A Survey on Atlas-Based Segmentation of Medical Imaging

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Abstract : **Image segmentation is very important and essential step in many imaging applications. It takes an important role in medical field also. In medical image processing and analysis, so many tasks like visualization of Region of Interest (ROI), object representation description, delineation of objects anatomical structure, feature extraction, etc. which need the accurate segmentation of image. Accurate spine segmentation allows for improved identification and quantitative characterization of abnormalities of the vertebra, such as vertebral fractures. Many image segmentation methods for medical image analysis have been presented in this paper. In image processing, image segmentation is the process of partitioning a digital image into multiple regions where each of the pixels in a region is similar to some characteristics or computed properties, such as color, intensity, or texture.**

Keywords: Vertebral fractures, vertebrae segmentation, atlas-based segmentation.

I. INTRODUCTION

Image segmentation is the area with widest application in image processing, especially in the field of medical imaging. In case of medical image segmentation the aim is to study anatomical structure, locate tumor, lesion and other abnormalities, and measure tissue volume to measure the growth of tumor[7,8]. Using the process of image segmentation the image can be divided into different region. From that segmented image the desired objects can be separated from the background, measured, counted or in other means quantified. In case of medical applications, manually segmenting a vertebra is time consuming and subjective. Therefore fully automated or semi-automated methods are required for most clinical applications with increasing the accuracy, consistency, and reproducibility of the analysis, in the meantime allowing clinicians to focus more on their other work. The result taken from image segmentation process is the main parameter for further image processing research; this result will also determine the quality of further image processing process. Image segmentation algorithms play a vital role in medical applications, i.e., diagnosis of diseases related to brain, heart, knee, spine, pelvis, prostate and blood vessel, and pathology localization. Therefore, Image segmentation is still a very hot area of research for image processing field [9]. Just to show the clinicians' increasing amount of work in the field of cardiovascular disease [10] will point out some statistical details. This shows that automatic image segmentation and analysis could have a large impact in this field. However, issues like low spatial (or temporal) resolution, poor contrast, ill-defined boundary or other noise place additional demands on segmentation. Therefore it is not true to believe that segmentation can be achieved using pixel's intensities information only. One possible solution for this is use of a prior knowledge. One way to do this is to integrate the knowledge within the segmentation process in the form of the model which will be used as a sample for segmentation of desired object. The vertebral column, also known as spine, is a bony skeletal structure which forms the central weight-bearing axis of the human upper body. Multiple medical imaging modalities, such as radio-graphs, CT, MRI and PET, are used to evaluate spine anatomy and diagnose spinal pathology. Using current generation of scanning techniques, CT is the most spatially accurate modality to assess the morphology of the vertebra. Spine segmentation is a fundamental step for most subsequent spine image analysis and modeling tasks [6].

Vertebra segmentation is challenging due to the complex shape and variable architecture of vertebrae across the population, similar structures in surrounding area, pathology, and the spatial inter-relation between vertebrae and ribs. In recent years, a number of spine segmentation algorithms for computed tomography (CT) images have been proposed. In early work, segmentation of vertebrae was achieved by unsupervised image processing approaches such as adaptive thresholding, region growing and boundary adjustment, or region-based segmentation such as watershed and graph-cut [13,14,15]. Level set methods had also been adopted since they can handle the complex topological merging and breaking in the vertebrae [16,17,18]. In region-based techniques, [19] devised statistical and heuristic methods to detect key features for vertebral body segmentation as well as [20] presented a technique based on watershed algorithm, directed graph search, curved reformation and vertebra template to automatically partition and segment the spinal column. In [21] applied mathematical morphology and watershed for the labeling and segmentation of vertebrae. More recent methods were mostly based on geometric models, statistical anatomical models, or probabilistic atlas. The models incorporated prior knowledge about the vertebra anatomy. The models were fit to the target image data either through forces derived from the image or via a deformable registration framework [22,32]. These models are often sensitive to the initial pose estimation, which are done either manually or automatically. In [33] applied the atlas approach in the segmentation of osteoporotic vertebrae with compression fractures. Author in [34] constructed a deformable integral spine model encoded as a necklace model by learning the appearance of vertebrae boundaries from a set of training images. More recently, machine learning techniques had been applied in the segmentation of vertebrae [35][36].

