Automatic MRI Prostate and Central Gland Segmentation using Holistically Nested Networks with Short Connections

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Abstract. Accurate and automated prostate and central gland segmentation on MR images is essential for aiding the prostate cancer diagnosis system. This work presents a 2D orthogonal volumetric deep learning method to automatically segment the whole prostate and central gland from T2-weighted axial MR images. The method also generates high density 3D surfaces from the low-resolution (z-axis) MR images. In the past research works, most methods focus on axial image alone, for example, 2D based segmentation of the prostate from each 2D slice. Those methods suffer the problems of over-segmenting or under-segmenting the prostate at apex and base, which is the major contribution of errors. The proposed method leverages the volumetric context to effectively reduce the apex and base segmentation ambiguities. It also overcomes the jittering or laddering surface artifacts when constructing a 3D surface from 2D segmentation or 3D U-Net segmentation approaches. The experimental results demonstrate that the proposed method can achieve 92.4%±3% Dice similarity coefficient (DSC) for prostate and DSC of 90.1%±4.6% for central gland without trimming any ending contours at apex and base. Our experiments illustrate the feasibility and robustness of the 2D volumetric Holistically Nested Networks with Short Connections method for MR prostate and central gland segmentation. The proposed method achieves a competitive performance with the current literature methods.

Keywords: deep learning, holistically nested networks, prostate, segmentation, MRI.

1 Introduction

In the past decade, the traditional MR prostate segmentation spans the domain of atlas, shape, region and machine learning based methods. We demonstrate a few typical works from the traditional perspectives. Klein et al. [1] proposed an automatic segmentation method based on atlas matching. The atlas consists of a set of prostate MR images and corresponding pre-labeled binary images. Non-rigid registration is used to register the patient image with the atlas images. The best match atlas images are selected, and the segmentation is an average of the resulting deformed label images and thresholding value by a majority voting rule. Shape-based models are widely used for MRI prostate segmentation. Yin et al. [2] proposed an automated segmentation model based on normalized gradient field cross-correlation for initialization, and graph search-based framework for refinement. Ghose et al. [3] proposed to use texture feature from approximation coefficients of a Haar wavelet transform for propagation of a shape, and Active Appearance Model (AAM) to segment the prostate. Toth et al. [4] extended the traditional AAM model to include intensity and gradient information and used level-set to capture the shape statistical model information with a multi-feature landmark free framework. A registration scheme is used to locate the coarser prostate region. Many successful approaches were proposed that use feature-based machine learning. Habes et al. [5] proposed a SVM-based algorithm that allows automated detection of the prostate on MRI images. The developed method utilizes SVM binary classification on 3D MRI volumes. Automatically generated 3D features, such as median, gradient, anisotropy, and eigenvalues of the structure tensor, are used to generate the classification binary masks for segmentation. Liao et al. [6] proposed a unified deep learning framework by using a stacked independent subspace analysis network to learn image features in a hierarchical and unsupervised manner.

Most recently, the deep learning-based methods were integrated into MRI prostate segmentation and achieved striking performance as compared to the traditional approaches. The major works stem from the MICCAI PROMISE 12 challenge. Most of the works focus on 3D-Unet architectures to volumetric segmentation. Yu et al. [7] proposed a 3D volumetric U-Net convolutional neural network (ConvNet) with mixed residual connections between corresponding scale layers. It takes the 3D spatial contextual information in the deep learning architecture and produces the volume-to-volume prediction. Milletari et al. [8] proposed 3D volumetric V-Net (U-net alike) architecture with the 3D volumetric convolution to perform end-to-end prediction. Each stage of the U-Net compromises one to three convolutional layers (residual block) to learn the residual function. This method also proposed a novel objective function based on Dice coefficient maximization, which is optimized during training. Meyer et al. [9] proposed multi-stream 3D convolutional neural networks to segment the prostate from the high resolution scanned MR images (axial, sagittal, coronal). It is based on 3D U-Net. The input images are processing in an analysis (downsampling) and synthesis (upsampling) path at four scale levels. The network has three analysis streams, where the streams process axial, coronal, and sagittal scans individually. The three streams are then concatenated at the lowest resolution level. Skip connections are established from each stream to the respective level of the synthesis path. Zhu et al. [10] proposed the UR-Net architecture. It utilizes a Bidirectional Convolutional LSTM (BDC-LSTM) layer as the basic building block, and leverages U-Net as the main framework. The BDC-LSTM takes three adjacent slices as input, and utilizes the interslice and intraslice information to guide feature extraction. The U-Net functions as the standard encoding and decoding path to process MRI data. Jia et al. [11] proposed a coarse-to-fine prostate segmentation. An atlas based image registration is first applied to get the coarse boundary. Then, a VGG-19 based CNNs functions as pixel-based classifier to predict if the pixel belongs to prostate boundary. The deep CNNs training and testing are patch based. The center of the patch represents the pixel.

