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SEGMENTATION OF LUMBAR VERTEBRAE FROM CLINICAL CT USING ACTIVE SHAPE MODELS AND GVF-SNAKE

Samah Al-Helo[1], Raja' S. Alomari[1,2], Vipin Chaudhary[2], M. B. Al-Zoubi[1]

[1]Dept. of Computer Information Systems, University of Jordan, Amman 11942, Jordan.
[2]Dept. of Computer science and Engineering, University at Buffalo, SUNY, Buffalo, NY 14260

ABSTRACT

Lumbar area of the vertebral column bears the most load of the human body and thus it is responsible for the major portion of lower back pain from which 80% to 90% of people suffer from during their lifetime. Vertebra related diseases are mainly fracture and are usually diagnosed from X-ray radiographs or CT scans depending on the severity of the problem. In this paper, we propose a fully automated lumbar vertebra segmentation that accurately and robustly produces a smooth contour around each of the vertebrae. This segmentation is very useful in any subsequent CAD system for diagnosis and quantification of vertebrae fractures. It also serves the radiologist during the clinical routine. Our method shows an excellent level of vertebra boundary smoothness that was visually approved by our collaborating radiologist for each vertebra and each case from our fifty cases dataset that includes both normal and abnormal cases.

Index Terms— CT, Segmentation, Lumbar Fracture, Active Shape Model.

I. INTRODUCTION

Clinical radiology has been attracting various researchers for over two decades with high interest in automating (or semi-automating) various steps during the diagnosis. Most of diagnosis tasks start with a localization and a segmentation step where anatomical organs are identified and segmented before performing diagnosis. We work on the lumbar area from the vertebral column. Our work concentrates on the clinical work flow of the diagnosis task. The choice of lumbar area is motivated by the fact that most of the clinical abnormalities causing lower back pain are caused by some abnormality in the lumbar area. Lower back pain is the second most common neurological ailment in the United States after headache [1].

Various researchers have been working on segmentation and labeling tasks for the vertebral column. We classified these efforts into three categories based on the target anatomical structure into: vertebra, inter vertebral disc, and soft tissues. In our recent related work [2], we presented an exhaustive survey of these methods for various medical modalities including: X-ray radiography, dual X-ray radiography, CT, and MRI. These modalities are the most commons ones in various clinical settings that target the vertebral column. These efforts also varies in the area of interest; some efforts target the full vertebral column scan while others concentrate on specific areas: cervical, thoracic, lumbar, Sacrum, and Coccyx. In the clinical standard, MRI and CT are captured for specific area of interest due to the expensive scanner time. A scanning task for the lumbar area alone takes about 25 minutes in our collaborating radiology center. Next, we review the recent related efforts in vertebrae segmentation.

Fig. 1. (Left) Normal Vertebrae. (Middle) Compression Fracture at L4-5. (Right) 3D reconstruction.

In this paper, we present a robust and efficient method for accurately segmenting the lumbar vertebrae and prepare them for further CAD tasks. After preprocessing the image and labeling each vertebrae (based on our previous work), we train an active shape model for the shape of the vertebra at each vertebra level starting from L1 down to L5. The method places the mean shape on the vertebrae and allows the point distribution to converge to the vertebrae shape. We obtained clinically accurate segmentation of the vertebra on all cases upon visual and careful evaluation from an expert radiologist.

The rest of this paper is organized as follows: Section II reviews the recent related work to the problem in this paper, section III details our flow of the method from reading the CT volume until the final segmentation contour. Section IV describes our data and shows our experimental settings and then we conclude in section V.

II. RELATED WORK

Computer-Aided Diagnosis (CAD) has been attracting various interdisciplinary researchers for over two decades. Next, we mention the most related work. For an exhaustive list of efforts, we refer the reader for our recent work [2]. Smyth et al [3] used Active Shape Models (ASMs) to locate vertebrae in lateral Dual X-ray (DXA) images of the spine. They searched for many vertebrae together improving robustness in location of individual vertebrae by making use of constraints on shape provided by the position of other vertebrae. Their results showed that their method performed as accurately as the human operators and was fast comparable to manual segmentation. Later, Zamora et al [4] proposed a hierarchical approach for vertebrae segmentation from X-ray images. They used two customized active shape models. Their results are then addressed by a customized implementation of the Generalized Hough Transform. Their results on data sets of cervical and lumbar images showed that the proposed hierarchical approach produces errors of less than 3 mm in 75% of the cervical images and 6.4 mm in 50% of the lumbar images.