II. LITRATURE SURVEY

In many segmentation applications grey level information is not sufficient to distinguish between various structures. Different anatomical structures often have similar grey level values and only differ from one another with respect to their locations. In these cases spatial information needs to be incorporated in the segmentation process. Model based methods such as, active contours, statistical shape models and atlas based approach are example of this category. Atlas-guided approaches are a powerful tool for medical image segmentation when a standard atlas or template is available[7]. The atlas is generated by compiling information on the anatomy that requires segmentation and this atlas is then used as a reference image for segmenting new images.

A. Vertebrae position and rotation estimation

In [4], propose a fully automatic method, for the assessment of spinal deformity in idiopathic scoliosis, measuring the axial vertebral rotation in CT data. Scoliosis is traditionally defined as an abnormal lateral curvature of the spine, observed in the coronal plane. For assessing the severity of the deformity, an anterior-posterior radiography is used where the Cobb angle is measured [37]. A scoliotic deformity is always 3D, because it also includes an axial rotation of the vertebrae and not only a displacement and rotation in the coronal plane. This axial rotation limits the use of the Cobb angle because it only measures on the projection of the curve onto a 2D plane. Also, more recent research has shown that the axial vertebral rotation (AVR) is more relevant for both understanding the underlying causes of scoliosis, but also for deciding upon treatment and monitoring the progression of the disease [38-40]. Hence, there is a need for other measurement methods that can better assess the full 3D deformity of the spine in scoliosis, i.e. measure the axial vertebral rotation. There are number of different methods for measuring AVR have been proposed, where most of them are manual methods like Cobb, Stokes and Aaro-Dahlborn [41][42]. Manual methods suffer from being time-consuming, complex and related with a relatively high intra- and inter-observer variability. Hence, there is an interest in developing more automatic methods. The methods in [43-45] are limited in measurement accuracy, since they only use 2D axial images when estimating the rotation, whereas the method by [12] utilizes the full 3D information available. However, all four methods require more or less manual interaction, and therefore intra- and inter-observer variability is still likely to occur. The purpose of [4] is to propose a method that overcomes some of the limitations of the previously presented computerized methods. The method in [4] is fully automatic, measures the axial vertebral rotation in 3D based on CT data and is sufficiently computationally efficient to be integrated into a clinical workflow. This method is not only limited to measure the AVR but also able to estimate the full pose of each vertebra.

B. Atlas-based Registration

Image registration is a well known concept, frequently applied in a number of different areas, for instance geophysics, robotics and medicine [2]. Registration aims at transforming a model or a template image to align it with a target image so that their corresponding parts are spatially aligned. If the transformation is linear, such as rotation, scaling and translation, the registration is called rigid registration. If the transformation is non-linear, such as shape change and warping, the registration is called non-rigid registration. A frequently applied categorization of different image registration algorithms is to classify them as either parametric or non-parametric [8]. Parametric methods refer to methods, where a parameterization has been performed to reduce the number of degrees of freedom in the estimated displacement field. Non-parametric methods, on the other hand, independently estimate a displacement vector for each voxel. The purpose of [2] is to present a CUDA based GPU implementation of a registration algorithm, known as the Morphon, and to investigate whether the achieved speedup is sufficient for integrating non-rigid registration into time-constrained clinical workflows. The Morphon differs from more commonly used registration algorithms, since it is phase-based and not intensity-based. [3] Given the approximate pose of each vertebra, the spine model is then registered to the spine of the patient, vertebra by vertebra, first with an affine registration followed by a deformable registration. The vertebrae were registered in the order L5 to T1. The reason for applying this sequential registration process is two-fold. Firstly, it provides a more robust registration than using only a deformable registration, since the applied regularization in deformable registration has a bias to penalize affine transformations unless employing curvature regularization as proposed by Fischer and Modersitzki (2003). Secondly, the registration of sub-volumes has the advantage of allowing the use of graphics processing units (GPUs) for improved computational performance. The GPU is typically not applicable to use when working with large data volumes, which is due to the current limitations regarding the amount of memory available on the GPUs, causing many GPU-based implementations of registration algorithms to be limited to data sets of the size 256*256*256 or smaller, (Han et al. 2009, Guet al. 2010). In this work, we have decided to employ image registration based upon phase difference. This is due to the fact that the local phase of a signal is invariant to signal energy and provides sub-pixel accuracy by varying smoothly. Especially the first reason, invariance to signal energy, is relevant in the case of model-based registration, since the signal intensities of the spine model and the patient data are not likely to match. Hence, the uses of simple similarity measures, e.g. the sum of squared intensity differences, are unlikely to perform well in this scenario. In addition, the use of phase-difference is more attractive then using more elaborate measures, e.g. mutual information, since they come with an additional computational cost. The local phase of an image can be estimated using oriented quadrature filters (Granlund and Knutsson 1995). The initial affine registration is done employing the algorithm described by Hemmendor_ et al. (2002) and implemented on the GPU using the compute unified device architecture (CUDA) by Eklund et al. (2010). The final deformable registration uses the registration algorithm known as the Morphon. This method was introduced by Knutsson and Andersson (2005) and implemented in CUDA by Forsberg et al. (2011). The following subsections provide a brief introduction to phase-based image registration (affine and deformable).

