Machine Learning Powered Automatic Organ Classification for Patient Specific Organ Dose Estimation

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Background

Body part recognition is essential in automatic medical image analysis as it is a prerequisite step for anatomy identification and organ segmentation [1-2]. Accurate body part classification facilitates organ detection and segmentation by reducing the search range for an organ of interest. As a result, we can quickly and efficiently identify an organ of interest at a higher accuracy when compared to current text-based body part information in DICOM (Digital Imaging and Communications in Medicine) headers[3].

Multiple techniques have been developed using multi-class random regression and decision forests to classify multiple anatomical structures ranging from 6-10 organs on tomographic (CT) scans[4-5]. These classifiers can discriminate even between similar structures such as the aortic arch and heart[1]. However, these prior works focus on a general anatomical body part classification, but organ-specific classification has not been studied for applications such as organ dose estimation.

Accordingly, we present a machine learning powered automatic organ classifier for CT datasets with a deep convolutional neural network (CNN) followed by an organ dose calculation. We labeled 16 different organs from axial views of CT images. A 22-layer deep CNN using the NVIDIA Deep Learning GPU Training System (DIGITS) was trained and validated with a 646 CT scan dataset. The resultant classified organ was automatically mapped to the slab number of a mathematical hermaphrodite phantom to determine the scan range of ImPACT CT dose calculator. This technique can be used for patient-specific organ dose estimation since the locations and sizes of organs for each patient can be calculated independently, rather than other simulation based methods.

Evaluation

We compiled a dataset of 12,748 CT images of 63 patients from the clinical PACS (Picture Archiving and Communication System) of Massachusetts General Hospital with an Institutional Review Board (IRB) approval. We first developed preprocessing software to annotate and categorize these images into 16 different body parts in axial views: Brain; Eye Lens; Nose; Salivary Gland; Thyroid; Upper Lung; Thymus; Heart; Chest; Abdomen 1; Abdomen 2; Pelvis 1; Pelvis 2; Urinary Bladder; Genitals; and Leg. As can be seen in Fig. 1(A), we only utilized the scans of regions that could be clearly defined as one of the aforementioned body parts. This is an optimized organ classification choice for the following organ dose estimation task. The gaps account for transition regions, which were not used for the training algorithm due to their lack of clear regional definition. Each scan has different background image noise because of radiation dosage level, image reconstruction filter selection, and CT scanner vendors.
For 16 organ recognition, we applied GoogLeNet7 using 22 convolutional layers including 9 inception modules and 4 sizes of basis or kernel filters (7 × 7, 5 × 5, 3 × 3, and 1 × 1). 75% of images were used for training and 25% for validation. The GoogLeNet was trained using the NVIDIA toolchain of DIGITS and the DevBox with four TITAN GPUs with 7 TFlops of single precision, 336.5 GB/s of memory bandwidth, and 12 GB of memory. GoogLeNet was trained using a stochastic gradient descent (SGD) algorithm until 150 training epochs. Validation data sets were presented upon every epoch during the training process. The initial learning rate was 0.01 and decreased by three steps according to the convergence to loss function.

A total of 646 patients were included in this retrospective study, with a mean age of 66 years old (range 20–95 years). These patients represented a wide spectrum of body habitus, with a mean weight of 85.6kg (range, 45–181kg). Figure 2 is a representative example of classification results of patient organs after chest CT segmentation. As shown in Fig. 2 (C), the identified organs were labeled from HEAD5 (Thyroid) to TRUNK 5 (Abdomen1) a region including both kidneys and liver. Based on organ classification, we determined the corresponding scan range for the ImPACT CT dosimetry calculator. For example, the identified thyroid region (HEAD5) was mapped to slab number 171/208 of the adult phantom.
Discussion

Dedicated patient organ dose reports are an important part of modern radiation safety. Current organ dose estimation techniques use Monte Carlo simulations based on phantoms and mathematical description or image voxels. Considering an individual patient’s variance in organ position, orientation, and shape, it is often challenging to map a given CT slice to the slab number of a phantom model for accurate organ dose calculation.

The predicted organ location provided by our deep learning driven software also gives information about the volume of an organ in respect to a given scan region. For example, we can identify the thyroid (HEAD 5 region) in slices 10 to 138 with 99% accuracy, greatly improving patient-specific radiation dose estimation. As an extension of this algorithm, we will further train the model to more organ areas, covering all organs used in the ImPACT CT organ dose estimator, including pancreas, stomach, gall bladder, and colon, and facilitating longitudinal organ-specific dose calculations.

Conclusion

We propose a deep-learning organ classifier aid in the creation of patient and organ specific radiation dose estimation. Our preliminary results reveal higher than 96% accuracy in mapping of organs to phantom, providing high quality organ-specific radiation dose estimates at low cost. Further work includes training the model to classify more organ areas, covering all organs used in the ImPACT CT organ dose estimator.

References


Keywords

body part classification, organ dose estimation, convolutional neural network, ImPACT CT dosimetry