Fully Automatic Spinal Canal Segmentation for Radiation Therapy Using a Gradient Vector Flow-Based Method on Computed Tomography Images: A Preliminary Study

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Abstract— **Nowadays, radiotherapy is one of the key techniques for localized cancer treatment. Accurate identification of target volume (TV) and organs at risk (OAR) is a crucial step to therapy success. Spinal cord is one of the most radiosensitive OAR and its localization tends to be an observer-dependent and time-consuming task. Hence, numerous studies have aimed to carry out the contouring automatically. In CT images, there is a lack of contrast between soft tissues, making more challenge the delineation. That is the reason why the majority of researches have focused on spinal canal segmentation rather than spinal cord. In this work, we propose a fully automated method for spinal canal segmentation using a Gradient Vector Flow-based (GVF) algorithm. An experienced radiologist performed the manual segmentation, generating the ground truth. The method was evaluated on three different patients using the Dice coefficient, obtaining the following results: 79.50%, 83.77%, and 81.88%, respectively. Outcome reveals that more research has to be performed to improve the accuracy of the method.**

I. Introduction

Radiation therapy plays a very important role on localized cancer treatment. It involves using high dose of ionizing radiation with the aim of kill cancer cells by damaging their DNA [1]. Due to recent developments on computer technology and imaging techniques, intensity-modulated radiotherapy (IMRT) is widely used. The two main features that differ from conformal radiotherapy are the non-uniform intensity of the radiation beams and the use of computerized inverse planning [2]. During the treatment planning, the oncological specialist has to delineate both specific target volumes (TV) and organs at risk (OAR). This step is crucial since an imprecise contouring will entail a dose delivery in excess as well as unnecessary damages on radiosensitive healthy tissue. With the aim of standardize a definition of TV, The International Commission on Radiation Units and Measurement (ICRU) proposed the following terms: gross tumor volume (GTV), clinical target volume (CTV), and planning target volume (PTV) [3].

One of the most often OAR is the spinal cord, the structure responsible for carrying the information between brain and peripheral nervous system. Accurate identification of this structure is indispensable to prevent clinical complications. However, manual contouring tends to be observer-dependent, so guidelines [4], [5] and web-based platforms [6] are available for overcoming this limitation. In addition, in recent years there has been an increasing interest in applying image segmentation techniques to automate the contouring and hence reduce the time spent during the radiotherapy procedure [7].

Regarding spinal cord segmentation, owing to low contrast between this organ and the surrounding soft tissue in computed tomography (CT) images, the majority of research have focused on delineation of spinal canal rather than the own spinal cord. In this context, numerous studies have been published. Karangelis *et al.* [8] proposed a method for spinal canal segmentation based on 2D boundary tracking algorithm, which requires selecting an initial point to start. In a later study, Nyúl *et al.* [9] presented an algorithm for automated segmentation not only of spinal canal, but also of spinal cord. Their approach used a region-growing algorithm for spinal canal segmentation whereas spinal cord was extracted by a deformable model. Again, it was necessary to select an initial slice and seed point. Rangayyan *et al.* [10] carried out the detection and segmentation on pediatric patients. Firstly, Hough transform was applied to obtain a few seed voxels within spinal canal. Next, a fuzzy region-growing algorithm dealt with the segmentation problem. Burnett *et al.* [11] published a paper in which they described a deformable-model approach with the aim of semi-automatic segmentation. Mainly, the procedure detected edges using wavelets and then a deformable-model template was fitted. Using *prior* information, Huang *et al.* [12] developed a method to carry out automatic segmentation of the body contour and spinal canal. Once a seed point was detected within spinal canal, segmentation was performed using a fuzzy region-growing algorithm. In contrast to the studies described above, Archip *et al.* [13] presented a knowledge-based approach for an automatic image analysis. In particular, they combined *structural* and *procedural* knowledge to recognize both spinal canal and spinal cord as well as the lamina and the position of the outer thorax.

In almost all preliminary approaches, segmentation was carried out using either a region-growing algorithm or a deformable model. Furthermore, taking into account the low contrast between soft tissues in CT images, previous studies have focused on spinal canal segmentation instead of spinal cord. In this work, we propose a method with the purpose of delineating the spinal canal automatically. Our approach uses a deformable model to achieve such goal, specifically, the Gradient Vector Flow (GVF) snake [14].

