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Segmentation of Thoracic & Abdominal Anatomy Using Multi-Atlas Approach

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***Abstract*- Atlas-based segmentation methods using single templates have emerged as a practical approach to automate the process for brain or head and neck anatomy, but pose significant challenges in regions where large inter-patient variations are present. It shows that significant changes are needed to auto segment thoracic and abdominal datasets by combining multi-atlas deformable registration with a level set-based local search. Segmentation is hierarchical, with a first stage detecting bulk organ location, and a second step adapting the segmentation to fine details present in the patient scan. The first stage is based on warping multiple pre-segmented templates to the new patient anatomy using a multimodality deformable registration algorithm able to cope with changes in scanning conditions and artifacts**

Index terms- Atlas segmentation; image registration; level sets, Multi Atlas Fusion

1. INTRODUCTION

Atlas segmentation has emerged recently as an alternative to increase accuracy, compared to standard segmentation techniques, by incorporating both spatial information and voxel classification schemes into the algorithm's design. In a fundamental paradigm shift, the atlas-based approach relies on the existence of a map between a reference image volume (called an atlas) in which structures of interest have been segmented and validated by an expert, and the image to be segmented, called the subject.

A point-to-point map is generated by deformable image registration transfers structures from the atlas onto the subject dataset. In clinical evaluation studies, this approach has been shown to be superior to classical methods on structures that do not have a clear border, as their location is deduced from the atlas. The key element in this approach, however, is the accuracy of the deformable registration algorithm that is used to identify corresponding organs .Image segmentation is a concept that describes removal of or extraction of part of the image that contains meaningful data in comparison with the whole image. The main objective of segmentation is region partitioning that are different on visual basis or property wise and/or characteristically meaningful. Accurate segmentation of human anatomy is critically fundamental as well as most time consuming task in medical planning. This is required mainly for medical diagnosis, qualitative analysis & treatment planning.

II. HISTORICAL INTRODUCTION OF SEGMENTATION

A. Background

Segmentation is one of the fundamental problems in biomedical image analysis and refers to the process of tagging image pixels or voxels with biologically meaningful labels, such as anatomical structures and tissue types. Depending on the application, these labels might constitute a handful of, possibly disjoint, regions of interest (ROIs) and a "background", which may be referred to as the parts of the image one might ignore in subsequent analysis. Alternatively, the labels might densely cover a substantial portion or whole image, which is sometimes referred to as "parcellation."

The traditional approach to segment a given biomedical image involves the manual delineation (sometimes referred to as "annotation") of the ROIs by a trained expert. This practice, however, can be painstakingly slow, prone to error, hard to reproduce, expensive, and unscalable. Furthermore, the quality of the results will depend on the performance of the expert. Some segmentation algorithms, such as those that assign voxels to tissue types might not require the availability of training data in the form of manually delineated images (commonly called "atlases"). However, the class of methods we consider for this survey will depend on such training data and thus can be viewed as supervised learning algorithms.

B. Atlas-based Segmentation

The typical atlas-based segmentation procedure can be summarized in two- steps. First, a dense deformation field that maps each pixel in the atlas image onto the target image is computed using appropriate registration methods. Depending on the nature of the images and the target structures to be segmented, the registration methods use various types of forces, like pixel-based forces, region-based forces, statistical features, and geometrical features. Second, the deformation field computed in the preceding step is applied to the labels of the already segmented structures of interest in the atlas image, and this provides the segmentations of the corresponding structures in the target image.

C. Multi Atlas Fusion

There are broadly two classes of approaches for fusing the information coming from multiple atlases. The first class of approaches tries to combine the information from several atlases by creating an average atlas or a probabilistic atlas, and then register that to the target image. The second class of approaches registers each atlas independently to the target image, and then merges the segmentation results obtained from each individual atlas, based on certain optimal criteria. It has been noticed in many recent works that the second class of approaches is more robust to anatomical variations, and it can also profit more from the information coming from multiple atlases than the first class of approaches. In this thesis, we hence focus on this second class of approaches.

III. SYSTEM ARCHITECTURE

The architecture of the system mainly consists of five components. Steps or the overview proposed system is as shown in following figure.

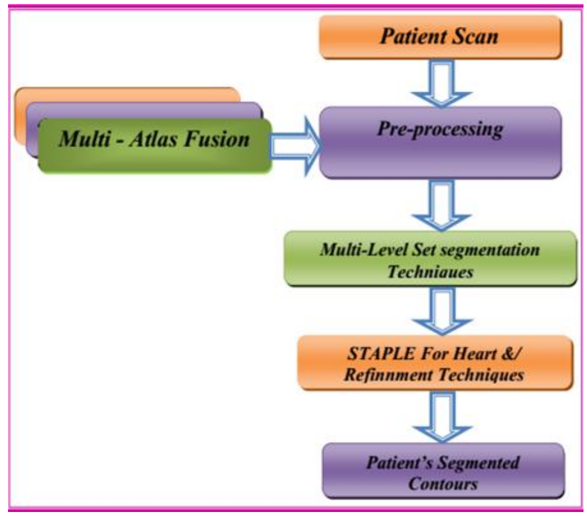

Fig. 1 Methodology of the Proposed work

A. Patient Scan

The standard dataset consists values that are extensively drawn from more than 150 manually delineated abdominal atlases. For the purpose of this study, total nine different CT scan images of patients are used, taken from clinical net source. This proposed approach, mainly focus on three substructures of abdomen. They are mainly liver, aorta & stomach. Thus dataset include these three substructure's labels.