Bauwens et al [5] proposed a new image segmentation technique which is a combination of two kinds of deformable models, namely: Gradient Vector Flow (GVF) and Active Shape Models (ASM) for vertebral segmentation using X-ray images. In some cases, GVF leads to erroneous contours which means further human post-processing. To solve this problem, the GVF was controlled by an active Shape Model of the vertebra to fasten the convergence process and to eliminate the false segmentation cases. Furthermore, Roberts et al [6] developed a quantitative classifier for vertebral fracture detection on 360 lateral Dual Energy X-ray absorptiometry scans using shape and appearance models. Their results showed that appearance-based classifiers gave significantly better specificity than shape-based methods in all regions of the spine, and this provides more powerful quantitative classifiers of osteoporotic vertebral fracture. Similarly, Roberts [7] developed a semi-automatic segmentation method which combines multiple Active Appearance Models (AAMs) to locate the full outlines of the vertebral bodies in order to detect and quantify vertebral fractures due to osteoporosis. He used Dual energy X-ray Absorptiometry (DXA) scans, and digitized lumbar x-ray radiographs. His results was comparable to manual segmentation in 90% cases. Later, Roberts et al [8] provided a fully automatic method of segmenting vertebrae in spinal radiographs to help in diagnosis of osteoporosis by vertebral fracture assessment. They used parts-based model of small vertebral patches and Active Appearance Models (AAM). They compared their results to a gold standard of manual annotation by expert radiologists and found that their algorithm was successful to locate a plausible set of vertebrae in over 90% of cases but still in some cases there were 20% level shifted problem.

III. PROPOSED METHOD

Initially, we start with the CT volume and select the middle slice as a starting point for segmentation. In this work, we have two steps to train: 1) Inter vertebral disc localization (that leads to vertebra localization as illustrated below). 2) Active Shape Models (ASMs) for each vertebra level.

For the first training task, we train our model proposed in [2] by allowing a radiologist to place a point inside each disc for the six discs enclosing the five lumbar vertebrae. We then save this data with the corresponding images to train the model for the disc localization step that we use to extract the vertebrae center points (vertebrae labels).

The second training task, we allow the radiologist to select a fixed set of points (16 points) for each vertebra starting from L5 up to L1. We then produce a separate model for each vertebra level and prepare the training data required for an Active Shape Model (x,y coordinates and the image itself). Fig. 2 shows a sample image with the 16 points on the edges of each vertebra as selected by our collaborating radiologist.

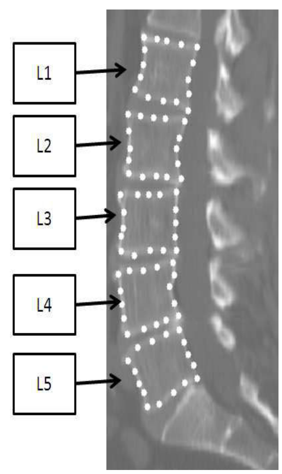

Fig. 2. Training Data Preparation.

We now describe the steps of our method for automatic segmentation of the lumbar vertebrae from CT in three main steps:

III-A. Vertebra localization

Our automatic method starts by a localization step that provides a point inside each vertebra. We utilize our related work that localize lumbar discs from clinical MRI [2]. However, in this paper, we aim at vertebra localization rather than the disc localization. Moreover, the images are CT rather than MRI as in [2]. We initially utilize our two-level probabilistic model [2] for disc localization. Then we take the average point between every two discs and consider this as the vertebra localization point as shown in Fig. 3.

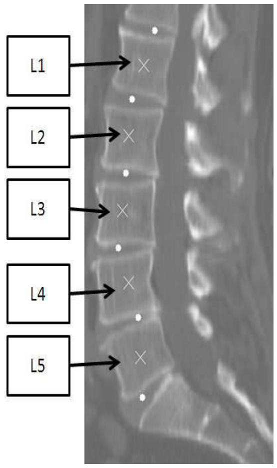

Fig. 3. Automated vertebrae localization. Filled circles are disc labels from [2]. Crosses are the average location between each two disc labels.

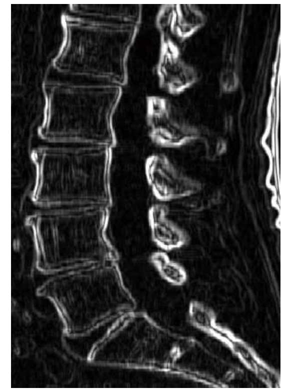

Fig. 4. Range Filter 3x3 window on the CT image.

III-B. Vertebra Point Distribution by ASM

This step aims at modeling the rough shape of the vertebra. We use the active shape model [9] that has been proving its robustness and suitability for segmentation of such anatomical structures where edges are clearly distinguished from the surrounding areas. In CT scans, vertebra show a good level of vertebra edge as we see in Fig. 1. In our work, we have a separate model for each vertebra level. To prepare the training data, we allow the radiologist to manually mark 16 landmark points for each vertebra as shown in Fig. 2. We name these landmark points from $\mathtt{k}_1$ to $\mathtt{k}_{16}$. Similar to [9], we initially calculate the mean shape $\bar{x} = \frac{1}{N}\sum_1^N x$ where N is the size of the training data. Then each vertebra shape x_i, where $i \in \{1, \ldots, N\}$, is recursively aligned to the mean shape $\bar{x}$ using generalized Procrustes analysis to remove translational, rotational, and isotropic scaling from the shape.