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II. Material and Methods

A. Data Set and Ground Truth

The method was tested on three different patients. The main properties of the data set are presented in Table I. Case 1 and 2 were oncological patients acquired on a Siemens Sensation 40 scanner at *Fundación Instituto Valenciano de Oncología (IVO)*, Valencia, Spain. On the other hand, case 3 was a traumatic patient acquired on a Siemens Sensation 64 scanner at the Department of Radiological Sciences, University of California, Irvine, School of Medicine, USA, from Yao *et al.* [15], downloadable from [16]. Thus, a total of 3 patients and 960 images spanning thoracic and lumbar levels were segmented. All images had a 512 × 512 pixel size and a 12-bit bit depth.

TABLE I. Main Characterisitcis of the Analyzed Cases

	Age	***Number of images***	***In-plane spatial resolution***	***Slice thickness***
Case 1	58	325	0.94 × 0.94 mm	2 mm
Case 2	49	210	0.89 × 0.89 mm	2 mm
Case 3	-[a]	425	0.31 × 0.31 mm	1 mm

a. Information not available.

Manual segmentation was carried out by an experienced radiologist. The expert delineated the spinal canal slice-by-slice with the goal of performing a quantitative evaluation. This delineation was performed using an in-house application with a graphical user interface developed in MATLAB. The Dice similarity coefficient (DSC) was computed for this purpose [6].

B. Proposed Method

The presented algorithm was implemented using MATLAB 2013a (The MathWorks, Inc., Natick, MA, USA) and ran on a personal computer, with Intel Core i5 processor, 2.4 GHz, 4 GB of RAM, and Windows 7 Home Premium as operating system.

The approach proposed in this paper entails three main steps. The first one is to detect a seed point for each slice, automating the segmentation in this way. The second one is to carry out a rough segmentation of the spinal canal. The last one is to refine the segmentation obtained in the previous step. The user must select the volume under study and afterwards the whole process is completely automatic.

1) Spinal Canal Detection

In order to automate the algorithm, firstly the spinal canal was detected using the method proposed by Díaz-Parra *et al.* [17]. Díaz-Parra *et al.* method deals with the detection of seed points within spinal canal. Briefly, their approach exploits the idea that spinal canal is surrounded by cortical bone in an axial cross-section. Thus, thoracic and lumbar levels can be extracted combining 2D and 3D information. The detection algorithm can be divided into three main steps. Firstly, after setting high contrast between spinal canal and bone, a set of morphological operations are carried out to find the maximum possible number of voxels forming part of the spinal canal. Secondly, a 3D connectivity analysis is defined to extract only that object conforming the spinal canal. Finally, centroid extraction for each slice of the *spinal canal* object is performed. Moreover, interpolation and extrapolation of data is applied since, in the majority of cases, not all slices are presented in the *spinal canal* object. Stand out the importance of this step, as if accurate detection is not obtained, the following task will produce imprecise results. An extensive explanation of the method is provided in [17].

2) Coarse Segmentation

Once the points lying within the spinal canal were detected, a 10 × 10 cm region of interest (ROI) was set to reduce the computational burden of the whole segmentation algorithm. Firstly, a thresholding at 160 HU was carried out (Fig. 1a and 1d). We aimed to obtain a rough segmentation of only those slices in which spinal canal was completely surrounded by spine. To determine which ones satisfied this condition, for each slice, a flood-fill operation on background starting from the point previously detected was performed. Thus, if spinal canal was actually surrounded by spine, the hole was filled, as shown in Fig. 1b. However, if spinal canal was not presented as a hole, the entire background was also set to white (Fig. 1e). Afterwards, the difference image between the filled image and the thresholded image was computed, obtaining Fig. 1c and 1f. Finally, the objects connected with the border of the image were removed. After removal, if spinal canal was as a hole in the slice under study, then a coarse segmentation was obtained; if not, the outcome was as an image of logical *zeros*.

3) Segmentation by Gradient Vector Flow Snake

In this step, we obtained a refined segmentation using a parametric active contour, namely Gradient Vector Flow (GVF) snake [14]. Given an initial contour, snake moves under the influence of two main forces: one internal and one external. The internal force tries to keep the smoothness of the contour whereas the external one attracts contour to edges of the object to be segmented. Particular advantages of the GVF snake over a traditional snake [18] are its insensitivity to initialization and its ability to move into boundary concavities. In our approach, the initial contour is defined from the coarse segmentation.

