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Efficient cellular automaton segmentation supervised by pyramid on medical volumetric data and real time implementation with graphics processing unit

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ABSTRACT

In surgery simulation, the extracted tissue data can be operated repeatedly in a Virtual-reality (VR) system which provides a good alternative to classical training method. Fully automated segmentation techniques cannot guarantee the efficiency and precision in general case. This paper describes a user interactive segmentation method: given a labeled 2D image plane in Multi-Planar Reformation (MPR), the rest tissues are segmented automatically by a cellular automaton in multi-scale domain. Labels image generated in higher level Gaussian pyramid can be extended to lower level ones according to selected resolution. An edge indicator function is also set to avoid over-segmentation in Laplacian pyramid. The evolution can be observed and guided with volume rendering results. The proposed method shows the merits of higher precision, real time response in GPU framework and few interactions are required.

1. Introduction

Surgical operations need to be performed with a high grade of efficiency, security and care. But the absence of learning and training of surgical operations under realistic conditions is the major problem. Virtual-reality (VR) based surgery simulation and Computer Assisted Diagnosis (CAD) opens up new fields in medical training and education, which allow unlimited repeatable operations with objective assessment. In a computer-assisted system, the surgeon is provided with a realistic environment with haptic input devices and virtual surgical interactions with static or deformable organ models.

In simulation of soft biological tissue deformation Bruyns et al. (2002) explain how to use a very simple framework to build a generalized cutting scheme. This method allows for any arbitrary cut to be made within a virtual object, and can simulate cutting surface, layered surface or tetrahedral objects using a virtual scalpel, scissors, or loop cautery tool.

A realistic multimodal surgery simulation technique has been presented in Lim, Hu, Chang, & Tardella (2006), which implements a mesh free numerical scheme for realistic soft tissue deformation and cutting simulation. With the development of GPU technology, parallel computing becomes more and more popular. Abd-Elmoniem, Youssef, and Kadah (2008) present a fast graphics processing unit (GPU) solution scheme for high-speed nonlinear finite element analysis for surgical simulation, this computing model provides a low cost means for performing realistic biomechanical simulations at, or nearly at real-time speed.

The level of realism of a VR surgical training system depends mostly on the quality of the tissue extracted, elastodynamic tissue behavior and response efficiency. In these surgery simulation applications, tissue segmentation is often an essential part to study the tissue anatomical information. Fully automated segmentation techniques are being constantly improved, however, no automated image analysis technique can be applied fully autonomously with guaranteed results in general case. So semi-automatic segmentation techniques that allow user interactions may be reasonable in clinical systems.

Several powerful techniques of interactive segmentation have been proposed recently. Mortensen and Barrett (1999, 1998) proposed the methods called intelligent scissors, which compute boundary or region information for image segmentation. Region growing method has been presented in Hojjatoleslami and Kittler (1998), this method uses two novel discontinuity measures, average contrast and peripheral contrast, to control the growing process. A new region growing method (Dehmeshki, Amin, Valdivieso, & Ye, 2008) has been proposed for lung nodule analysis, which uses a combination of fuzzy connectivity, distance and intensity information as the growing mechanism and peripheral contrast as the halting criterion. An interactive version of region growing can be found in Hadwiger et al. (2008). Hao and Shen (1991) present a fast level-set framework based on the watershed algorithm (Vincent, Soille, & Wang, 2007) for the segmentation of complicated structures from a volumetric data set, this method gives fast and accurate excellent result.

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Based on graph cut technique, Boykov and Jolly (2001), Boykov, Veksler, and Zabih (2001), Boykov and Kolmogorov (2004) treat the segmentation task as an energy minimization problem and proposed maxflow/min-cut algorithm. The interactive graph cuts can be applied to N-dimensional (N-D) images and multi-labeling tasks.

A cellular automaton framework was also proposed in Vezhnevets and Konouchine (2005), which can perform multi-label segmentation in N-D images, this process allows construction of new families of algorithms with specific properties, but traditional method has the shortcoming of low efficiency and complex interaction on volumetric data. A GPU-based method (Kauffmann & Piché, 2009) performs organ segmentation in N-D medical image datasets by computation of weighted distances using the Ford–Bellman algorithm (FBA). The GPU implementation of FBA gives an alternative and optimized solution to other graph-based segmentation techniques. But the segmented result is sensitive to the time of iterations and the algorithm cannot fully converge in some cases.

