

A novel deep learning-based method for prostate segmentation in T2-weighted magnetic resonance imaging

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Abstract. We propose a novel automatic method for accurate segmentation of the prostate in T2-weighted magnetic resonance imaging (MRI). Our method is based on convolutional neural networks (CNNs). Because of the large variability in the shape, size, and appearance of the prostate and the scarcity of annotated training data, we suggest training two separate CNNs. A global CNN will determine a prostate bounding box, which is then resampled and sent to a local CNN for accurate delineation of the prostate boundary. This way, the local CNN can effectively learn to segment the fine details that distinguish the prostate from the surrounding tissue using the small amount of available training data. To fully exploit the training data, we synthesize additional data by deforming the training images and segmentations using a learned shape model. We apply the proposed method on the PROMISE12 challenge dataset and achieve state of the art results. Our proposed method generates accurate, smooth, and artifact-free segmentations. We achieve an average Dice score of 91.2 on training and validation data. Our two-step segmentation approach and data augmentation strategy may be highly effective in segmentation of other organs from small amounts of annotated medical images.

1 Introduction

Segmentation of prostate in T2-weighted magnetic resonance imaging (MRI) is an essential step for many tasks in treatment planning and intervention [13,38]. Automatic segmentation methods are highly desirable because they can increase the speed and reproducibility of the segmentation. In the past decades, many studies have proposed (semi-)automatic methods for prostate segmentation in T2-weighted MRI [36,9,15]. However, fully automatic prostate segmentation is very challenging because of the inter-patient variability in the prostate size, shape, and appearance, variations in the scanners and scanning protocols, and similarity of the prostate with the surrounding tissue.

A large number of the methods proposed for prostate segmentation in T2-weighted MRI use atlases [11,21]. In these methods, a number of MR images

with known prostate segmentation are registered to the target image. Mutual information, cross-correlation, image feature correspondence, and the image gradient are among the image similarity metrics used for registration. The deformed prostate segmentation masks of the atlas images are combined to infer the segmentation of the prostate in the target image. Therefore, atlas-based methods turn the segmentation problem into a registration problem. A critical choice in these methods is how to combine/fuse the registered segmentation masks. One can rank the segmentation masks based on some image similarity metric and choose the most similar segmentation, or use more elaborate methods such as majority voting, STAPLE, or iterative label fusion [4,11,12]. In general, atlas-based methods can produce poor segmentations, especially if the target image is very different from the population of the images in the atlas. To achieve acceptable results, some atlas-based methods rely on additional steps based on statistical shape models [21,22,7]. Moreover, most of the atlas-based methods follow a global registration strategy, which makes them unnecessarily sensitive to the anatomical features that are far away from the prostate and increases the computational time. To overcome these shortcomings, some studies have proposed two-step registration approaches in which a global registration is first performed to identify the location of the prostate in the image. In the second stage, a local registration is performed by focusing on the prostate region [35,25].

Another class of methods includes those based on deformable models such as active shape models and level sets [37,16,10,30,32]. A great appeal of these methods is that they are based on sound theory from physical sciences and mathematics. However, these methods can be very sensitive to initialization [31] and a good initialization may be hard to obtain. Moreover, the quality of segmentation can be poor where the edge information is not strong. Therefore, some of these methods depend on manual initialization or rely on other prior information in the form of shape models to regularize the generated segmentation mask [33,3].

Some studies have proposed methods based on graph cuts [5,18]. Although these methods are versatile, they have their own limitations. For example, they produce poor results at the locations of weak edges and typically need post-processing steps in order to obtain satisfactory results. Recently, some studies have shown that the performance of graph cut-based methods can be substantially improved by using active contours and by formulating the graph cut method in terms of super-voxels instead of raw voxel intensities [27,28].

Because of the difficulties faced by the methods mentioned above, a large number of studies have tried to combine the advantages of two or more of these frameworks. Many of these methods also use some type of machine learning to achieve improved results. For example, several studies have combined probabilistic learning of the distribution of prostate texture or voxel intensities with shape models [29,20,1]. Supervised and un-supervised machine learning methods such as random forests and clustering methods have also been combined with deformable models and atlas-based methods for prostate segmentation in T2-weighted MRI [19,8,6].

Despite the great efforts and numerous methods that have been proposed in recent years, automatic segmentation of prostate in T2-weighted MRI still remains a challenge. Most of the proposed methods achieve much lower performance than manual segmentation. If the test images are different than the images used for model development, e.g., due to inter-patient variability or different scanning protocols, the performance of these methods can deteriorate substantially.

In recent years, deep convolutional neural networks (CNNs) have achieved unprecedented results in segmentation of natural images [17,2,24]. Compared to the more traditional segmentation methods, the new CNN architectures that have been proposed for dense segmentation possess a number of highly desirable characteristics: 1) they have a very high capacity that enables them to effectively describe the large variations that exist in the training data, 2) they are able to explain local and global information at different resolutions simultaneously, 3) in many applications they can achieve quite satisfactory results without the need to additional steps to refine their segmentation, which also implies that they can be trained end-to-end as a single module, and 4) even though they have long training times, their inference time is very fast. Consequently, many studies have recently employed CNNs for segmentation of medical images [14] and, in general, they have reported very promising results. For segmentation of the prostate in T2-weighted MR images, in particular, deep CNNs with volumetric convolutional filters have been shown to achieve very good results [23]. One study resampled the ground-truth segmentation to generate prostate masks with different resolutions for more effective training of a deep CNN [34]. The trained CNN was applied on sub-volumes of the input image and averaging of the probability maps estimated for all sub-volumes was used to obtain the final prostate segmentation. The proposed method achieved state of the art results, which was attributed to the use of short and long residual connections in the network. Another study proposed a deep CNN with 2D and 3D residual connections and achieved state of the art results [26].