TABLE II. Parameters of the GVF Snake

Parameter	***Selected Value***	***Meaning***
μ	0.2	Regularization
α	0.5	Elasticity
β	1	Rigidity
γ	1	Viscosity
κ	1.4	External force weight

Then, GVF algorithm was only applied on the images where a coarse segmentation was obtained from the previous step. The value used and the meaning of each parameter are shown in Table II. In addition, three iterations were computed since initial contour was set closed to the object of interest. Afterwards, outcome of the segmentation obtained in this step was used to establish the initial contour of the remaining slices, i.e. those slices where the spinal canal was not entirely surrounded by spine. Thus, for a given slice, it was established as an initial contour the one obtained from the segmentation of the closest slice. The values of the parameters controlling the algorithm and the number of iterations were the same as those previously defined.

Figure 1. Outcome of coarse segmentation step. (a-c) Spinal canal is presented as a hole. (d-f) Spinal canal is not completely surrounded by bone.

III. Results and Discussion

The outcome of the spinal canal segmentation is presented in Table III. Dice coefficient was of 79.50%, 83.77%, and 81.72% for case 1, 2, and 3, respectively. In addition, time performance of the whole automatic segmentation was also computed for each case. Fig. 2a and 2b show the outcome after applying the developed algorithm to case 1 and case 3, respectively. A complete spinal canal segmentation of case 1 is displayed in Fig. 3.

TABLE III. Outcome of the Spinal Canal Segmentation

	Dice coefficient	*Time performance*
Case 1	79.50%	13.6 min
Case 2	83.77%	8.9 min
Case 3	81.72%	39.6 min

The obtained results suggest that our method may be independent of the scanner used for image acquisition, as it was obtained a value of DSC very similar in all cases (around 81%). However, only one traumatic patient (case 3) was analyzed. We expect to apply the proposed method to both oncological and traumatic patients.

Regarding to the obtained DSC values, these must be improved because of the application to which this work is aimed, i.e. radiation therapy. The exact knowledge about spinal canal localization and its delineation is crucial to avoid unnecessary damages and achieve a successful treatment. In the near future, in addition to Dice coefficient, we also plan to evaluate the segmentation method using the Jaccard coefficient [6]. Other studies have used other ways to evaluate de segmentation. For instance, Hausdorff distance is used in [10].

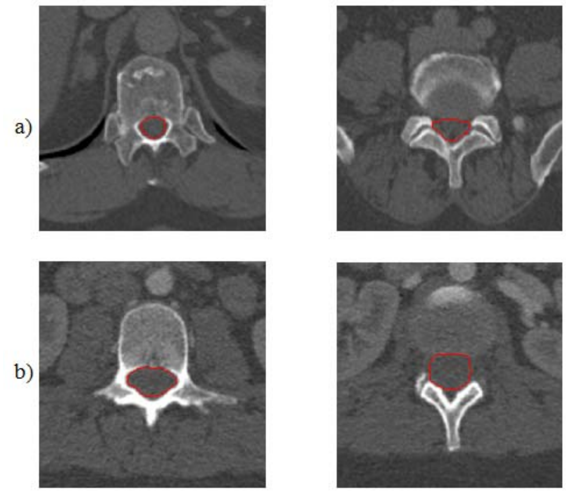

Figure 2. Outcome of automatic spinal canal segmentation (red lines). Segmentation in case 1 (a) and case 3 (b).

Figure 3. 3D visualization of the spinal canal segmentation (red shape) of case 1.

A very important aspect is the choice of GVF parameters, which are summarized in Table II. This is a non-trivial problem due to the huge variety of possible combinations. Therefore, the main guide to make a decision is by trial and error. Nonetheless, knowing the physical meaning of them can be useful. For instance, elasticity and rigidity parameters control how much the active contour (or snake) can deform to adapt to object edges. As we expected that spinal canal had a round shape, we were interested in a rigid snake rather than an elastic snake. On the other hand, viscosity and external force weight coefficients are related to the resistance that the snake perceives during its deformation. Then, as initial contour was set close to boundaries of interest, only three iterations were computed and the external force was set larger than viscosity so that snake could reach the boundary of spinal canal within that temporal period. Finally, the parameter μ is a regularization parameter that should be set according to the noise present in the image. We fixed it to the default value [14].

IV. Conclusions

Segmentation of organs at risk is an essential component in radiotherapy. In this sense, image segmentation techniques let automate this task and hence reduce the workload of the clinical. In particular, spinal cord is a radiosensitive organ that has to be precisely delineated to protect it. In this preliminary study, we have proposed an automated method for spinal canal segmentation, which houses spinal cord, using a GVF algorithm.

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References

[1] National Cancer Institute, "Radiation therapy for cancer," *cancer.gov*. [Online]. Available: http://www.cancer.gov/cancertopics/factsheet/Therapy/radiation. [Accessed: 14-Mar-2014].

