Project Proposal

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Non-android Project

Motivation

One of the prominent applications of Magnetic Resonance Imaging (MRI) is spine imaging given its unparallelled contrast resolution enabling differentiation of intraspinal soft tissue structures, the spinal cord, and the vertebral column **[1]**. More specifically, spine MRI is commonly used for diagnosis and treatment planning of several spinal pathologies, namely intervertebral disk (IVD) herniation, slipped vertebra, spinal canal stenosis, and IVD degeneration **[2]**. A standard multi-echo protocol acquiring sagittal T1- and T2-weighted images on a 3T system may reasonably elucidate the root cause of nerve-compression-guided back pain by visually distinguishing unhealthy intervertebral structures from normal ones **[Figure 1]**. While tremendous strides have been made in recent decades developing conventional gradient echo pulse sequences that offer a combination of enhanced SNR and contrast to enable differential visualization of IVDs, nerve roots, and osteophytes [1], quantitative computer-aided diagnosis, and even related research studies have been lagging, as methods have largely depended on manual localization and segmentation of anatomy, both error-prone and labor-intensive **[3, 4]**. In the context of disc pathologies and canal stenosis, segmentation of structures such as lumbar IVDs is a prerequisite step to quantitative computer-aided diagnosis **[5]**, and particularly challenging due to large dynamic range of sizes, shapes, and appearance of IVDs and surrounding vertebra in this region **[6]**.

Accordingly, we are interested in a fully automatic image processing pipeline for differential segmentation of the lumbar vertebra, the discs, and the spinal cord from 2D sagittal T1/T2 MR images. These segmentation masks will be fed into an ML classification algorithm as a preliminary effort towards computer-aided diagnosis of IVD degeneration **[Figure 2]**.

__Figure 1__ (A) T2-weighted (left) and T1-weighted (right) sagittal MR images of healthy spine (note: healthy e.g. hydrated IVD nucleus appearing as bright ellipses) (B) Blood vessel (left) and IVD (right) pathologies resolved by 3T Sagittal T2-weighted images of the lumbar spine. **[1]**

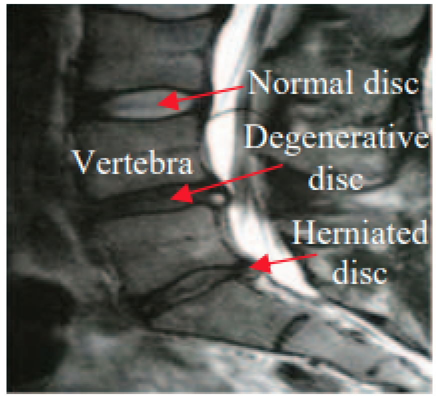


Figure 2 *Sagittal T2-weighted MR images can aid in diagnosis and quantification of disc degeneration and herniation* ***[7] .***

Related Work

In 2014, Mir et al. proposed a hybrid morphological processing and unsupervised watershed algorithm for segmentation of lumbar IVDs [6]. While their contour lines look promising across a spectrum of spine images, they did not quantify segmentation performance. In 2015, Chen et al. proposed and validated a learning-based localization and segmentation algorithm that segments seven IVDs in a T2 weighted MR image of the spine [10]. This method first localizes the center of each of the IVDs and then classifies the image pixels around the center as background or foreground. Here, foreground pixels comprise the IVDs. One limitation of this method is that it assumes that the image contains at least seven IVDs. If the input image has less than seven IVDs, the algorithm still returns seven center points, where the points that are not associated with an IVD could drive the algorithm to produce an incorrect result.

The two methods discussed above are exemplary of the current efforts in spine segmentation. As can be seen, the approaches to segmentation vastly differ and are yet not making use of machine learning algorithms to assist in the classification of results. Thus, through our project, we hope to learn from and expand the previously constructed segmentation techniques while also applying our own machine learning algorithm to use the segmented images to classify the images into normal and abnormal groups.

