# Volume Rendering and Lattice-Boltzmann Method

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**Résumé –** Une méthodologie de segmentation originale créée en couplant une technique de rendu volumique direct et une méthode Lattice Boltzmann 3D est proposée dans ce papier. La stratégie sous-jacente réside dans le clustering de séquences d'images médicales en prenant en considération non seulement les niveaux de gris des voxels, mais aussi la loi de comportement des tissus vivants rencontrés. A l'aune de cette nouvelle approche, une séquence d'anévrisme cérébral est traitée dans le but de segmenter la paroi de l'anévrisme et les vaisseaux sanguins parents.

**Abstract –** An original segmentation methodology created by coupling a direct volume rendering technique and a Lattice Boltzmann 3D method is proposed in this paper. The underlying strategy lies in the opportunity to cluster medical images sequences by taking into consideration not only the grey levels of voxels but also the constituve law of the encountered living tissues. Under this new concept, a brain aneurysm sequence is processed with the objective of segmenting the wall of the aneurysm and the parent blood vessels.

## 1 Introduction

In 3-D medical images, rendering volumetric data by using volume rendering method, which projects 3-D data to 2-D screen, is commonly becoming more popular. In the mean time, volume rendering is a powerful technique in medical visualization. The core of this technique is a transfer function (TF), which separates different tissues in medical images, by projecting the volumetric data into colors and opacity space. Classical transfer function algorithms [1] are time-consuming and difficult to fine tune or seldomly take potiental physical background into consideration for computing feature abstraction.

In order to solve this drawback, we choose the lattice Boltzmann method for optimizing the clustering of medical imaging taking into consideration the grey level of each voxel and the nature of the encountered tissues in the brain for example. The Lattice Boltzmann method is a low-order method which has the advantages of high computing efficiency and ease of parallelization and implementation for a large number of physical parameters [2].

In consequence, this paper first presents some recalls on the volume rendering techniques. Then in second, the Lattice Boltzman method (LBM) with its reaction-diffusion version is introduced. In a third part, the key issues of the K-means clustering [3] are synthetised. In a fourth part, the new LBM-based K-means transfer function method is designed (Fig.1). Finally, the proposed method is applied for studying a brain aneurysm. A preliminary result is shown demonstrating the relevance in the coupling of the transfer function of volume rendering technique with LBM.

## 2 Related work

The key element of volume rendering is the transfer function (TF) which defines different tissues in medical images. Based on mechanism design, design of transfer function methods can be divided into 2 main areas: image-centric and data-centric [4].

In image-centric TF algorithms, user interface allows to directively interact with rendering result to change the optical properties [5] [6], but intecations are time-consuming and difficult to fine tune.

In data-centric TF algorithms, data features are intro-

duced. This improves the feature-recognition ability of TF by extending or manipulating the feature space [7] such as visibility [4], information divergence [8], feature clustering [9]. However, potiental physical backgrounds are seldomly used for the feature abstraction.

The Lattice Boltzmann method has been applied in the last decade for image processing tasks such as smoothing [10] and segmentation [11]. Yet, to our knowledge, there exists no work coupling Lattice Boltzmann method (LBM) with volume rendering techniques.

## 3 Lattice Boltzmann Method

In recent years, the LBM has become a common tool for the numerical simulation of fluid flows [12]. Today the LBM is used for the simulation of complex systems and the evolution turns to specific domains such as image processing [10]. A key feature is the ability to link the interaction term in the model with a physical model. The numerical LBM scheme is developed by discretizing the continuum Boltzmann equation [2]. In this paper the most common lattice Boltzmann model is used. It is based on a linearized BGK collision term [2]:

$$f_i(\vec{r}+\Delta r, t+\Delta t) - f_i(\vec{r},t) = \Omega_i \qquad (1)$$

and with BGK expression of $\Omega_i$

$$f_i(\vec{r}+\Delta r, t+\Delta t) - f_i(\vec{r},t) = -\frac{1}{\tau}[f_i(\vec{r},t) - f_i^0(\vec{r},t)] \quad (2)$$

where the coefficient $\tau$ is the relaxation time, $f_i$ is a particles distribution and $f_i^0$ represents the Maxwell-Boltzmann equilibrium distribution function. The LBM is an iterative method performed using successive steps, the first one being the streaming of distribtion of particles $f_i$ and the second the collision phase of $f_i$ at each node of the lattice. Each iteration represents time $\Delta t$ and $f_i$ covers the distance $\Delta r$.

