

- New Center Selection

  This step is to selected the new centers of the clusters. This step is implemented in GPU. Each thread is responsed to calculate a element of u. The pseudo code is shown in Fig. 2.

- Distance Calculation

  The distance between a data point and the cluster center in this step, d is calculated in this step. The thread i calculates $d(x_i, \theta_j)$, $j \in \{1, 2\}$. The pseudo code is shown in Fig. 3.

- Objective Function Calculation

  This stpe is to calculate the objective value by objective function, the distance matrix is recalculated on GPU in this step. The objective value J is calculated by CPU. The pseudo code is shown in Fig. 4.

- Membership Updating

  This stpe is to calculate the new membership matrix *u* for next iteration, and this step is performed on GPU. The pseudo code is shown in Fig. 5.

- Optimization Checking

  This step is to check whether the objective function is converged or not. If $|J_m-J_{m-1}| \leq \varepsilon$, then FCM stops. ε is a small positve constant.

- Image output

  The final value is calculated in the steps above. This value is utilized to verify the color of the pixels. If the value of a pixel is greater the final value of center, it is black, and vice versa. Final image is converted to binary image with black and white color of pixels.

```
/* mf matrix after exponential modification
   center matrix stores the center of each
   cluster;
   md is a distance matrix for storing mf *
   data;
   data is image data (each pixel between 0~1)
   U is the update matrix;
   Cluster_n is the number of centers in
   cluster;
   tid is thread id (GPU  thread) belong to
   img.x * img.y;
   data is the pixel matrix of the input image;
*/
tid = get_thread_id // get the thread id
for i := 1 to cluster_n do
        mf(tid,i)=pow(U(tid,i),exponent)
End

md(tid)=mf(tid)*data
for i := 1 to cluster_n do
     // fill the distance matrix
        center(tid,i)=md(tid,i)/column sum(mf)
```

Figure 2. The pseduo code of step of the selection of new center.

```
/* dist matrix stores the distance between each
   data point to center
*/
tid = get_thread_id // get the thread id
for i := 1 to cluster_n do
       dist(tid,i)=abs(center(tid)-data)
End
```

Figure 3. The pseduo code of step of calculation of distance between center and a data point.

```
/* obj_fnc is the sum of the dist matrix */
tid = get_thread_id // get the thread id
for i := 1 to cluster_n do
        dist(tid,i)= pow(dist(tid,i),exponent)
End
for i := 1 to cluster_n do
        dist(tid,i)= dist(tid,i)*mf(tid,i)
End
/* Obj_fnc is calculated by CPU*/
Obj_fnc=sum(dist)
```

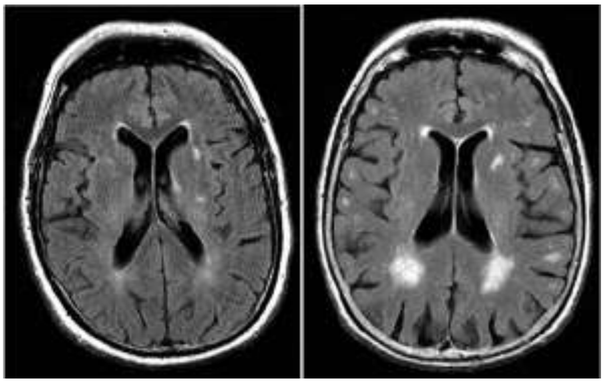
Figure 4. The pseduo code of step of objective value.

```
/* U_new is new U matrix used to replace U for
   the next iteration
*/
tid = get_thread_id // get the thread id
for i := 1 to cluster_n do
   tmp(tid,i)= pow(dist(tid,i),-2/(exponent-1))
End
//calculate new U, expo != 1
for i := 1 to cluster_n do
        U_new(tid,i)= tmp(tid,i)/column_sum(tmp)
End
```

