MEDICAL IMAGE SEGMENTATION TECHNIQUES FOR VIRTUAL ENDOSCOPY

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Abstract: Virtual endoscopes give internal views of the human body without penetrating it, based on a set of parallel cross-sections produced with any computer tomography method. This paper presents some ideas concerning the design and implementation of a software system, which acts like a virtual endoscope. It takes into account the general requirements of the system, gives a solution that uses a multi-step algorithm, and finally shows the resulting 3-D images. Most of the algorithmic steps have several possible solutions. Our virtual endoscope establishes 3-D internal views based on sets of 2-D slices, which originate from magnetic resonance imaging devices. The chain of the applied image processing methods consists of the followings: (1) Adequate pre-filtering to eliminate the low-frequency intensity non-uniformity (INU) artifact, and high-frequency "salt-and-pepper" disturbances; (2) Segmentation of the stack of MRI slices using an enhanced fuzzy C-means algorithm; (3) 3-D surface recovery algorithm based on level set methods and fast marching methods; (4) Interactive visualization using modern computer graphics technologies, providing the possibility to measure distances, areas, volumes as well. The quality of service provided by the chosen method mainly depends on the resolution of input images.

Keywords: image segmentation, fuzzy logic, image reconstruction, medical applications, computer tomography.

1. INTRODUCTION

Traditional endoscopes penetrate the human body in order to provide high-resolution internal views of cavities and hollow organs. Even though such examinations are mostly considered non-invasive, the procedure causes pain, or at least discomforts the patient, who consequently needs some kind of sedation or anesthesia.

Magnetic resonance imaging (MRI) is a non-invasive diagnostic tool that views the internal anatomy of the human body in 2-D cross sections called slices. A virtual endoscope establishes 3-D internal views based on these sets of 2-D slices, using modern image processing techniques and computer graphics as well. Besides the comfort provided, another relevant advantage is the fact, that it can create images of any body part, not only the hollow ones.

This paper presents a new concept of the virtual endoscope, developed in the Biomedical Engineering Laboratory at TU Budapest. During the development process, MRI brain images are used for testing the methods, but the algorithm is capable to process other kinds of medical images, too. Consequently the virtual endoscope will have several medical applications.

In order to create a virtual endoscope based on magnetic resonance images, the following image processing tasks need to be performed (see Fig. 1.):

(1) filtering the initial MR images; (2) segmentation of the 2-D slices, classification of their pixels into a set of clusters, whose cardinality is set according to the requirements of medical scientists; (3) a shape recovery algorithm is applied to reconstruct the 3-D image of the object; (4) visualization via modern computer graphics tools.

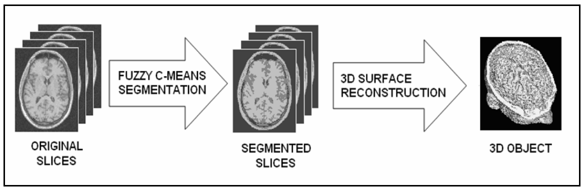

Fig. 1. Main steps of image processing

2. METHODS

2.1. Magnetic resonance imaging

Magnetic resonance imaging provides parallel cross sections of the investigated part of the human body. This study is based on a set of 171 slices of the human brain, each of them having 256×256 pixels, thus having a resolution around 1 pixel per mm.

2.2. Filtering methods

Magnetic resonance images tend to have two main noise types, having several possible sources for each.

High frequency noise manifests as isolated white and black pixels scattered over the whole set of cross sections. They are generally referred to as salt-and-pepper noise. Several implementations use low-pass averaging filtering techniques in order to eliminate these noises (Ahmed *et al*, 2002). This technique really works fast, it considerably reduces the noise level, but also erects an obstacle to the segmentation as it hides the sharp edges behind an introduced blur. In spite of its slightly higher computational needs, the median filter is a better choice, because it completely eliminates the isolated noisy pixels unless more then 5% of the image pixels are contaminated.

Low frequency noises are caused by the unwanted presence of an intensive bias field that turns some parts of the MR images darker than others. Efficient adaptive methods have been introduced in order to estimate the distribution of the bias field (Pham, and Prince, 1999; Liew, and Yan, 2003).

2.3. Segmentation of MRI brain slices using a modified fuzzy C-means (FCM) algorithm

The standard FCM algorithm presented by Bezdek and Pal (1991), groups the values x_k , $k = 1..N$ into a number of c clusters, using the objective function

$$J_B = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ik}^{p} (x_k - v_i)^2 , \qquad (1)$$

where v_i represents the prototype value of the i th cluster, u_{ik} represents the fuzzy membership of the k th voxel with respect to cluster i , and p is a weighting exponent. By definition, for any k we have: $\sum_{i=1}^{c} u_{ik} = 1$. To minimize the objective function, it is necessary to assign high membership values to those voxels, whose intensities are situated close to the prototype values of their particular clusters.

Ahmed *et al* (2002) proposed a modification to the original objective function by introducing a term that allows the labeling of a voxel to be influenced by the labels in its immediate neighborhood. This effect acts as a regularizer, and biases the solution toward piecewise-homogeneous labeling. The modified objective function is given by:

$$J_A = \sum_{i=1}^{c} \sum_{k=1}^{N} \left[u_{ik}^{p} (x_k - v_i)^2 + \frac{\alpha}{N_k} \sum_{r=1}^{N_k} u_{ik}^{p} (x_{k,r} - v_i)^2 \right] \quad (2)$$

where $x_{k,r}$ represents the neighbor voxels of x_k , and N_k stands for the number of voxels in the neighborhood of the k th voxel. The parameter α controls the intensity of the neighboring effect. This combination of filtering and segmentation made it possible to estimate the contaminating bias field, but considerable reduced its performance against the clock.

In the followings, we will introduce some modifications to this algorithm, in order to reduce its computational needs. It is obvious, that a set of MR brain image slices contains approximately 10^7 voxels. The intensity of the voxels is generally encoded with 8 bit resolution, that is, there are only 256 possible levels of intensity for each voxel. If we perform a median filtering preceding the fuzzy classification, then the formula of this latter does not have to treat each voxel separately. We only need to know, how many voxels of each existing gray level are present in the whole stack of filtered slices. This information is reflected by the histogram. This technique is not applicable using the formulation of Ahmed *et al*, (2002).

So the proposed enhanced fuzzy C-means algorithm consists of the following steps:

Step 1. First we apply a median filtering to each pixel, using a 3×3 neighborhood. This means, that the nine intensity values situated in the vicinity of the given pixel are sorted increasingly, and the filtered value will be the one situated in the middle. Let us