More precisely, the herein lattice Boltzmann method is used in a specific version where the collision fonction $\Omega_i$ is implemented as a reaction-diffusion equation [13]:

$$f_i(\vec{r}+\Delta\vec{r}, t+\Delta t) = D(f_i, f_i^0, \tau, g_i) + R(T_i, \rho), \quad (3)$$

where $D$ is a diffusion term and $R$ a reaction term; $\rho$ represents the density of the fluid with $\rho = \sum_i f_i$ on each node, $T_i$ are thresholds and $g_i$ is the probality of transmission of $f_i$ from a node to another. $g_i$ depends on the encountered medium. Briefly, the reaction-diffusion LBM solves a reaction-diffusion equation at the microscopique scale. In the context of TF, the successive iterations of the LBM lead to find the best configuration for volume rendering. In particular, 2D Intensity Gradient Magnitude (IGM) histogram [4] must reveal several singularities allowing to cluster more easily the considered images.

## 4 K-means clustering

Clustering is one of the most classical methods of data mining, which is used to discover unknown classification in a dataset. It offers great performance for idenitifying intra-connection between objects [14] for example.

The K-means clustering is a hard-clustering algorithm, which is a representative of the prototype-based objective function clustering methods. K-means clustering is utilized for importance curves clustering [15]. In the proposed method, the aim of using K-means clustering method is to compute the thresholds for clustering tissues in volumic dataset. The K-means equation is as follows,

$$\arg\min_{C} \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2, T_i = m_i \qquad (4)$$

where $p$ is one voxel of volume dataset; $m_i$ is the average value of class $C_i$. ($p$ and $m_i$ are both multidimensional variables). $T_i$ are the thresholds which are used as parameters of LBM segmentation.

## 5 Matching LBM and TF

Fig.1 exibits a synoptic of our LBM-based K-means transfer function design method for medical visualization. Two major algorithms are included in our transfer function algorithm namely LBM and K-means clustering method.

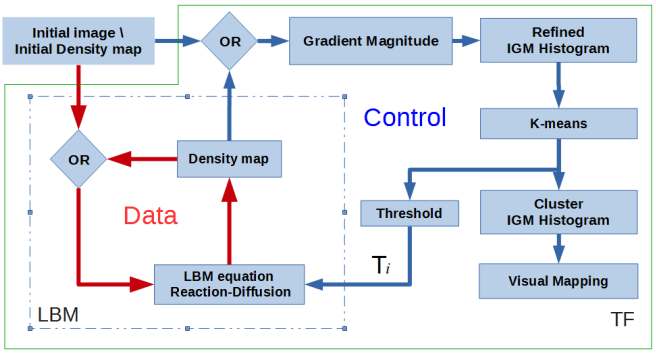


FIG. 1: Matching LBM and TF

Initialy with the volume dataset and then with the density map produced at each LBM iteration, K-means clus-

tering algorithm clusters the classes in the volume, and then computes optimal thresholds with the objective to differentiate living tissues. These thresholds are adressed to the LBM block (Fig.1) which is implemented for solving a reaction-diffusion equation at a microscopic scale. This innovative TF continuously iterates and modifies the dataset. With the refined dataset, the 2D IGM histogram is computed. Then the IGM is clustered into several regions, each region coresponding to a specific tissue, by K-means algorithm. Subsequently, the refined IGM and volumetric dataset are applied to render the volume and generate the visualization result.

