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Automatic Extraction and Analysis of Ventricular Myocardium in CT& MRI Images using ASM&AAM Models

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ABSTRACT

Accurate Ventricular segmentation on computed tomography (CT) images is a challenging task because of inter and intra-patient variations in Ventricular shapes, similar intensity with its nearby organs. We proposed a Ventricular segmentation method based on region growing approach. First of all, basic theory of region growing approach is introduced. Secondly, a pre-processing method using anisotropic filter and Gaussian function is employed to form Heart likelihood images for the following segmentation. Thirdly, an improved slice-to-slice region growing method combined with centroid detection and intensity distribution analysis is proposed. Finally, the superior Ventricular region is extracted by applying the morphologic operation. Experiments on a variety of CT images show the effectiveness and efficiency of the proposed method. There are several reasons make the accurate segmentation in Ventricular difficult. Firstly, the image is always very noisy and the partial volume effect causes the Ventricular boundary ambiguous. Secondly, the overlaps result in gaps and cavities. Thirdly, there are large variations in human Ventricular geometric properties like Ventricular size and shape between patients, this can be worse if the patient has ventricular operations before due to alcoholic cirrhosis or Ventricular tumor

KEY WORDS —. Myocardium segmentation, left right ventricle, shape segmentation, contour evolution.

I. INTRODUCTION

Abdominal CT images have been widely studied in recent years. Some of the current interests are the automatic diagnosis of Heart pathologies and three-dimension rendering. The first and fundamental step in all these studies is the automatic Heart segmentation, which is still a complex problem. There are several reasons make the accurate segmentation in Heart difficult. Firstly, the image is always very noisy and the partial volume effect causes the Heart boundary ambiguous. Secondly, the overlaps result in gaps and cavities. Thirdly, there are large variations in human Heart geometric properties like Heart size and shape between patients, this can be worse if the patient has Heart operations before due to alcoholic cirrhosis or Heart tumor. Besides, even the same organ in the same patient may exhibit different intensity values. Finally, the nearby organs such as right kidney, stomach, spleen and abdominal wall, have similar intensity values with Heart, which makes it harder to extract Heart only. A few literatures and algorithms about this research topic with high automation have been proposed. They can be categorized into four groups: Intensity based approaches: The most common procedure is to apply threshold operators to discard regions with intensity outside the Heart range. But the thresholds affect the result directly and hard to determine. Prior knowledge based approaches: The topological, distance and orientation relations are the most common used prior knowledge. They always combine with other approaches. Statistical based approaches: A statistical model discrimination of the Heart is established from quantities of data sets, and then the model is used to pre-process the images and obtained Heart likelihood images for further process.

Active contour models: It is the most popular used method in Heart segmentation, including fast marching level set method snake model. But they are useful only when a good initial estimate is present. Most of the models compound the computing time and get unsatisfied results for the slices with fuzzy Heart boundary. We present a segmentation method based on improved region growing. The paper is organized as follows. In the region growing method is introduced, the principle methods and theories in our Heart segmentation process are described. The experimental results are presented.

II. DIFFERENT METHODS

Clustering methods:

1. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center
2. Re-compute the cluster centers by averaging all of the pixels in the cluster
3. Repeat steps 2 and 3 until convergence is attained (e.g. no pixels change clusters).

In statistics and machine learning, the k-means algorithm is clustering algorithm to partition n objects into k clusters, where k < n. It is similar to the expectation-maximizatio algorithm for mixtures of Gaussian in that they both attempt to find the centers of natural clusters in the data. The model requires that the object attributes correspond to elements of a vector space. The objective it tries to achieve is to minimize total intra-cluster variance, or, the squared error function. The k-means clustering was invented in 1956. The most common form of the algorithm uses an iterative refinement heuristic known as Lloyd's algorithm Lloyd's algorithm starts by partitioning the input points into k initial sets, either at random or using some heuristic data. It then calculates the mean point, or centroid, of each set. It constructs a new partition by associating each point with the closest centroid. Then the centroids are recalculated for the new clusters, and algorithm repeated by alternate application of these two steps until convergence, which is obtained when the points no longer switch clusters (or alternatively centroids are no longer changed). Lloyd's algorithm and k-means are often used synonymously, but in reality Lloyd's algorithm is a heuristic for solving the k-means problem, as with certain combinations of starting points and centroids, Lloyd's algorithm can in fact converge to the wrong answer. Other variations exist, but Lloyd's algorithm has remained popular, because it converges extremely quickly in practice. In terms of performance the algorithm is not guaranteed to return a global optimum. The quality of the final solution depends largely on the initial set of clusters, and may, in practice, be much poorer than the global optimum. Since the algorithm is extremely fast, a common method is to run the algorithm several times and return the best clustering found. A drawback of the k-means algorithm is that the number of clusters k is an input parameter. An inappropriate choice of k may yield poor results. The algorithm also assumes that the variance is an appropriate measure of cluster scatter.