Proposal
Simply put, our task can be summarized as follows:

- Given a sequence of 2D T1/T2 Spine MRIs, identify images where the orientations of Spine is upright facing to the viewer, so it is useful in diagnosing;
- For the selected MRIs, segment spinal cord, vertebraes and discs;
- Based on the segmentation, extract relative region components for classifying normal/abnormal discs

Methods

Segmentation

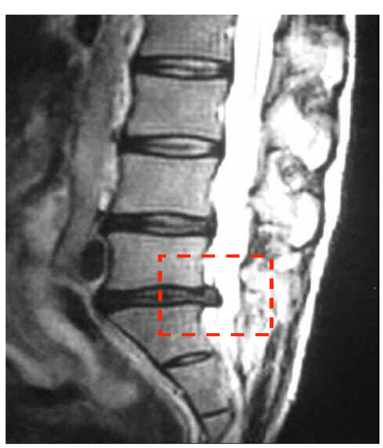
We would likely identify the central sagittal cross section by calculating the correlation of each sagittal edge image with a 'sandwich' edge model of an IVD contained within 2 disk structures [8], and selecting the image with maximum net correlation score. The intensity profile along the central column of this image may be analyzed to derive templates for IVD and/or vertebral bodies for matched filtering or template matching protocols. For IVD and vertebral segmentation, any combination of Hough transform, template matching, and edge-based algorithms such as the watershed algorithm will be attempted post contrast enhancement and denoising in order to dampen over-segmentation [6]. Furthermore, we have access to both T1 and T2-w sagittal spine images, so multimodality mask generation and combination might be of use as well, for extracting regions that look very different or very similar across the two contrasts.

The spinal cord will likely be segmented using a combination of thresholding to extract the canal surrounded by the bright CSF region in T2 images, followed by morphological opening and closing with linear structuring elements.

Classification

The ideal input (of each disc) to the classification model will likely looks like the red rectangle in figure 3. To build such a rectangle box, a naive way would be to simply connect the centroid of adjacent vertebra and draw a rectangle. Some further processing (e.g. mean normalization, rotation or PCA) might need to be applied. A wide variety of classification model is applicable, for example, LDA [9] we learnt in class, or utilizing pre-trained deep learning models [11, 12].

Figure 3 Cropped region (red) for classification



References

[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC2080848/
[2] H. An, P. Anderson, V. Haughton, J. Iatridis, J. Kang, J. Lotz, R. NatarajanJr., T. Oegema, P. Roughley, L. Setton, J. Urban, T. Videman, G. Andersson, and J.Weinstein, ''Introduction. Disc degeneration: Summary,'' Spine, vol. 29, pp. 2677--2678, 2004.
[3] P. Violas, E. Estivalezes, J. Briot, J. Sales de Gauzy, and P. Swider, "Objective quantification of intervertebral disc volume properties using MRI in idiopathic scoliosis surgery," J. Magn. Reson. Imag., vol. 25, pp. 386–391, 2007.
[4] R. Niemelainen, T. Videman, S. Dhillon, and M. Battie, "Quantitative measurement of intervertebral disc signal using MRI," Clin. Radiol., vol. 63, pp. 252–255, 2008.
[5] S. Michopoulou, L. Costaridou, R. Speller, E. Panagiotopoulos, A. Todd-Pokropek, "Segmenting degenerated lumbar intervertebral discs from MR images", *Proc. IEEE Med. Imag. Conf.*, pp. 4536-4539, 2008.
[6] A.h. Mir, "Segmentation of lumbar intervertebral discs from spine MR images", *International Conference on Innovative Applications of Computational Intelligence on Power Energy and Controls with their impact on Humanity (CIPECH)*, pp. 85-91, Nov 2014.
[7] C.S. Ling et al., "Semi-automated vertebral segmentation of human spine in MRI images," *International Conference on Advances in Electrical, Electronic and System Engineering*, pp. 120-124, Nov 2016.
[8] A. Neubert et al., "Automatic 3d segmentation of vertebral bodies and intervertebral discs from MRI," in Int. Conf. Digital Imag, Comput., Tech. Appl., pp. 19–24,Dec. 2011.
[9] Rathi, V. P., and S. Palani. "Brain tumor MRI image classification with feature selection and extraction using linear discriminant analysis." *arXiv preprint arXiv:1208.2128* (2012).
[10] Chen C, Belavy D, Yu W, Chu C, Armbrecht G, Bansmann M, et al. Localization and segmentation of localization and segmentation of 3D intervertebral discs in MR images by data driven estimation. *IEEE Trans Med Imaging*(2015) **34**(8):1719–29.
[11] Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." *arXiv preprint arXiv:1409.1556* (2014).
[12] Szegedy, Christian, et al. "Inception-v4, inception-resnet and the impact of residual connections on learning." *AAAI*. Vol. 4. 2017.