[2] A. Taylor and M. E. B. Powell, "Intensity-modulated radiotherapy--what is it?," *Cancer Imaging*, vol. 4, no. 2, pp. 68–73, Mar. 2004.

[3] C. F. Njeh, "Tumor delineation: The weakest link in the search for accuracy in radiotherapy," *J. Med. Phys.*, vol. 33, no. 4, pp. 136–140, Dec. 2008.

[4] C. L. Brouwer, R. J. H. M. Steenbakkers, E. van den Heuvel, J. C. Duppen, A. Navran, H. P. Bijl, O. Chouvalova, F. R. Burlage, H. Meertens, J. A. Langendijk, and A. A. van 't Veld, "3D Variation in delineation of head and neck organs at risk," *Radiat. Oncol.*, vol. 7, no. 1, p. 32, Mar. 2012.

[5] T. A. van de Water, H. P. Bijl, H. E. Westerlaan, and J. A. Langendijk, "Delineation guidelines for organs at risk involved in radiation-induced salivary dysfunction and xerostomia," *Radiother. Oncol.*, vol. 93, no. 3, pp. 545–552, Dec. 2009.

[6] J. Kalpathy-Cramer, M. Awan, S. Bedrick, C. R. N. Rasch, D. I. Rosenthal, and C. D. Fuller, "Development of a software for quantitative evaluation radiotherapy target and organ-at-risk segmentation comparison," *J. Digit. Imaging*, vol. 27, no. 1, pp. 108–119, 2014.

[7] G. A. Whitfield, P. Price, G. J. Price, and C. J. Moore, "Automated delineation of radiotherapy volumes: are we going in the right direction?," *Br. J. Radiol.*, vol. 86, no. 1021, Jan. 2013.

[8] G. Karangelis and S. Zimeras, "An accurate 3D segmentation method of the spinal canal applied to CT data," in *Image Processing for Medicine*, M. Meiler, D. Saupe, F. Kruggel, H. Handels, and T. Lehmann, Eds. Leipzig, Germany: Springer Berlin Heidelberg, 2002, pp. 370–373.

[9] L. G. Nyúl, J. Kanyó, E. Máté, G. Makay, E. Balogh, M. Fidrich, and A. Kuba, "Method for automatically segmenting the spinal cord and canal from 3D CT images," in *Computer Analysis of Images and Patterns*, 2005, vol. 3691, pp. 456–463.

[10] R. M. Rangayyan, H. J. Deglint, and G. S. Boag, "Method for the automatic detection and segmentation of the spinal canal in computed tomographic images," *J. Electron. Imaging*, vol. 15, no. 3, Jul. 2006.

[11] S. S. C. Burnett, G. Starkschall, C. W. Stevens, and Z. Liao, "A deformable-model approach to semi-automatic segmentation of CT images demonstrated by application to the spinal canal," *Med. Phys.*, vol. 31, no. 2, p. 251, Jan. 2004.

[12] S. Huang, J. Jia, R. Cao, G. Li, M. Cheng, and Y. Wu, "Automatic segmentation of the body and the spinal canal in CT images based on a priori information," in *5th International Conference on Bioinformatics and Biomedical Engineering*, Wuhan, 2011, pp. 1–4.

[13] N. Archip, P.-J. Erard, M. Egmont-Petersen, J.-M. Haefliger, and J.-F. Germond, "A knowledge-based approach to automatic detection of the spinal cord in CT images," *IEEE Trans. Med. Imaging*, vol. 21, no. 12, pp. 1504–1516, Dec. 2002.

[14] C. Xu and J. L. Prince, "Snakes, shapes, and gradient vector flow," *IEEE Trans. Image Process.*, vol. 7, no. 3, pp. 359–369, Mar. 1998.

[15] J. Yao, J. E. Burns, H. Munoz, and R. M. Summers, "Detection of vertebral body fractures based on cortical shell unwrapping," in *Medical Image Computing and Computer Assisted Intervention*, 2012, vol. 7512, pp. 509–516.

[16] spineweb.digitalimaginggroup.ca, "Spine Web." [Online]. Available: http://spineweb.digitalimaginggroup.ca/. [Accessed: 14-Mar-2014].

[17] A. Díaz-Parra, E. Arana, and D. Moratal, "A fully automated method for spinal canal detection in computed tomography images," in *36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Chicago, USA, 2014.

[18] M. Kass, A. Witkin, and D. Terzopoulos, "Snakes: Active contour models," *Int. J. Comput. Vis.*, vol. 1, no. 4, pp. 321–331, 1988.