Compression-based methods:

Compression based methods postulate that the optimal segmentation is the one that minimizes, over all possible segmentations, the coding length of the data. The connection between these two concepts is that segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. The method describes each segment by its texture and boundary shape. Each of these components is modeled by a probability distribution function and its coding length is computed as follows:

1. The boundary encoding leverages the fact that regions in natural images tend to have a smooth contour.
2. This prior is used by huffman coding to encode the difference chain code of the contours in an image. Thus, the smoother a boundary is, the shorter coding length it attains.
3. Texture is encoded by lossy compression in a way similar to minimum description length (MDL) principle, but here the length of the data given the model is approximated by the number of samples times the entropy of the model. The texture in each region is modeled by a multivariate normal distribution whose entropy has closed form expression. An interesting property of this model is that the estimated entropy bounds the true entropy of the data from above. This is because among all distributions with a given mean and covariance, normal distribution has the largest entropy. Thus, the true coding length cannot be more than what the algorithm tries to minimize.

Histogram-based methods:

Histogram based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels. In this technique, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image. Color or intensity can be used as the measure A refinement of this technique is to recursively apply the histogram-seeking method to clusters in the image in order to divide them into smaller clusters. This is repeated with smaller and smaller clusters until no more clusters are formed.

Histogram-based approaches can also be quickly adapted to occur over multiple frames, while maintaining their single pass efficiency. The histogram can be done in multiple fashions when multiple frames are considered. The same approach that is taken with one frame can be applied to multiple, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram can also be applied on a per pixel basis where the information result is used to determine the most frequent color for the pixel location. This approach segments based on active objects and a static environment, resulting in a different type of segmentation useful in Video tracking.

Edge detection:

Edge detection is a well-developed field on its own within image processing. Region boundaries and edges are closely related, since there is often a sharp adjustment in intensity at the region boundaries. Edge detection techniques have therefore been used as the base of another segmentation technique. The edges identified by edge detection are often disconnected. To segment an object from an image however, one needs closed region boundaries.

Region growing methods:

The first region growing method was the seeded region growing method. This method takes a set of seeds as input along with the image. The seeds mark each of the objects to be segmented. The regions are iteratively grown by comparing all unallocated neighboring pixels to the regions. The difference between a pixel's intensity value and the region's mean, δ, is used as a measure of similarity. The pixel with the smallest difference measured this way is allocated to the respective region. This process continues until all pixels are allocated to a region.

Seeded region growing requires seeds as additional input. The segmentation results are dependent on the choice of seeds. Noise in the image can cause the seeds to be poorly placed. Unseeded region growing is a modified algorithm that doesn't require explicit seeds. It starts off with a single region A_1 – the pixel chosen here does not significantly influence final segmentation. At each iteration it considers the neighbouring pixels in the same way as seeded region growing. It differs from seeded region growing in that if the minimum δ is less than a predefined threshold T then it is added to the respective region A_j. If not, then the pixel is considered significantly different from all current regions A_i and a new region A_{n+1} is created with this pixel.

Partial Differential Equation based methods:

Using a Partial Differential Equation (PDE) based method and solving the PDE equation by a numerical scheme, one can segment the image.

Level Set methods:

Curve propagation is a popular technique in image analysis for object extraction, object tracking, stereo reconstruction, etc. The central idea behind such an approach is to evolve a curve towards the lowest potential of a cost function, where its definition reflects the task to be addressed and imposes certain smoothness constraints. Lagrangian techniques are based on parameterizing the contour according to some sampling strategy and then evolve each element according to image and internal terms. While such a technique can be very efficient, it suffers from various limitations like deciding on the sampling strategy, estimating the internal geometric properties of the curve, changing its topology, addressing problems in higher dimensions, etc. In each case, a partial differential equation (PDE) called the level set equation is solved by finite differences.