Then, we model the remaining variance around the mean shape for each vertebra with principal components analysis (PCA) to extract the eigenvectors of the covariance matrix associated with 98% of the remaining point position variance according to the standard method for deriving the ASM's linear shape representation.

However, we do not use the original CT image for training the ASM of each vertebra. Rather, we apply the range filter $\mathtt{R}$ first on the image to obtain a better edge enhancement for vertebrae. $\mathtt{R}$ is the range filter operator where the intensity levels in each 3x3 window are replaced by the range value (maximum - minimum) in that window. This operator $\mathtt{R}$ has high values in abrupt-change regions and small values in smooth regions as shown in Fig. 4.

To apply ASM for detection of the point distribution of the vertebra body boundary, we apply the mean shape $\bar{x}$ around the vertebra point produced by the localization step (cross inside each vertebra). Then, we allow the ASM to converge and obtain the boundary. We feed this boundary to the GVF snake in the next step.

III-C. Vertebra boundary delineation by GVF snake

The Active Shape Model (ASM) can capture the rough boundary of the vertebra as a point distribution model. However, fine detailed delineation of the vertebra body need a more refining model. We select the GVF-snake proposed by Xu and Prince [10] because it has been proved to move toward desired image properties such as edges including concavities. GVF-snake is the parametric curve that solves:

$$\mathbf{x}_t(s,t) = \alpha\mathbf{x}''(s,t) - \beta\mathbf{x}''''(s,t) + \mathbf{v} \qquad (1)$$

where α and β are weighting parameters that control the contour's tension and rigidity, respectively. x'' and x'''' are the second and fourth derivatives, respectively, of x. $\mathbf{v}(x,y)$ is the gradient vector flow (GVF), $s \in [0,1]$, and t is time component to make a dynamic snake curve from $x(s)$ yielding $x(s,t)$.

GVF-snake requires an edge map that is a binary image highlighting the desired features (edges) of the image. Most researchers use Canny edge detector or Sobel operator on the original image such as [11] for liver segmentation. We present the GVF-snake with a canny edge map applied on our range-filtered image $\mathtt{I}$.

We apply the GVF-snake by initializing its contour to the contour produced by the Active Shape Model, that is the points $\mathtt{k}_1$ to $\mathtt{k}_{16}$. Fig. 5 shows the same example after the convergence of the GVF-snake.

IV. DATA AND RESULTS

Our data are obtained from our collaborating radiologist who works for a radiology center. All data are in DICOM format and are anonymized before we receive them. We received an anonymized clinical report along with each case showing all abnormalities at each disc level. Among fifty cases, there are thirty abnormal cases and twenty normal ones. Each abnormal case has at least one vertebra with an abnormality including various types of fracture and, specifically, compression fracture, wedge compression fracture, and spondolysis.

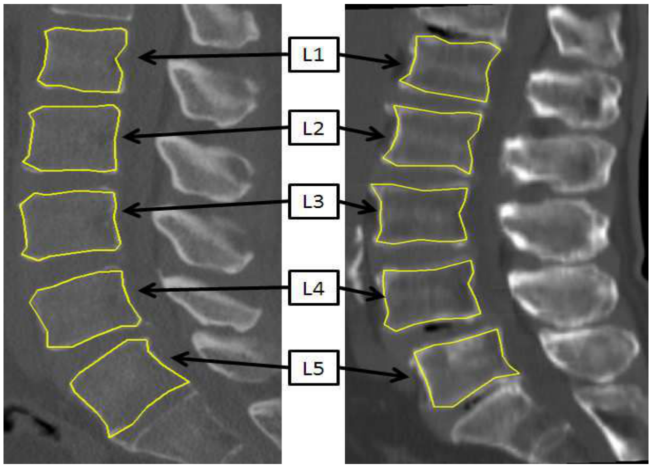

Fig. 5. Final contour for two cases. Images are contrast-enhanced for visual convenience.