2 The proposed method

We propose a new CNN-based method for segmentation of the prostate in T2-weighted MR images. The details of the method and results will be published in a future paper. Here, we summarize some of the main ideas.

We argue that the difficulty in achieving human-level performance in this task is due to the large variability in the shape, size, and appearance of the prostate in these images. Based on the results achieved by CNNs in segmentation of natural images, we think that theoretically they should be able to achieve human-level performance in prostate segmentation in T2-weighted MRI. However, this is not easy to achieve in practice because it is hard to effectively train large CNNs with small amounts of annotated data. To reduce this gap and effectively utilize the capacity of deep CNNs with limited training data, we suggest two strategies:

1. We suggest training two CNNs. The first, *global*, CNN will accept the entire image as its input and generate a soft prostate segmentation mask. This initial segmentation is then used to determine the location and the extent of the prostate in the image. A second, *local*, CNN will then work on a sub-volume of the image. This will allow the second CNN to focus on learning features that are most relevant for accurate delineation of the prostate boundary, which is a major challenge due to similarity with the surrounding tissue and scarcity of the training data.
2. We use massive data augmentation for training of the two CNNs. Here, our argument is that even 50 training images are not sufficient to train large CNNs. Therefore, we synthesize additional realistic data by deforming the training images and their segmentation masks using displacement fields computed based on a prostate shape model. To further improve the training and avoid local minima, random displacements and noise are introduced during training. Moreover we identify the images that are more difficult to segment and use this information in an active learning framework.

A schematic representation of the steps involved in our fully-automatic segmentation method is shown in Figure 1. A schematic representation of the CNN architecture is shown in Figure 2.

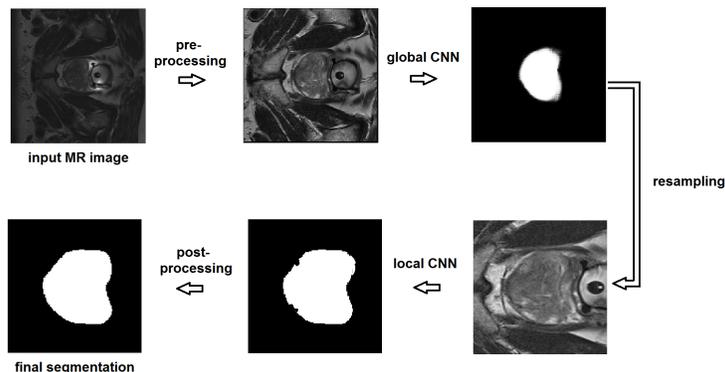


Fig. 1. A schematic representation of the steps involved in the proposed segmentation method.

2.1 Training and evaluation

We used the data from the PROMISE12 challenge [15]. This dataset consists of 50 training and 30 test images, which have been acquired at different centers and using different scanners and scanning protocols. The dataset is very challenging because of the large variation in the voxel size, field of view, and dynamic range

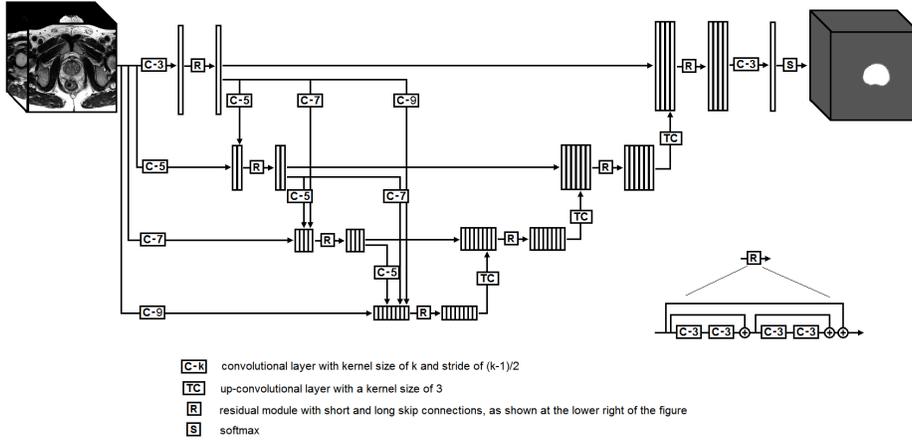


Fig. 2. A schematic representation of the CNN architecture used in this study. The network shown in this figure has a depth of 4. The global and local networks used in this study had depths of 5 and 3, respectively.

of the images as well as in the appearance of the prostate. Approximately half of the images include an endorectal coil.

We used a five-fold cross validation approach. Each time, the two CNNs were trained on 40 of the images and evaluated on the remaining 10 images.

3 Results

Table 1 shows the average and standard deviation of the Dice score on the training and validation images. In order to show the effect of the different steps in our segmentation pipeline, we have shown the resulting Dice score after each step. Our proposed method achieves a high final Dice score of 91.2 with a low standard deviation of 2.0.

	Global CNN	Local CNN	Post-processing
Training	85.0 ± 3.9	91.0 ± 2.3	91.2 ± 2.2
Validation	84.9 ± 4.1	90.4 ± 2.3	91.2 ± 2.0

Table 1. Mean \pm standard deviation of the Dice score for training and validation images after each step in the segmentation pipeline.

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