The level set method was initially proposed to track moving interfaces by Osher and Sethian in 1988 and has spread across various imaging domains in the late nineties. It can be used to efficiently address the problem of curve/surface/etc. propagation in an implicit manner. The central idea is to represent the evolving contour using a signed function, where its zero level corresponds to the actual contour. Then, according to the motion equation of the contour, one can easily derive a similar flow for the implicit surface that when applied to the zero-level will reflect the propagation of the contour. The level set method encodes numerous advantages: it is implicit, parameter free, provides a direct way to estimate the geometric properties of the evolving structure, can change the topology and is intrinsic. Furthermore, they can be used to define an optimization framework as proposed by Zhao, Merriman and Osher in 1996. Therefore, one can conclude that it is a very convenient framework to address numerous applications of computer vision and medical image analysis. Furthermore, research into various level set data structures has led to very efficient implementations of this method.

Graph partitioning methods:

Graph partitioning methods can effectively be used for image segmentation. In these methods, the image is modeled as a weighted, undirected graph . Usually a pixel or a group of pixels are associated with nodes and edge weights define the (dis)similarity between the neighborhood pixels. The graph (image) is then partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes (pixels) output from these algorithms are considered an object segment in the image. Some popular algorithms of this category are normalized cuts, random walker, minimum cut, isoperimetric partitioning and minimum spanning tree-based segmentation.

Watershed transformation:

The watershed transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common local intensity minimum (LIM). Pixels draining to a common minimum form a catch basin, which represents a segment.

III. METHODOLOGY OF THE SYSTEMS

Image Pre-processing:

Anisotropic filter is a diffusion process, which can be used as a preprocessing step to enhance morphological definition of the input image by sharpening discontinuities, and remove noise in homogeneous regions while preserving object boundaries and fine details.

Anisotropic filtering

An illustration of texture filtering methods showing trilinear MIP map texture on the left and enhanced with anisotropic texture filtering on the right. In 3D computer graphics, anisotropic filtering (abbreviated AF) is a method of enhancing the image quality of textures on surfaces that are at oblique viewing angles with respect to the camera where the projection of the texture (not the polygon or other primitive on which it is rendered) appears to be non-orthogonal (thus the origin of the word: "an" for not, "iso" for same, and "tropic" from tropism, relating to direction; anisotropic filtering does not filter the same in every direction). Like bilinear and trilinear filtering it eliminates aliasing effects, but improves on these other techniques by reducing blur and preserving detail at extreme viewing angles. Anisotropic filtering is relatively intensive (primarily memory bandwidth and to some degree computationally, though the standard space-time tradeoff rules apply) and only became a standard feature of consumer-level graphics cards in the late 1990s. Anisotropic filtering is now common in modern graphics hardware and is enabled either by users through driver settings or by graphics applications and video games through programming interfaces. .

Performance and optimization

The sample count required can make anisotropic filtering extremely bandwidth-intensive. Multiple textures are common; each texture sample could be four bytes or more, so each anisotropic pixel could require 512 bytes from texture memory, although texture compression is commonly used to reduce this. A display can easily contain over a million pixels, and the desired frame rate tends to be as high as 30–60 frames per second or more, so the texture memory bandwidth can get very high (tens to hundreds of gigabytes per second) very quickly. Fortunately, several factors mitigate in favor of better performance. The probes themselves share cached texture samples, both inter- and intra-pixel. Even with 16-tap anisotropic filtering, not all 16 taps are always needed, because only distant highly oblique pixel fill tends to be highly anisotropic, and such fill tends to cover small regions of the screen, and finally magnification texture filters require no anisotropic filtering.

Gaussian function

Gaussian functions are widely used in statistics where they describe the normal distributions, in signal processing where they serve to define Gaussian filters, in image processing where two-dimensional Gaussians are used for Gaussian blurs, and in mathematics where they are used to solve heat equations and diffusion equations and to define the Weierstrass transform.

Gaussian functions centered at zero minimize the Fourier uncertainty principle.