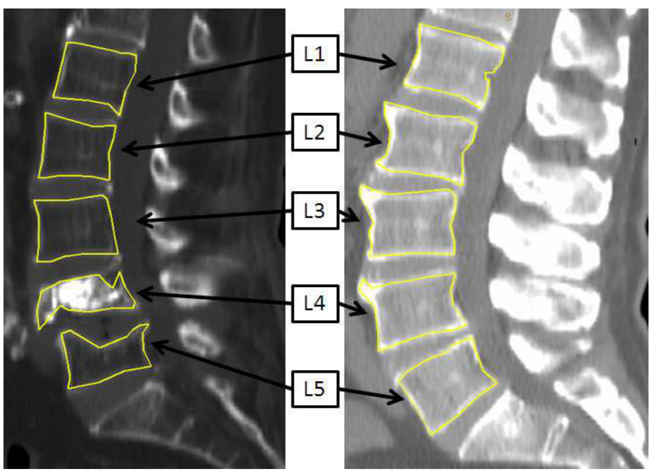

Fig. 6. Final contour for two cases. (Left) Severely abnormal L4 vertebra. Images are contrast-enhanced for visual convenience.

Figures 5 and 6 show four cases selected from our dataset to show the robustness of the final contour despite the various abnormalities in various lumbar levels. Our collaborating radiologist has visually and carefully tested each vertebra contour and approved the automated segmentation contour for all cases. We point out that the segmentation ground truth (similar to any medical segmentation task) is unknown. However, a clinically accepted segmentation is enough for such tasks and this is what we provide here. We don't study quantitative segmentation measurements such as contour distances and area overlap because our objective is clinical and aims at providing a smooth contour for each vertebra. We also point out that our next step is to perform automated diagnosis and quantification. We aim at detection of major fractures types and spondylolysis (vertebral slippage) and then quantify each abnormality. Our active shape model convergence provides good starting point for shape feature extraction such as vertebra height and width that indicates compression fracture abnormality. On the other hand, our GVF smooth contour allows measurements to be performed on the intensity levels of the vertebra which has been used as an indicator for bone mass measurement that indicates various bone diseases, specifically, Osteoporosis.

V. CONCLUSION

Lower back pain is mainly caused by some abnormality in the lumbar area of the vertebral column. These abnormalities are usually caused by discs, vertebrae, or soft tissues. We target the vertebrae abnormalities and thus we study CT scans for the lumbar area from our collaborating clinic. In this paper, we proposed a robust and efficient working method for segmenting the lumbar vertebrae from clinical CT volumes. This segmentation serves as the starting step for various diagnosis tasks such as vertebral fracture diagnosis. We described our method starting from the full CT volume until we obtained the smooth contour for each vertebra. On a fifty cases set, we robustly segmented all vertebrae as validated by an expert radiologist.

VI. REFERENCES

[1] National Institute of Neurological Disorders and Stroke (NINDS), "Low back pain fact sheet," *NIND brochure*, 2008.

[2] Raja' S. Alomari, Jason J. Corso, and Vipin Chaudhary, "Labeling of lumbar discs using both pixel- and object-level features with a two-level probabilistic model.," *IEEE TRANSACTIONS ON MEDICAL IMAGING*, vol. 30, no. 1, January 2011.

[3] P.P. Smyth, C.C. Taylor, and J.E. Adams, ," in *In Proceedings of the 3rd IEEE Workshop on Applications of Computer Vision (1996)*, FL, USA, Dec 1996, pp. 176 – 180.

[4] G. Zamora, H. Sari-Sarrafa, and R. Long, "Hierarchical segmentation of vertebrae from x-ray images," in *Proc of SPIE Med Imaging: Image Process*, 2003, vol. 5032, pp. 631–642.

[5] Bauwens J.-F., Benjelloun M., and Mahmoudi S., "A model-based vertebral segmentation method using gvf and asm," in *Intelligent and Advanced Systems*, 2007.

[6] M.Roberts, T.F.Cootes, E. Pacheca, and J.Adams, "Quantitative vertebral fracture detection on dxa images using shape and appearance models," *Acad. Rad.*, vol. 14, no. 10, pp. 1166–1178, Oct 2007.

[7] Martin G Roberts, *Automatic Detection and Classification of Vertebral Fracture using Statistical Models of Appearance*, Ph.D. thesis, University of Manchester, 2008.

[8] M.G. Roberts, T.F. Cootes, and J. Adams, "Segmentation of lumbar vertebrae using part-based graphs and active appearance models," in *In Proceedings of MICCAI 2009*, 2009, pp. 1017–1024.

[9] T. F. Cootes and C. J. Taylor, "Statistical models of appearance for medical image analysis and computer vision," in *Proc. of SPIE Medical Imaging*, 2001.

[10] Chenyang Xu and Jerry L. Prince, *Handbook of Medical Imaging*, Academic Press, Baltimore, MD, Sept 2000.

[11] F Liu, B Zhao, PK Kijewski, L Wang, and LH Schwartz, "Liver segmentation for ct images using gvf snake," *Medical Physics*, vol. 32, no. 12, pp. 3699–706, Dec 2005.