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Boundary Refinement Technique Using Laplace Transform for CT Spine Image Segmentation

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Abstract: Image segmentation is designated as partitioning an image into a predetermined number of non-overlapping regions. In medical applications, it is a primary processing most systems that support medical diagnosis, surgical planning and treatments. In general, this procedure is done manually by clinicians, which may be monotonous and time-consuming. To overcome the problem, a number of interactive segmentation methods have been proposed in the literature. But each method has some drawbacks, so we proposed a method which uses prior knowledge of anatomy. In this paper, we propose method to perform segmentation for CT images thoracic and lumbar vertebrae by applying Multiatlas-based segmentation with Laplace Transform. A total 12 CT spine images which consist of thoracic and lumbar vertebrae are used for evaluation. The proposed method is fully automatic as well as efficient. Evaluation of method gives average dice coefficient of 0.90.

Keywords: CT, Image segmentation, Label Fusion, Laplace Transform, Multiatlas, Pre-processing, spine, vertebrae.

I. INTRODUCTION

This Truthful analysis of the spine and spinal structures from medical images is an essential tool in many medical applications of spinal imaging. Study of the detailed shape of individual vertebrae can significantly assist early diagnosis, surgical planning and follow-up opinion of several spinal pathologies, such as spinal deformities, degenerative disorders, tumours and trauma. Also segmentation of individual vertebrae by computer-assisted methods may provide additional support to identification and handling of vertebral fractures. Robust and efficient segmentation algorithms on medical images are a challenging research topic of increasing interest especially from last few years. In case of medical applications, manually segmenting a vertebra is time consuming and tiresome. Therefore semi-automated or fully-automated methods are required for most medical applications which increase the correctness, stability, and reproducibility of the analysis, so that it will allow clinicians to focus more on their other work. The output taken from image segmentation process is the principal parameter for the quality of advance image processing process. Image segmentation algorithms play a fundamental role in medical applications, i.e., diagnosis of diseases related to heart, spine, pelvis, prostate, brain, knee and blood vessel. Therefore, Image segmentation is still a very interesting topic of research for the field of image processing [1].

Atlas is well-defined as the grouping of an intensity image (template) and its segmented image (the atlas labels). After registering the atlas template & the target image, the atlas labels are spread to the target image. This process is termed as atlas-based segmentation. In current years, researchers have investigated different registration techniques to align atlases to query subjects and also strategies for atlas construction. The segmentation of the vertebrae is not easy, mainly due to the complex shape, variable architecture of vertebrae across the population and neighbouring anatomy of similar intensity (e.g. other vertebrae, other bones and/or other tissues) [2].A number of segmentation algorithms for computed tomography (CT) images of spine have been proposed. Segmentation of vertebrae was accomplished by unsubstantiated image processing approaches such as adaptive thresholding, region growing and boundary adjustment, or region-based segmentation such as watershed and graph-cut[3]. In this paper, we proposed an improved atlas-base segmentations technique for segmentation of thoracic and lumbar vertebrae in the spine. The paper organization is as follows. Section 2 shows the prior work done in this field. The steps of the algorithm and the flow diagram is explained in section 3 and section 4 gives experimental results showing results of tested mages. Finally, Section 5 shows the conclusion part.

II. Literature Survey

Medical imaging is the technique of producing visual representations of the interior of a body for clinical examination and medical intervention, as well as visual representation of the function of some tissues or organs (physiology). Medical imaging looks for internal structures which are hidden by the skin and bones, as well as to detect and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. In an ultimate world we would be able to detect, treat and cure patients without causing any harmful side effects. With the help of medical imaging, it enabled doctors to see inside of a patient without having to cut them open. It also helps us to learn more about human behaviors and neurobiology.

The vertebral column, also known as spine, is a bony skeleton which forms the central weight-bearing axis of the human upper body. Just to show the clinicians' rising load of work in the field of cardiovascular disease [4] will point out some statistical details. This illustrates that automatic image segmentation and analysis could have a large effect on this field. Also there are some issues like poor contrast, low spatial (or temporal) resolution, unclear boundary or other noise place extra demands on segmentation. So, it is not always true to believe that segmentation can be achieved only using intensities information of pixels. One feasible solution for this is use of a prior knowledge. One approach to do this is to incorporate the knowledge within the segmentation process in the form of the model which will be used as a template for segmentation of required object. Numerous medical imaging modalities, such as radiographs, CT, MRI and PET, are used to assess spine anatomy and detect spinal pathology. Using modern generation of scanning techniques, CT is the most spatially accurate modality to assess the morphology of the vertebra [5].