## 6 Application on aneurysms images

A brain aneurysm is a vascular disorder as a small hernia due to a weakening in the wall of a blood vessel which mainly occurs at the bifurcation of vessels. An aneurysm may rupture leading sometimes to a subarachnoid hemorrhage with the consequence of high mortality rates.

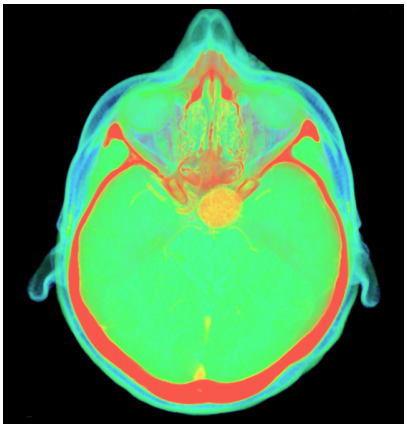

FIG. 2: Volume data composed of 80 slices

Medical imaging bring an essential contribution to the detection and analysis of brain aneurysm of patients. In the light of this, computed tomography angiography (CTA) has a crucial role in providing diagnosis for the care and follow-up of patients with brain aneurysms. In this paper the studied aneurysm has been recorded on 464 slices with a 3D CTA scan (Fig. 2) and is issued from the data base of the Thrombus project (FP7-269966).

Many projects work on the analysis and treatment of brain aneurysms and a specific need is required to be able to estimate the evolving of an aneurysms after an endovascular treatment. In this framework, image processing techniques such as volume rendering bring essential means of patient follow-up.

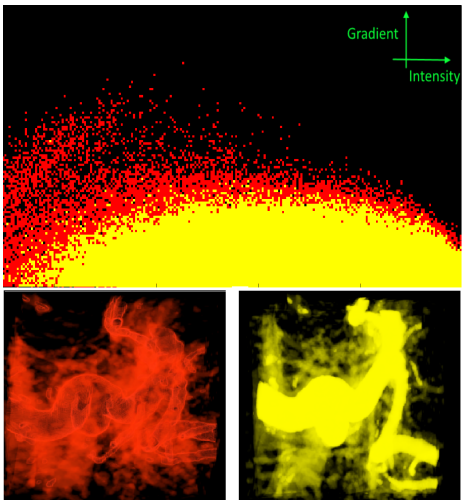


FIG. 3: Clustering result of histogram without LBM. Top: IGM histogram. Bottom: parent vessel (red) and blood (yellow).

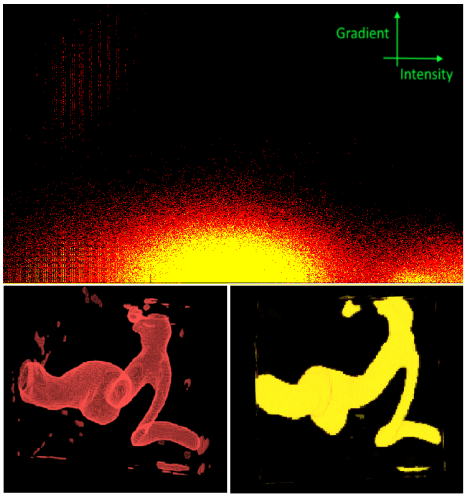


FIG. 4: Clustering result of histogram with LBM. Top: IGM histogram. Bottom: parent vessel (red) and blood (yellow).

We applied our transfer function method on brain aneurysm sequence. The result shows that proposed TF was comparable with K-means based TF. The Fig.3 (top) displays the IGM histogram calculation results of K-means clustering algorithm (without LBM). It can be seen that K-means algorithm clusters the IGM into 2 parts, red part is the vessel boundary, the yellow part is the blood within intracranial aneuryms and parent blood vessel. Fig.4 (top) displays the IGM histogram of the pro-

posed method with LBM. Comparing with the results in Fig.4 (bottom), it can be seen that dataset is less sensitive to noise than without LBM. The volume rendering results are more distinctive and clearer than Fig.3 (bottom). By using LBM, the underlying objective is to reveal arches within 2D IGM histogram in order to detect the different living tissues in medical images [6]. Using one threshold $T$ issued from K-means, the solving of the reaction-diffusion equation via LBM leads to reveal several arches. In this example the yellow arches correspond to the blood and the red arches correspond to the parent vessel.