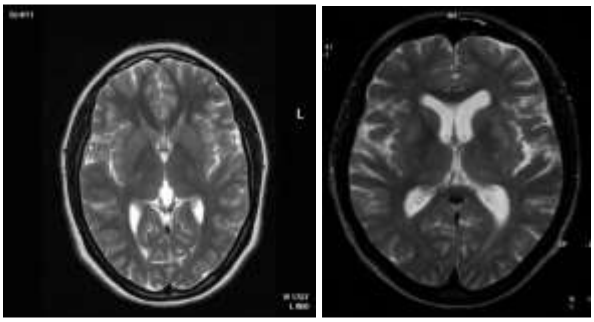
Figure 5. The pseduo code of step of new *u* membership matrix.

III. Experiment

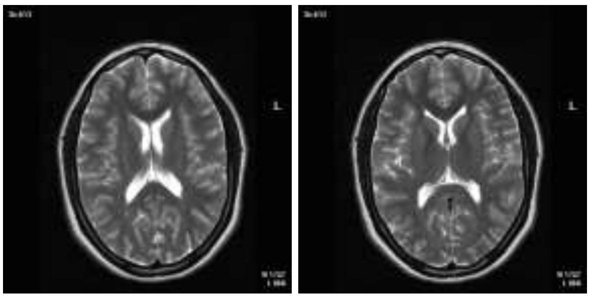
In this work, the proposed GPU based FCM algorithm is implemented on two different NVIDIA GPU devices, such as NVIDIA GTX 660Ti (Kepler) with 1344 CUDA cores and 6GB GDDR3 RAM, and NVIDIA GTX 980 (Maxwell) with 2048 CUDA cores and 7GB GDDR3 RAM. The hosts (CPU) are Intel Xeon E3-1230 v2 3.30GHz and Intel Xeon E3-1231 v3 3.40GHz with 64GB RAM, respectively. The CUDA version is 6.5. The input brain MRIs are download from the brain web datasets [19].



MRI1(a) MRI1(b)



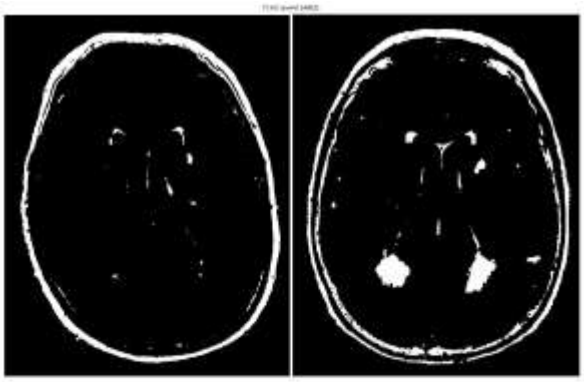
MRI2 MRI3



MRI5 MRI6

Figure 6. The original brain MR image.

Fig. 6 shows the input images and Fig. 7 shows the processed images. The experimental results shows that the proposed algorithm can obtain the same quality results as original FCM, and it can achieve significant speed up over the original FCM executed on very powerful CPU. The comparison of the performance between the proposed GPU based FCM algorithm and traditional FCM is show in Table 1. The Cost/Performance (CP) ratio shows that the proposed algorithm is valuable for analysis of MR brain image.



MRI1(a) MRI1(b)

MRI2 MRI3

MRI4 MRI5

Figure 7. The proceed brain MR image by GPU-based FCM algorighm.

TABLE I. COMPARISON OF PERFORMANCE

	CPU Intel E3-1230 V2	CPU Intel E3-1231 V3	GPU NVIDIA GTX 660Ti	GPU NVIDIA GTX 980
MRI1(1280*801)	17.57*	15.0	11.26	9.6
MRI2(512*512)	4.89	4.34	3.56	3.0
MRI3(1150*1280)	25.18	23.89	16.92	15.6
MRI4(512*512)	5.08	5.03	3.52	3.1
MRI5(512*512)	5.13	4.48	3.41	3.0

* Seconds

IV. Conclusion

For the segamentation of brain MRI, FCM is a commonly used and efficient algoritm. However, it is computational-consumming algorithm. In this paper, we present a Parallel FCM algorithm based on GPU to enhance the computation performance. The experimental results show that the proposed algorithm can achieve the better performance over the tranditional FCM executing on CPU. In the future, we will redesign other MRI processing methods on GPU to enhance the performance.

