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Automated segmentation and area estimation of neural foramina with boundary regression model

Xiaoxu He[a,b,*], Andrea Lum[a,b], Manas Sharma[a,b], Gary Brahm[a,b], Ashley Mercado[a,b], Shuo Li[a,b,*]

[a] Digital Imaging Group (DIG), London, ON, Canada N6A 4V2
[b] Department of Medical Imaging, University of Western Ontario, London, ON, Canada N6A 3K7

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ABSTRACT

Accurate segmentation and area estimation of neural foramina from both CT and MR images are essential to clinical diagnosis of neural foramina stenosis. Existing clinical routine, relying on physician's purely manual segmentation, becomes very tedious, laborious, and inefficient. Automated segmentation is highly desirable but faces big challenges from diverse boundary, local weak/no boundary, and intra/inter-modality intensity inhomogeneity. In this paper, a novel boundary regression segmentation framework is proposed for fully automated and multi-modal segmentation of neural foramina. It creatively formulates the segmentation task as a boundary regression problem which models a highly nonlinear mapping function from substantially diverse neural foramina images directly to desired object boundaries. By leveraging a seamless combination of multiple output support vector regression (MSVR) and multiple kernel learning (MKL), the proposed framework enables the domain knowledge learning in a holistic fashion which successfully handles the extreme diversity posing a tremendous challenge to conventional segmentation methods. The performance evaluation was conducted on a dataset including 912 MR images and 306 CT images collected from 152 subjects. Experimental results show that the proposed automated segmentation framework is highly consistent with physician with average DSI (dice similarity index) as high as 0.9005 (CT), 0.8984 (MR), 0.8935 (MR+CT) and BD (boundary distance) as low as 0.6393 mm (CT), 0.6586 mm (MR), 0.6881 mm (MR+CT). Based on this accurate automated segmentation, the estimated areas, highly correlated to their independent ground truth, have been achieved with correlation coefficient: 0.9154 (CT) and 0.8789 (MR). Hence, the proposed approach enables an efficient, accurate and convenient tool for clinical diagnosis of neural foramina stenosis.

1. Introduction

Neural foramina stenosis (NFS), clinically defined as the narrowing of the bony exit (see Fig. 1(a)) of the spinal nerve root, is caused by abnormalities in vertebral and intervertebral disc, such as a decrease in the height of an intervertebral disc, or osteoarthritic changes in the facet joints [1,2]. Symptoms of NFS are very common, affecting up to 80% of the population worldwide, and may cause pain, disability and economic loss [3–5]. For example, each year more than 400,000 Americans suffer from lower back or leg pain [6,7]. Diagnosis and treatment of NFS, often require segmentation of neural foramina images from multiple imaging modalities for estimating its area as quantitative analysis [1,8–10]. Here, MR and CT imaging are often simultaneously required as MR is better to display the stenosis caused by disc abnormality and CT is better to display the stenosis caused by vertebra abnormality (as shown in Fig. 1(b)). For efficient diagnosis and timely treatment of NFS, manual segmentation by physician is bound to be infeasible for neural foramina images because of its known tediousness, inefficiency, and inconsistency [8,10].

Computer processing methods are highly desirable, but face big challenges due to the following complexities in segmentation of neural foramina (as shown in Fig. 1(c)):

1. *Complex appearance inhomogeneity*: Two types of appearance inhomogeneity are included:
   (1) *Inter-modality intensity difference*: In different modalities, the intensity profile of neural foramina is completely different [10].
   (2) *Intra-modality appearance variation*: Even for one specific modality, the structures passing neural foramina are inhomogeneous and this inhomogeneity varies with different subjects, positions, and spine abnormalities [3].
2. *Great boundary variations*: Two types of boundary variations are included:
   (1) *Diverse boundary shape variation*: The boundary shape of

* Corresponding authors. Department of Medical Imaging, University of Western Ontario, London, ON, Canada N6A 3K7.
E-mail addresses: xhe244@uwo.ca (X. He), slishuo@gmail.com (S. Li).