## 7 Conclusion and Forthcoming

This paper presents a new algorithm in which solving a reaction-diffusion equation at a mesoscopic scale via the LBM method leads to the optimization of a consistent volume rendering method in regard to the complexity of the cerebral medical images with cerebral aneuryms. The promizing potential of the proposed method lies in the using of several thresholds updated along the successive iterations of the LBM code leading to the concept of dynamic clustering of medical images sequences.

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## References

[1] P. Ljung *et al.*, "State of the art in transfer functions for direct volume rendering," *Computer Graphics Forum*, vol. 35, no. 3, pp. 669–691, 2016.

[2] D. A. Wolf-Gladrow, *Lattice-gas cellular automata and lattice Boltzmann models: An Introduction*. Springer Science & Business Media, 2000, no. 1725.

[3] R. Maciejewski *et al.*, "Abstracting attribute space for transfer function exploration and design," *IEEE Transactions on visualization and Computer Graphics*, vol. 19, no. 1, pp. 94–107, 2013.

[4] L. Cai *et al.*, "Automatic transfer function design for medical visualization using visibility distributions and projective color mapping," *Computerized Medical Imaging and Graphics*, vol. 37, no. 78, pp. 450 – 458, 2013.

[5] H. Guo, N. Mao, and X. Yuan, "Wysiwyg (what you see is what you get) volume visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 12, pp. 2106–2114, Dec 2011.

[6] Y. Wu and H. Qu, "Interactive transfer function design based on editing direct volume rendered images," *IEEE Transactions on Visualization and Computer Graphics*, vol. 13, no. 5, 2007.

[7] R. Maciejewski, I. Woo, W. Chen, and D. Ebert, "Structuring feature space: A non-parametric method for volumetric transfer function generation," *IEEE Transactions on Visualization and Computer Graphics*, vol. 15, no. 6, pp. 1473–1480, 2009.

[8] M. Ruiz *et al.*, "Automatic transfer functions based on informational divergence," *IEEE Transactions on Visualization and Computer Graphics*, vol. 17, no. 12, pp. 1932–1941, 2011.

[9] T. Zhang *et al.*, "A clustering-based automatic transfer function design for volume visualization," *Mathematical Problems in Engineering*, vol. 2016, 2016.

[10] Y. Chen, Z. Yan, and Y. Qian, "An anisotropic diffusion model for medical image smoothing by using the Lattice Boltzmann method," in *7th Asian-Pacific conference on medical and biological engineering*. Springer, 2008, pp. 255–259.

[11] S. Chen and G. D. Doolen, "Lattice boltzmann method for fluid flows," *Annual review of fluid mechanics*, vol. 30, no. 1, pp. 329–364, 1998.

[12] S. Succi, *The lattice Boltzmann equation for fluid dynamics and beyond*, ser. Numerical mathematics and scientific computation. Oxford : New York: Clarendon Press ; Oxford University Press, 2001.

[13] Y. Chen, "Lattice boltzmann method based medical image segmentation," in *Image and Signal Processing, 2009. CISP'09. 2nd International Congress on*. IEEE, 2009, pp. 1–5.

[14] S. Lloyd, "Least squares quantization in pcm," *IEEE Trans. Inf. Theor.*, vol. 28, no. 2, pp. 129–137, Sep. 2006.

[15] C. Wang, H. Yu, and K.-L. Ma, "Importance-driven time-varying data visualization," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 6, pp. 1547–1554, 2008.