B. Multi –Atlas Fusion

Some of those methods are listed below:
1) Majority Voting:

"Majority voting (MV)" is the simplest fusion. Let *N* be the number of atlases. Let *V* be the number of voxels in the target image. Let *Yp* denote the label assigned to the *p*th voxel in the output image. Let *Xj* represent the *j*th input labeled image (corresponding to the *j*th atlas) after applying the transformation that maps the *j*th atlas to the output intensity image. Let *Xj* be the label assigned to the *p*th voxel of *Xj*. Let *D* be the total number unique label values (including the background label) in the input labeled images. Let *L* = {*l*1, · · · , *lD*} represent the set of all possible labels to be assigned. The original formulation of majority voting is a maximization problem of the following form.

$$Yp = \max[\sum_{j=1}^{N} \delta\left(X_p^j, l_1\right), \left(X_p^j, l_2\right), \left(X_p^j, l_3\right), \ldots \sum_{j=1}^{N} \delta\left(X_p^j, l_D\right)]$$

…. 1

Where δ is Kronecker delta function

2) Global Weighted Voting:
Unlike majority voting, “Global Weighted Voting” (GWV) attaches a weight to each atlas while counting its vote. The weight for each atlas is determined globally; the more the similarity, the higher the weight, and vice versa. The original formulation of GWV is as follows.

$$Yp = \max[\sum_{j=1}^{N} \omega^{j}\delta(X_{p}^{j}, l_{1}), \sum_{j=1}^{N} \omega^{j}\delta(X_{p}^{j}, l_{2}), .. \sum_{j=1}^{N} \delta(X_{p}^{j}, l_{D})] \quad ...2$$

Where ω^j is the global weight assigned to the decisions made by the j^{th} atlas.

3) Local Weighted Voting:
LWV method computes the similarity measure locally for each voxel, within a specified neighborhood. In other words, LWV is similar to GWV except that, not a single global weight is assigned to the entire atlas; rather, for each voxel, an individual weight is assigned based on the local similarity. Let ω^{j}_{p} represent the weight assigned to the j^{th} atlas, at p^{th} voxel. Then the original formulation of LWV can be expressed as follows;

$$Yp = \max[\sum_{j=1}^{N} \omega_{p}^{j}\delta(X_{p}^{j}, l_{1}), (X_{p}^{j}, l_{2}), ... \sum_{j=1}^{N} \omega_{p}^{j}\delta(X_{p}^{j}, l_{D})] .. \mathbf{3}$$

IV. STAPLE ALGORITHM THEORY

STAPLE algorithm is one of the widely used methods to measure simultaneous truth & performance level estimation. This algorithm calculates a probabilities map of organ shape & location. In the proposed used this computation of conditional probability is done in a suitable manner in accordance with our atlas approach selection. In STAPLE algorithm, voxels present in the organ shape is assigned with higher probability and vice-a-versa. As STAPLE is a maximum posteriory-approximation, so proposed approach is used this concept as a representation of the level set.

V. RESULTS AND DISCUSSION

In this section, number of abdominal CT images (samples / patient scan images) of different persons are tested using combined approach of multi-atlas fusion and multi-level set segmentation technique. Multi-atlas fusion segmentation is applied for the nine different CT scan images from patient‟s database.

Testing of algorithm:
The described algorithm is applied for abdominal image 1 from the database. Our standard patient‟s database for comparing standard atlas values is taken from available clinical net source.

Fig. 2 Original image 1 of abdominal anatomy from patient’s database

Segmentation of large organ tissue liver , soft tissue organ stomach and low contrast tissue aorta have been performed step by step and / or in a one run go. Following figure 6.2 shows the complete segmentation of liver, stomach and aorta region from the given „ original image 1‟.

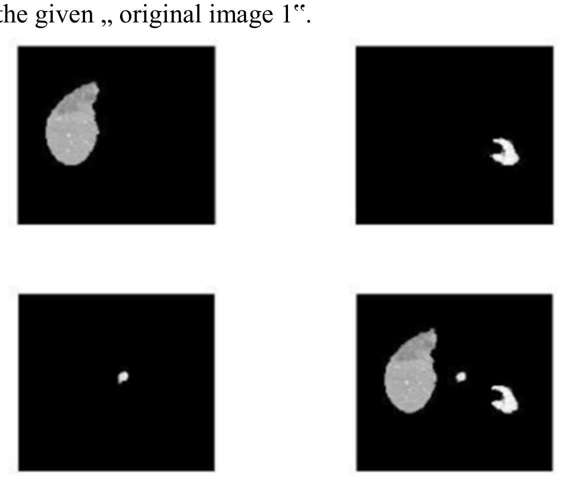

Fig. 3. Overall segmented image showing segmentation of liver, stomach and aorta along with combination of three together.

VI. CONCLUSION

The proposed system will test modern segmentation techniques coupled with an atlas-fusion segmentation approach for high resolution segmentation of clinical

CT images which are acquired for the purpose of radiotherapy planning. This approach will produce an accurate segmentation results even within the context of the variability in image shape & quality encountered in the course of standard image acquisition in the clinic. These methods have the potential to significantly improve the efficiency & accuracy of radiation treatment planning. It has been recorded minimal execution or performance time with better quality segmentation.

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