In many segmentation applications grey level information is not sufficient to differentiate between various structures. Different anatomical structures often have same grey level values and only vary from one another with respect to their locations. In these cases spatial information needs to be integrated in the segmentation process. There are different model based methods such as, active contour; 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 on hand[6]. The atlas is created by assembling information on the anatomy that requires segmentation and this template is then used as a reference image for segmenting new images.

A. Vertebrae position and rotation estimation

For evaluating the severity of deformity, anterior-posterior radiography is used where the Cobb angle is measured [7]. This axial rotation restricts the use of the Cobb angle because it only measures on the projection of the curve onto a 2D plane. Also, more recent research proposed by Skalli, Kuklo and Heidari 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. Thus, there is a need for other measurement methods that can better assess the full 3D deformity of the spine in scoliosis. Number of different methods for measuring AVR has been proposed, where most of them are manual methods like Cobb, Stokes and Aaro-Dahlborn. Hence, there is an interest in developing more automatic methods. The methods proposed by Kouwenhoven, Zhang are limited in measurement accuracy, since they only use 2D axial images when estimating the rotation, whereas the method by [8] utilizes the full 3D information available. However, all four methods require more or less manual interaction, and hence intra- and inter-observer variability is still possible to occur. The purpose of [9] is to present a method that beats some of the drawbacks of the previously proposed computerized methods. That method is fully automatic, measures the axial vertebral rotation in 3D based on CT data and is satisfactorily computationally capable to be integrated into a clinical workflow as well as this method not only restricted to measure the AVR but also able to compute the full pose of each vertebra.

B. Atlas-based Registration

Image registration is a famous concept, commonly applied in a number of different areas, for example geophysics, robotics and medicine. Registration aims at converting a model image to align it onto a target image so that their subsequent parts are spatially aligned. If the transformation is linear, such as rotation, scaling and translation, the registration is known as rigid transformation. If the transformation is non-linear, such as shape change and warping, the registration is called non-rigid transformation. In [10] 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 GPU is typically not appropriate to use when there is large data volumes, this is because of the current limitations related to the amount of memory available on the GPUs. So they proposed to make use of image registration based upon phase difference. The reason invariance to signal energy is applicable in the case of model-based registration, as the signal intensities of the spine model and the patient data are not likely to match. Thus, 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 effective than using more complicated measures, e.g. mutual information, as they come with an additional computational cost. The final deformable registration uses the registration algorithm known as the Morphon. This method was introduced by Knutsson and Andersson and implemented in CUDA by Forsberg. The purpose of [11] is to present a CUDA based GPU implementation of a registration algorithm, known as the Morphon, and to examine whether the achieved speedup is adequate for incorporating non-rigid registration into time-constrained clinical workflows.

C. Label Fusion

Label fusion is the concept of merging propagated atlas labels, is one of the core components of MAS. The most primitive and easiest fusion methods are best atlas selection and majority voting. In best atlas selection, a single atlas is employed, which is generally chosen based on examining the match between the atlas which is registered and inputted image intensities, for example, as detained by the registration cost function (e.g., mutual information, normalized cross-correlation, or sum of squared differences). Depending on a single atlas ignore potentially useful information in all other atlases. On the other side, Majority voting chooses the most repeated label at each location, therefore using information from all atlases at all locations.

III. Proposed System

The proposed system architecture is shown in fig. 1.The proposed system consists of four steps as shown above figure. These steps are as follows:

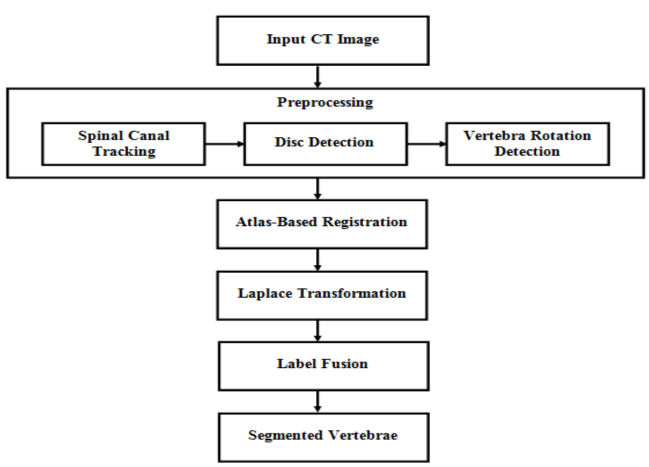


Fig. 1: Architecture of proposed system

1) Preprocessing

Initially preprocessing is done on the input image. Preprocessing consists of the following sub-steps:

a. **Spinal canal tracking:** Seed points for the spinal canal are detected using the Hough transform on a thresholded axial image in the middle of the image volume. A growing and moving circle is used to detect the center of the spinal canal, and where the growing and moving circle process is repeated for each image as the spinal canal is tracked in both the cranial and the caudal direction.

b. **Disc detection:** Given that the vertebrae are located anterior to the spinal canal, an intensity profile, running through the vertebrae, is sampled. The distinctive pattern of the intensity profile can be used to detect the position of the discs.

c. **Vertebral rotation estimation:** In an image slice located between the detected discs, an initial axial vertebral rotation is estimated based upon minimizing an error measure for assessing the lateral symmetry between two halves of the image.