C. Label Fusion

Label fusion, i.e., the step of combining propagated atlas labels, is one of the core components of MAS. The earliest and simplest fusion methods are best atlas selection (Rohl_ng et al., 2004) and majority voting (Heckemann et al., 2006; Klein et al., 2005; Rohl_ng et al., 2004). In best atlas selection, a single atlas is utilized, which is usually chosen based on examining the match between the registered atlas and novel image intensities, for example, as captured by the registration cost function (e.g., sum of squared differences, normalized cross-correlation, or mutual information). Relying on a single atlas disregards potentially useful information in all other atlases. Majority voting chooses the most frequent label at each location, therefore using information from all atlases at all locations; however, it has the drawback that it ignores image intensity information[46].

III. PROPOSED SYSTEM

The method used in this work for vertebra segmentation is inspired and to a large extent based upon the work presented in [3, 4], although some components have been changed and others have been added. This has been done to improve the performance but also since the work in [3, 4] was targeted at scoliotic spines. The most notable differences are the use of multiple gray-level atlases instead of a single binary model in the registration step, and the subsequent use of label fusion. The employed method consists of a preprocessing step, where an approximate position and rotation (pose) of each vertebra in the spines of both the target data set and the atlases are estimated. The preprocessing is followed by a registration step, where each atlas is registered to the target data set. The labels of the registered atlases are merged to a single label volume using label fusion to form the segmentation of the spine vertebrae in the target data set.

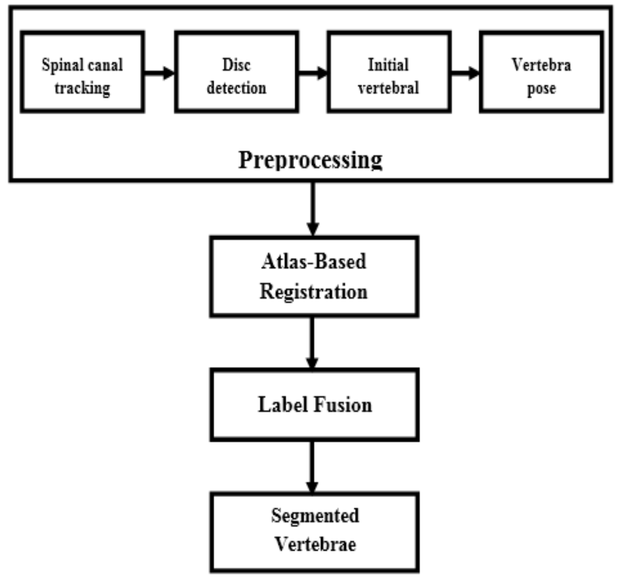

Fig. 1 Proposed System

IV. CONCLUSION

The aim of this study is to develop segmentation method for medical imaging applications. In particular, the main concept involves the segmentation of thoracic and lumbar vertebrae in the spine[1]. The spinal column forms an important support structure in the human body and mainly consists of the vertebral bones. As such, the vertebrae form an important part of the diagnosis, treatment planning and the understanding of various conditions affecting the spine. Thus, an accurate segmentation of the vertebrae is of relevance in several applications. The segmentation of the vertebrae is challenging, mainly due to shape variation and neighboring structures of similar intensity (e.g. other vertebrae, other bones and/or other tissues). The employed method is based upon atlas-based segmentation, where a number of atlases of the spine are registered to the target data set. The labels of the deformed atlases are combined using label fusion to obtain the final segmentation of the target data set. The proposed method is automated segmentation method so because of this clinicians can handle more number of patients.

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