The product of two Gaussian functions is a Gaussian, and the convolution of two Gaussian functions is again a Gaussian,

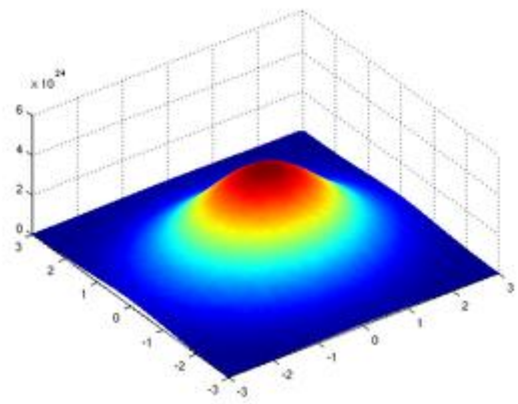
with $c = \sqrt{c_1^2 + c_2^2}$.

Taking the Fourier transform of a Gaussian function with parameters a, b = 0 and c yields another Gaussian function, with parameters ac, b = 0 and 1/c. So in particular the Gaussian functions with b = 0 and c = 1 are kept fixed by the Fourier transform (they are eigenfunctions of the Fourier transform with eigenvalue 1).

The fact that the Gaussian function is an Eigen function of the Continuous Fourier transform allows to derive the following interesting identity from the Poisson summation formula:

$$\sum_{k\in\mathbb{Z}} \exp\left(-\pi \cdot \left(\frac{k}{c}\right)^2\right) = c \cdot \sum_{k\in\mathbb{Z}} \exp(-\pi \cdot (kc)^2)$$

Two-dimensional Gaussian function



Gaussian curve with a 2-dimensional domain

In two-dimensions, one can vary a Gaussian in more parameters: not only may one vary a single width, but one may vary two separate widths, and rotate: one thus obtains both circular Gaussians and elliptical Gaussians, accordingly as the level sets are circles or ellipses.

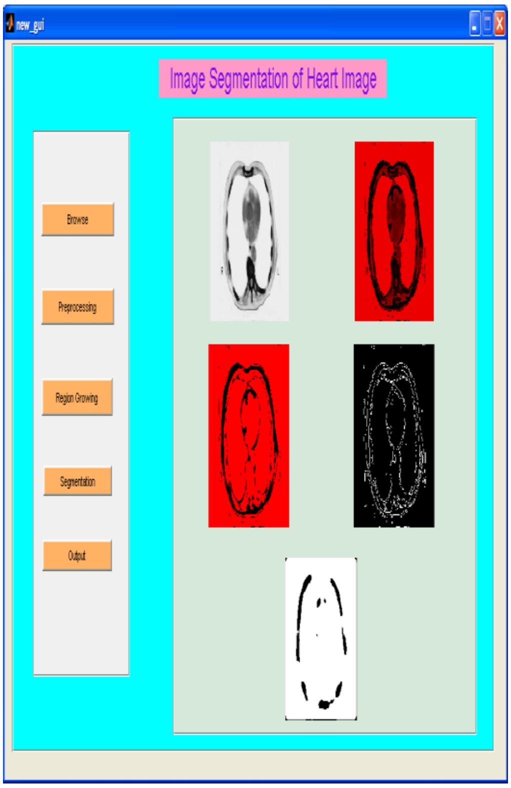
Applications

Some of the practical applications of image segmentation are:

1. Medical Imaging
    - Locate tumors and other pathologies
    - Measure tissue volumes
    - Computer-guided surgery
    - Diagnosis
    - Treatment planning
    - Study of anatomical structure

2. Locate objects in satellite images (roads, forests, etc.)
3. Face recognition
4. Fingerprint recognition
5. Traffic control systems
6. Brake light detection

IV. OUTPUT IMAGES



V. CONCLUSION

In this paper, we propose an effective method for automatic Heart segmentation from CT images based on region growing approach. The method takes the image sequence continuity on topology and intensity into account, combines region growing method with centroid detection and intensity analysis. Besides, morphologic operation is applied to guarantee a fast and accurate Heart region. The experimental results of the Heart segmentation demonstrate the efficiency and effectiveness of the proposed method. We can conclude that our method gives out efficient and effective performance for Heart segmentation on CT&MRI images

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