2) Atlas-based Registration

Here atlas is nothing but the template image which is used as a model or reference for segmentation of new patient's image. Also that atlas is manually segmented as well as labeled image. As we know registration is nothing but warping of input image with template image so at the time of registration we take input image which is preprocessed and remaining images from dataset as atlases. For registration we use Morphon algorithm proposed in [12]. The Morphon is an algorithm where a source image, $I_S(x)$, is iteratively deformed, $I_D(x)=I_S(x + d(x))$, until the phase-difference between the target image, I_S, and the deformed image, I_D, has been minimized. This process is performed over multiple scales, starting on coarser scales to register large global displacements and moving on to finer scales to register smaller local deformations. The algorithm itself consists of the following three sub-steps: local displacement estimation, displacement field accumulation, deformation.

3) Laplace Transformation

Laplacian filters are derivative filters used to find areas of rapid change (edges) in images, therefore it often used for edge detection. Since derivative filters are very sensitive to noise, it is common to smooth the image (e.g., using a Gaussian filter) before applying the Laplacian. This two-step process is called the Laplacian of Gaussian (LoG) operation. This is used to refine boundary of segmented vertebrae.

4) Label Fusion

The final step is to merge the labels of the different deformed atlases into a single atlas volume. In this case, a straight forward majority voting has been employed for label fusion.

IV. EXPERIMENTS AND RESULTS

4.1 Dataset

The dataset used in this experiment was obtained from Sai Hi-Tech Diagnostic Center, Nashik. Since the existing system and the proposed system both deals finding out the deformities in the thoracic and lumbar part of spine so the modality that is been chosen is Computed Tomography or CT. CT images are considered as the best images to find out diseases related to bones. The dataset contained spine CT data from 12 patients ranging in age from 30 to 60 years. The studies were performed with spine CT protocol, with in-plane resolution ranging from 0.31 to 0.45mm, and slice thickness ranging from 1mm to 3mm.A total of 50 thoracic and lumbar vertebrae were evaluated. All thoracic and lumbar vertebrae were manually segmented to build atlases for the validation our algorithm.

4.2 Evaluation Methodology

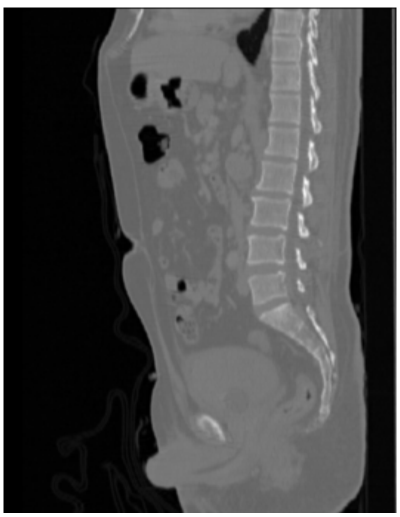
To test the efficiency of the proposed system we are using dice coefficient. The ground truth data was compared with the segmentations obtained from the proposed system using the DICE coefficient, defined as

$$DICE = \frac{2 * |GT \cap S|}{|GT| + |S|}$$

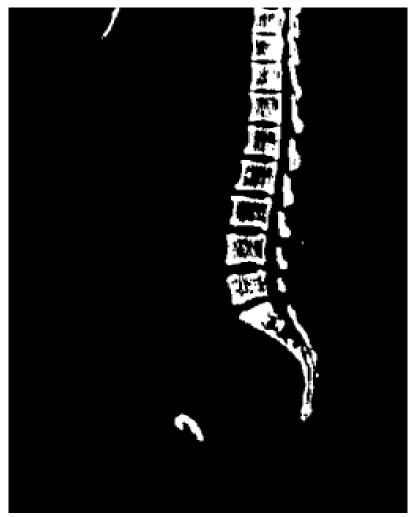
where GT and S which refer to the ground truth and the computed segmentations respectively.