We develop a system for automatic prostate and central gland segmentation in T2-weighted (T2W) MRI using Holistically Nested Networks with Short Connections (HNNsc). For a given axial image, our method applies 2D HNNsc prediction to each orthogonal view (axial, coronal, and sagittal) to generate 2D VOIs (Volume of Interest), and merge the three VOIs into 3D cloud points. Then, geometric mesh reconstruction and optimization are used to reconstruct the 3D dense surface. The last step is to convert the 3D surface back into axial VOIs for performance measurement. Most existing MR prostate segmentation methods generate the boundary VOIs with axial image alone. Due to the lower z-axial resolution (i.e. 3 mm), most methods only apply to 2D axial slices, ignore the coarse features from sagittal and coronal views. The primary concern is that the low z resolution might introduce larger segmentation errors. 3D U-Net takes the spatial context with certain constraint; however, the 3D volume is still constructed from a low z-resolution image.

In this paper, we aim developed a feasible system for MRI prostate and central gland segmentation. We employ multiscale and multilevel learning, regions cues using 2D Holistically-nested Networks with short connections (HNNsc) to solve the segmentation issues on MR images. The proposed method takes advantage of the 2D HNNsc and applies it to a volumetric context. At the current stage of integrating deep learning methods into medical image segmentation, the ideal state is to come up with a standalone deep learning system that can segment the target object end-to-end. In reality most existing deep learning systems more or less predict the segmented object with noise. For example, small noise can be generated from the deep learning model. Those scattered points or smaller regions mainly contribute to large Hausdorff distance errors. To overcome the problem, we utilize 3D surface reconstruction and 3D mesh optimization to effectively reduce noise from deep learning generated results. The experiments illustrate the promise and robustness of the proposed automatic segmentation pipeline, which achieves comparable performance to the state-of-the-art results in the current literature. In addition, the 2D based deep learning approach can train large number of images to fit into a general-purpose graphics card, such as Nvidia K20x with 6GB texture memory.

2 Methods

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3 Discussion and Conclusion

In this work, we propose a 2D orthogonal volumetric HNNsc deep learning framework to accurately segment the MR prostate and central gland. The framework uses the axial, sagittal and coronal images to reconstruct high-density 3D prostate and central gland surfaces from the low resolution axial images. Traditional 2D schemes with axial image alone suffer from miss-interpolation issues at apex and base. Even with the latest proposed deep learning methods, irregular shapes and scattered small regions appear in the central part, apex, and base part of the predicted heatmaps. To overcome the problems, our post-processing steps can approximate the real prostate and central gland 3D shapes from deep learning predicted heatmaps, and effectively reduce the noise regions and miss-interpolated contours at the apex and base of axial images.

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In conclusion, we present a 2D-volumetric HNNsc framework to automatically segment the MR prostate and central gland from axial images alone. The preprocessing step enhances the MR image quality and converts the low resolution axial image to high resolution orthogonal view images. The 2D HNNsc deep learning model exploits multi-features (MRI+CED pair) to generate reasonable segmentation heatmaps. The short connections from deep side-output layers back to all shallower side-output layers ensure more robust prediction. The HNNsc model improves the segmentation performance from the HNN model by 2% in mean DSC. The post-processing step refines the 3D smooth surfaces from the HNNsc generated noisy cloud point set, and converts the highly dense 3D surface back to a low resolution axial image. The experimental results verify that the proposed framework is a relatively simple, feasible and reliable approach for prostate segmentation tasks. In addition, the proposed framework achieves close to state-of-the-art performance as compared with other literature results. In the current literature, we are the first to propose the deep learning model for both MR prostate and central gland segmentation, which can substantially aid the prostate cancer detection in a CAD system.

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