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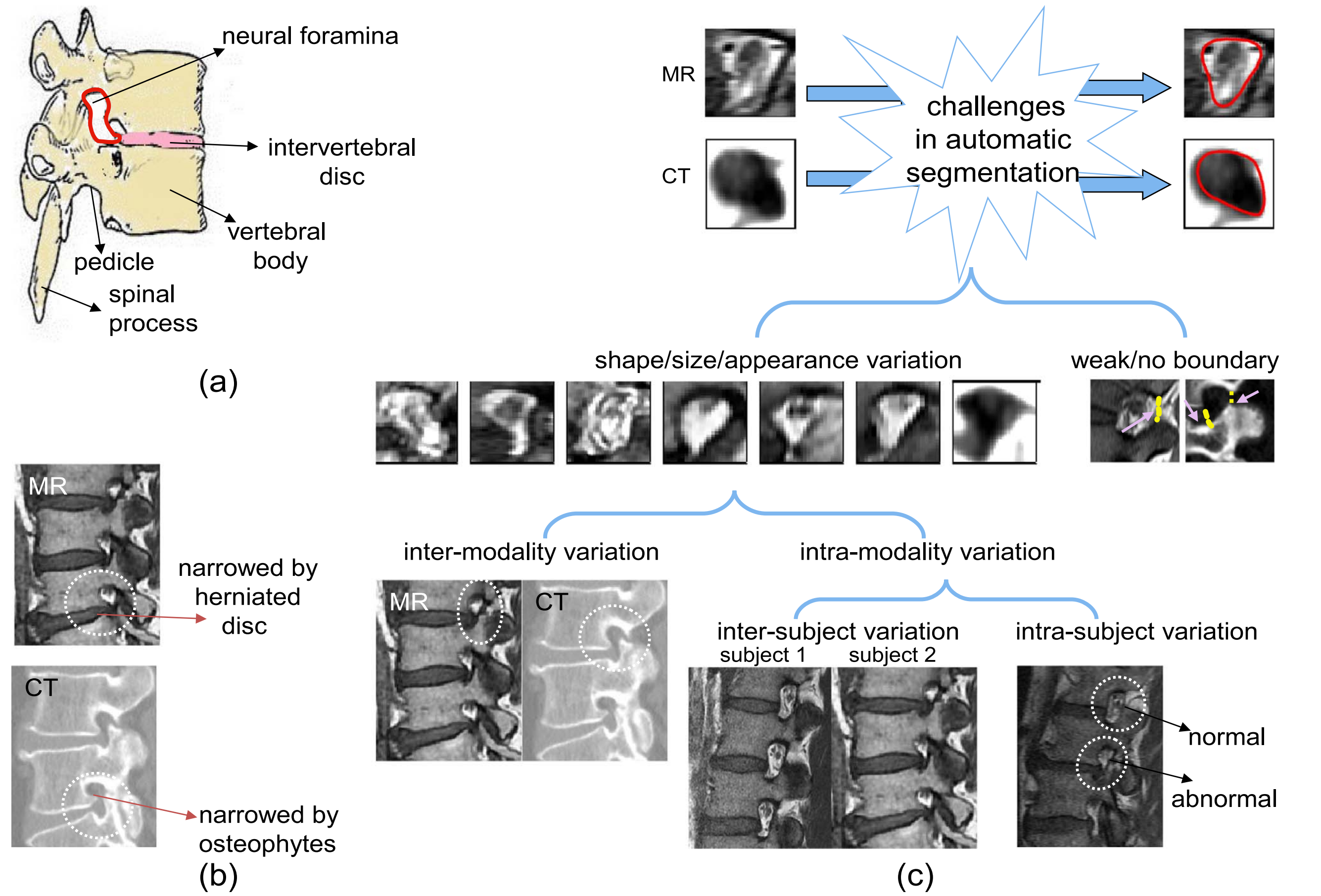

Fig. 1. (a) The anatomy of neural foramina; (b) two common modalities used in clinical diagnosis of NFS: MR and CT; (c) the complexities in segmentation of neural foramina. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

neural foramina varies with different positions in spine, subjects, and spine abnormalities [11,12]. For example, the shape of boundary in normal and stenosed state is obviously different [5,12].

(2) *Local weak/no boundary*: Low intensity contrast around some parts of boundary leads to local weak/no boundary problem. For example, in CT imaging, local weak/no boundary problem commonly appears (marked in green dotted line) as neural foramina has highly similar intensity profile with the surrounding intervertebral disc.

All these mentioned complexities bring great challenges (as shown in Fig. 2) to conventional computer processing methods:

- *Infeasibility caused by great variations in intensity profiles* (Fig. 2(a)): Intensity-based methods are very sensitive to inhomogeneous intensity profiles which commonly appear in MR imaging; even worse, the intensity profiles in MR and CT are completely different. So intensity-based methods can easily be confused when segmenting images from different modalities in a single framework [13–15].
- *Infeasibility caused by inhomogeneous intensity distribution* (Fig. 2(b)): Region-based segmentation methods are very sensitive to inhomogeneous intensity distribution inside neural foramina, which brings a noise disturbance when seeking the optimal region partition. So region-based segmentation methods [15,16] stops at a false region.
- *Infeasibility caused by the combination of great boundary diversity and local weak/no boundary* (Fig. 2(c)): Semi-automated methods, based on the evolution of an initialized boundary, are sensitive to the combination of great boundary diversity and local weak/no boundary as it breaks the required assumption which considers boundaries as small deformations of an initialized boundary, and the intensity contrast around a boundary is homogenous and strong [17,18]. So semi-automated methods fail to evolve the true boundary.
- *Infeasibility caused by the weak edge, no edge, and noisy edge* (Fig. 2(d)): Edge-based methods [19] are sensitive to local weak/no edge around the desired boundary, and are easily be disturbed by the noisy edge, which is strong but does not lie in the desired boundary (indicated by line box). So edge-based methods leak the true edge of neural foramina.

Even worse, in clinical practice, these mentioned difficulties always simultaneously appear so that a more bigger challenge is posed to conventional computer processing methods. Due to the discussed enormity of the challenges, as far as we know, there is still no automated segmentation method proposed for neural foramina.

In this paper, we propose a novel regression segmentation framework for automated segmentation and area estimation of neural foramina from MR and CT images, for the first time. It creatively formulates the segmentation task as a boundary regression problem to associate extremely diverse images directly with desired boundaries. By leveraging the strength of sparse kernel machines, a highly nonlinear boundary regression model is learnt in holistic regression fashion. Such holistic regression fashion enables the learnt model with an accurate, efficient, and robust boundary prediction: (1) the holistic regression outputs where the locations of all the boundary points are regressed simultaneously instead of separately, therefore, the local weak part of the regressed boundaries are guided by the global shape prior learned from the training data; (2) the holistic regression input where each