4.3 Results

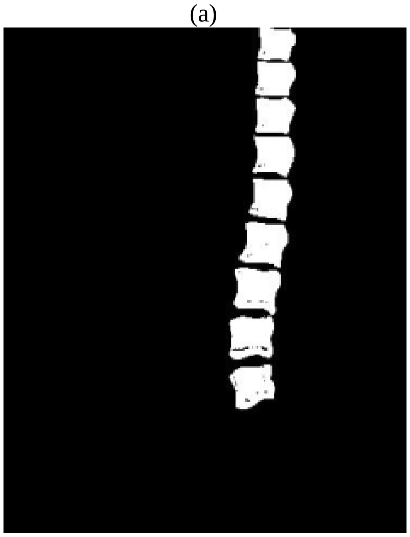
Figures shows the results of pre-processing of the sagittal view of the Spine CT image and segmentation using proposed system. Figs. 2 (a) shows the original CT Spine image. (b) is the image obtained by applying Pre-processing. Image shown in fig 2 (c) is the image obtained by Morphon algorithm (d) is the thoracic and lumbar portion of the spine vertebra obtained after Laplace Transformation (e) is the image of thoracic and lumbar portion of the vertebrae obtained by applying Label Fusion. Graphical representation of the results of whole dataset of Dice coefficient, Jaccard Coefficient , Precision and Recall is shown in fig 3(a),(b),(c) and (d) respectively. The results of the proposed system are found to be more efficient than the existing system.



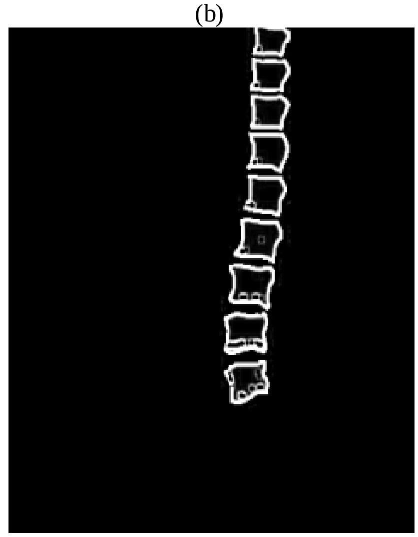
(a)



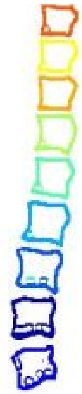
(b)



(c)



(d)



(e)

Fig. 2. Pre-processing and segmentation of image7 (a) Original image (b) Image after applying pre-processing(c) Image after applying Atlas-based registration (d) Image of vertebrae after applying Laplace Transform (e)) Image of vertebrae after applying Label Fusion.

(a) (b) (c) (d)

Fig. 3. Graphical representation of whole dataset (a) Dice Coefficient (b) Jaccard coefficient (c) Precision and (d) Recall

The results of both the existing system and proposed system are being compared by using Dice Coefficients, Jaccard Coefficient, Precision and Recall as metrics for evaluation. The results of which are been shown below in table 1.

Comparative Results for Existing and Proposed System

Dataset	Dice Coefficient		Jaccard Coefficient		Precision		Recall	
	Existing	Proposed	Existing	Proposed	Existing	Proposed	Existing	Proposed
Img1	0.84	0.87	0.72	0.77	0.70	0.71	0.90	0.93
Img2	0.83	0.86	0.71	0.75	0.68	0.70	0.90	0.92
Img3	0.83	0.87	0.71	0.77	0.70	0.71	0.89	0.93
Img4	0.82	0.84	0.69	0.73	0.67	0.68	0.90	0.93
Img5	0.85	0.89	0.74	0.80	0.68	0.70	0.93	0.98
Img6	0.88	0.93	0.79	0.86	0.72	0.73	0.93	0.99
Img7	0.88	0.93	0.79	0.87	0.72	0.74	0.93	0.99
Img8	0.86	0.89	0.75	0.80	0.67	0.70	0.92	0.98
Img9	0.88	0.90	0.79	0.81	0.72	0.73	0.92	0.96
Img10	0.86	0.89	0.75	0.8	0.70	0.72	0.93	0.97
Img11	0.86	0.87	0.75	0.77	0.68	0.70	0.93	0.97
Img12	0.85	0.88	0.74	0.79	0.71	0.73	0.93	0.97

V. CONCLUSION

In this paper a morphon algorithm followed by laplace transform and labeling has been presented for segmentation of vertebra from spine CT images, which is compared to the atlas-based segmentation. The study includes a dataset of 12 patients of age 30 to 60 of CT scan images of spine. It is seen that the proposed system proved to be more efficient than the existing system and give improved segmentation results as compared to the existing system.

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