This paper proposes an efficient 3D cellular automaton (CA) method for solving medical tissues extraction task. The task is to assign labels to all slices automatically, preferably achieving the result expecting to get. User only needs to specify certain 2D image pixels as seeds in the Multi-Planar Reformation.

The segmentation can be accelerated by pyramid algorithm according to the selected resolution. Segmented result in higher level pyramid can be extended to lower level as seeds to decrease computing time largely. This process allows to correct and guidance of labeling in the areas where the segmentation is difficult to compute, and does not require additional input when the computing is reliably. In order to apply in clinical routine, the same algorithm has been performed in GPU framework with a real time response.

The rest of this paper is organized as follows. In Section 2, the theoretical background and implementation of 3D CA method are discussed. Section 3 describes the improvement of CA segmentation supervised by Gaussian pyramid in detail, boundary controlling method in Laplacian pyramid is also presented. In Section 4, the experimental results of a selected MRI series are listed. The quality and speed of the proposed technique are discussed. Section 5 concludes the paper.

2. 3D cellular automaton segmentation

2.1. 3D CA evolution rule

Cellular automaton (CA) was originally conceived by Ulam and von Neumann in the 1940s to provide a formal framework for investigating the behavior of complex, extended systems. CAs are dynamical systems in which space and time are discrete.

The game of life (bacteria struggle and grow, Grow Cut named for this reason) is only one type of CA which has three fundamental properties (Ermentrout & Edelstein-Keshet, 1993): parallelism, locality and homogeneity. These properties mean that cells update is performed independently of each other and the CA system is parallel when its constituents evolve simultaneously and independently. The new state of a cell only depends on its and the neighborhood state, the evolution rule is universal in the whole space. Moreover, it is possible to build any type of automata by playing on structural and functional rules.

A cellular automaton can be described as a triplet $A = (S, N, \delta)$, where S is a non-empty state set, each cells can be in one of a finite number of k possible states. N is the neighborhood system, the state of a cell is determined by the previous states of a surrounding neighborhood of cells. δ is the evolution rule (transition function), the state of a cell is updated synchronously in discrete time steps according to this local, identical interaction rule.

N is commonly selected as von Neumann neighborhood or Moore neighborhood of p in 3D version (6 or 26 neighbors).

A 3D CA method can be described as:

Algorithm 1. 3D CA Evolution Rule

While(! Converged)
{
  $\forall p \in P$
    $l_p^{t+1} = l_p^t; \theta_p^{t+1} = \theta_p^t;$
    Converged = true;
  For $\forall q \in N(p)$
      Attack Rule (p, q)
  End for
}

where P is the set of cells inside user input, which can be changed in the next step. t is the time of iteration. g is a monotonous decreasing function to guaranteed the iteration to converge. l_p^t is the current cell label (state set), θ_p^t is the strength of the current cell. g and θ_p are bounded to $[0, 1]$. The evolution rule of this paper is selected as "the first attack success, the next iteration", that is: if any neighbor attacks current cell successfully, the program should jump to the next iteration.

Algorithm 2. 3D CA Attack Rule (p, q)

If $g(|q - p|) \cdot \theta_q^t > \theta_p^t$
  $l_p^{t+1} = l_q^t; \theta_p^{t+1} = g(|q - p|) \cdot \theta_q^t;$
  Converged = false;
  Break;
End if

2.2. Labels in MPR plane

According to traditional 2D CA method, the straightforward 3D version needs laying seeds in each slice, but in medical applications, the manual work is hard and not reasonable. CA method can be treated as growth and struggle for domination of 3D tissues data. The labeled object start to spread (grow) from the seed pixels and try to occupy all the volume. In MPR plane, user only needs laying the seeds in 2D images, the rest tissues can be segmented automatically and this operator may satisfy most expert clinician's habits. (Different operations in MPR plane are presented in Fig. 1.)

We select g as a simple function:

$$g(x) = 1 - \frac{|x|}{\max(C)} \tag{1}$$

where C is the gray level of image and x is the difference of p and q. The cell status will be updated if any neighbor attacks successfully in the first time.

3. Segmentation supervised by pyramid

3.1. Labels in gaussian pyramids

It is a heavy burden for computing on the whole volumetric data set. In CA evolution, the relationship of time cost and data magnitude are almost direct ratio, so we can use Gaussian and Laplacian pyramid method (Burt & Adelson, 1983) to produce additional layer data (see Fig. 2), which only are used as the guidance of