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About Author (s):

Che-Lun Hung received the M.S. and Ph.D. degrees in Department of Information Engineering and Computer Science from Feng Chia University and in Department of Computer Science from National Tsing Hua Univeristy in 2000 and 2010, respectively. In 2010, he joined the Department of Computer Science and Communication Engineering at Providence University as an assistant professor. He became associate professor at Providence University in 2013. His research interests are in the areas of Parallel and Distributed Computing, Proteomics, Genomics, Systems Biology, Next-Generation Sequencing and Computational Chemistry.

Yuan-Huai Wu received his B.S. degrees in Department of Computer Science and Communication Engineering. Now, he is M.S. student in Department of Computer Science and Information Engineering, Providence University, Taiwan.

Yaw-ling Lin was born on December 25, 1961 at Chang-Hua, Taiwan, ROC. He received the B.S. and M.S. degrees in Computer Science and Information Engineering from National Taiwan University in 1984 and 1986. He obtained the Ph.D. degree in computer science from Stony Brook University, USA, in 1993. He is currently a professor of the Department of Computer Science and Information Engineering, Providence University, Taichung, Taiwan. He was also the dean of the College of Computing and Informatics in Providence from 2004 to 2010. He was a visiting professor of Stony Brook University, USA in 2011. Dr. Lin was also provost of Providence University, Aug 2011 to Feburary 2013; he is currently dean of Research & Development Affairs and distinguished professor of Providence starting Feb 2013 to date. His current research interests include cloud computing, bioinformatics, computational geometry, and graph algorithms.

Yu-Chen Hu received his PhD. degree in computer science and information engineering from the Department of Computer Science and Information Engineering, National Chung Cheng University, Chiayi, Taiwan in 1999. Currently, Dr. Hu is a professor in the Department of Computer Science and Information Management, Providence University, Sha-Lu, Taiwan. He is a member of ACM and IEEE. He is also a member of Computer Vision, Graphics, and Image Processing (CVGIP), Chinese Cryptology and Information Security Association, and Phi Tau Phi Society of the Republic of China. His research interests include image and signal processing, data compression, information hiding, and data engineering.

Jieh-Shan George YEH received the bachelor's and master's degrees in Mathematics from National Taiwan University, Taiwan. He obtained his Ph.D. degree in Mathematics from the Ohio State University, USA. Dr. Yeh is an associate professor in the Department of Computer Science and Information Management, Providence University, Taiwan, since Sep. 2003. Prior to joining Providence University, Dr. Yeh held positions at Federated Department Stores and the Ohio State University. His research interests include, but not limited to, data mining, web mining, cloud computing, information security, XML, and database systems. He is a member of the IEEE and the ACM.

Chia-Chen Lin (M'08) received the B. S. degree in information management from the Tamkang University, Taipei, Taiwan, R.O.C., in 1992. She received the M.S. degree in information management and the Ph.D. degree in information management from Chiao Tung University, Hsinchu, Taiwan, in 1994 and 1998, respectively. She was a Visiting Associate Professor at Business School, University Illinois at Urbana Champain, during 2006 to 2007. She is currently a Professor in the Department of Computer and Information Management, Providence University, Sha-Lu, Taiwan. She serves editors in KSII Transactions on Internet and Information Systems, associate editors in Journal of Electronic Science and Technology, and Journal of Electronic Science and Technology. She already published 170 papers in the outstanding journals and conferences. Her research interests include image processing, image data hiding, mobile agent, and security.