Fast semi-supervised segmentation of the kidneys in DCE-MRI using convolutional neural networks and transfer learning

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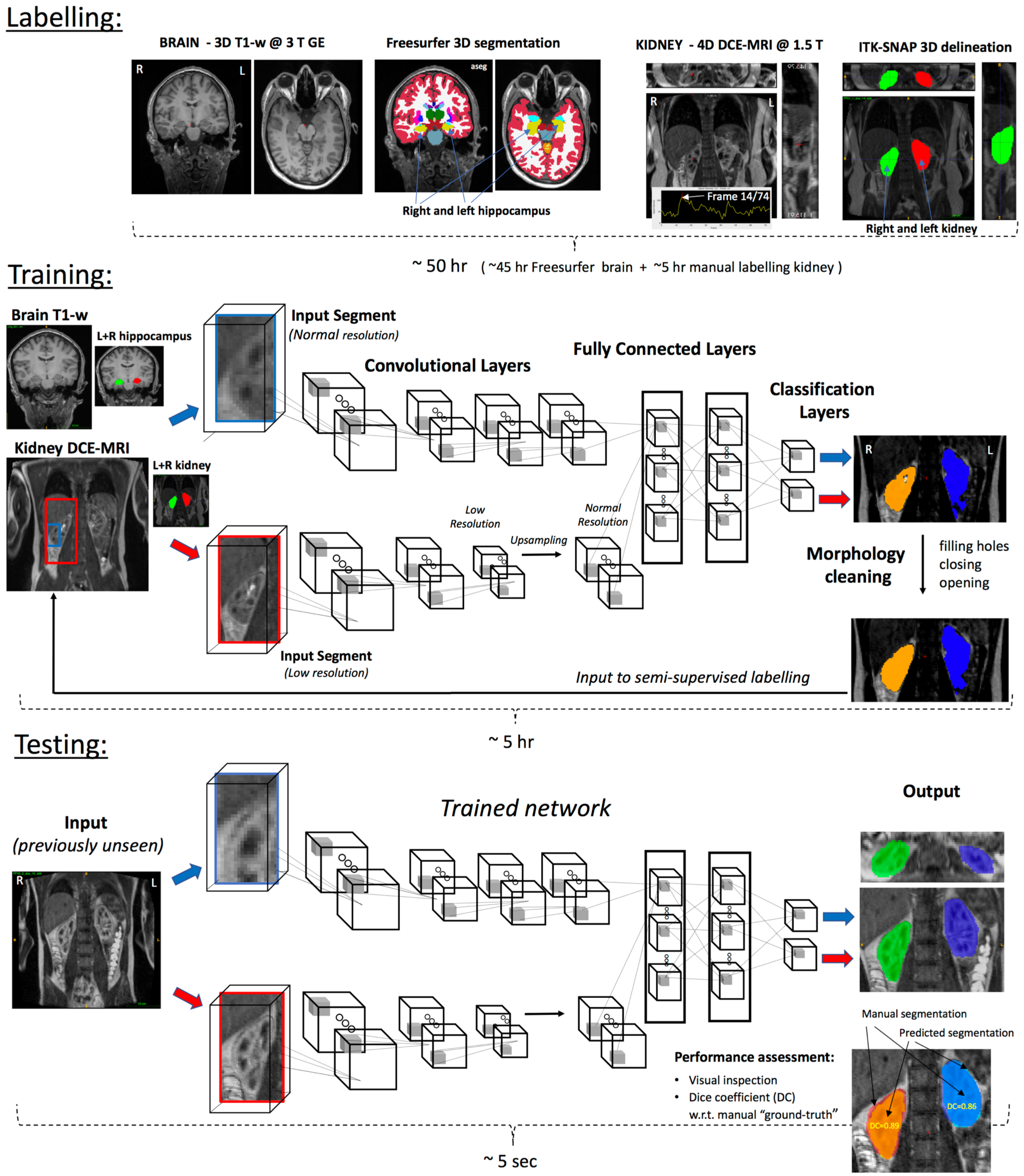
Introduction

- Object segmentation is arguably the holy grail of quantitative image analysis. In medical imaging, accurate segmentations make it possible to obtain crucial structural and functional tissue information, including localization, shape and volume estimation, and quantification of imaging-derived biomarkers. In the context of DCE-MRI of the moving kidneys, frame by frame segmentation of the left and right kidney will enable extraction of mean parenchymal signal intensity over time. These time courses can then be used in a pharmacokinetic modeling setting, fitting model parameters such as GFR to observed data. The aim of the present study was to develop a fast and robust kidney segmentation method applied to 3D DCE-MRI recordings, an important step in our development of segmentation-based predictions of GFR using machine learning.

Methods

- **DCE-MRI recordings.** In a cohort of 20 healthy volunteers kidney DCE-MRI data were continuously acquired on a 1.5 T Siemens Avanto scanner using a 3D SPGR sequence (see [1] for details).

- **Kidney segmentation.** A common stumbling block for supervised learning methods based on deep neural networks is the large number of labeled examples required for training. Creating labeled data for a segmentation model typically involves producing manual delineations, a time-consuming, difficult and often unreliable process. To reduce the need for manually labeled data we used transfer learning from a different problem: segmenting the left and right hippocampus in 3D T1-weighted MR images. After training a network to produce accurate hippocampus segmentations, we copied the weights to a CNN designed for segmenting kidneys, freezing the weights of the first few layers in this network during training. By combining transfer learning, dropout regularization, residual connections and semi-supervised learning through pseudo-labeling, we were able to train a three-dimensional convolutional neural network (CNN) [2] that can accurately segment both the left and right kidney, based on a small number of manually annotated training examples. For our experiments we were using a single standard NVIDIA GeForce 1080Ti GPU for training and executing the CNN model.



Results

- With our approach we were able to obtain 3D segmentation of both the left and right kidney in less than 7 seconds per volume. Average Dice coefficient across three unseen test volumes were 0.87, 0.85 for left and right kidney, respectively. The lower right part of Fig. 1 shows the manually delineated kidneys and the predicted segmentation. Note that the ground-truth is not exact, which makes the Dice coefficient a less reliable measure of success, requiring additional visual inspection for assessment.

Discussion

- The work described above is part of our current work aimed at uncovering the parenchymal signal intensity from each voxel, opening the door for voxel-wise prediction of GFR from DCE-MRI.
- A limitation of the experiments discussed so far is their restriction to labelling and testing only the time-frames where the kidney cortex show close to maximum enhancement. However, in recent work we have used deformable motion correction to construct training data for all images taken during the wash-in and wash-out phases in the DCE-MRI series. Using this approach we have developed a CNN that is able to segment all time-frames, resulting in a fast way to get time-series, and estimates of kidney volumes. A next step will be to segment the cortex, the medulla, and the renal pelvis, in addition to the aorta. This will enable assessment of antaomical kidney compartments and automated sampling of the arterial input function.
- Accurate segmentation of structures in medical images is crucial for a wide variety of disorders and organ systems, and our transfer learning based approach to segmentation is broadly applicable. By transferring knowledge from a task with ample supply of annotated training data to another with few training examples, one can enable application specific automatic segmentation with relatively modest need for manual input. We are currently investigating the breadth of applicability of this approach to CNN-based segmentation in medical images, across organs and image modalities.

References

[1] E. Eikefjord et al. Acta Radiol 2017;58:748-757. [2] K. Kamnitsas et al. Med Image Anal 2017;36:61-78.

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