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TrainingPhantoms.jl: Simple and Versatile Image Phantom Generation

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Abstract

Large collections of labeled data play a crucial role in supervised machine learning projects. Unfortunately, such datasets are quite rare in the medical domain. In this work, the Julia project *TrainingPhantoms.jl* is introduced, which provides a simple interface to generate large and diverse collections of randomly generated image phantoms. The proposed phantom generator has been successfully used to train an image quality enhancement network that managed to generalize to unseen experimental out-of-distribution data.

I. Introduction

Data plays a crucial role in the development and validation of most downstream tasks such as reconstruction, segmentation, denoising, or artifact reduction. Especially with the rise of machine learning methods in Magnetic Particle Imaging (MPI), the need for large labeled datasets is becoming even more apparent. However, appropriate datasets are only scarcely available in the medical domain. Besides a few exceptions [1], training such methods is hardly possible. The best known data collection in MPI, the *OpenMPIData* dataset [2], features various measurements of system matrices (SM) and scans of a few phantoms. However, corresponding ground truth data for the phantoms is not readily available and the size of the dataset is too small for training.

In the literature, various approaches with different levels of realism have been used to satisfy the demand for labeled training data, such as the MNIST dataset [3, 4], which consists of handwritten digits, MRI angiography data [5], simulated vessels [6], and randomly generated phantoms of different geometric shape [7–9].

To aid the generation of adequate phantom data, we developed the Julia package *TrainingPhantoms.jl*[1] that is able to generate large amounts of such phantoms with huge flexibility.

II. Methods and materials

The underlying requirement for the development of this work was the need for a vast amount of image data that closely resembles structures that are commonly encountered in MPI. Currently, generators for two types of structures are implemented. The first produces phantoms consisting of multiple ellipses or ellipsoids, respectively. Such structures are encountered directly after administering the tracer in form of a bolus or when enough tracer has collected in certain organs. The second type is meant to resemble blood vessels that are measured during angiography. In the following, we introduce both implemented types of phantoms, explain the underlying

[1] https://github.com/JuliaImageRecon/TrainingPhantoms.jl

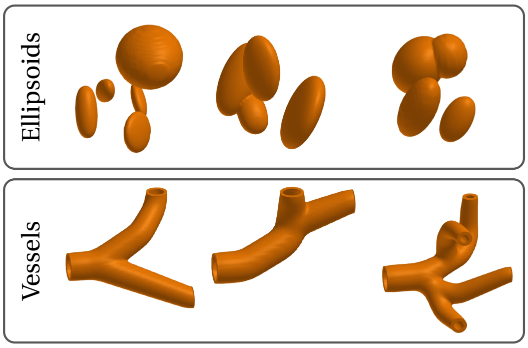

Figure 1: Surface rendering of a few randomly generated ellipsoid and vessel phantoms.

design decisions, and give a brief overview over the most important interface parameters.

Regardless of the type of phantom we wanted to have an interface that allows us to generate phantoms flexibly with regards to the specified grid size and dimension. Additionally, with respect to reproducibility, randomized routines are based on a seeded random number generator that can be passed as an additional parameter.

II.I. Ellipsoid phantoms

When it comes to the generation of ellipsoid phantoms there are a few additional requirements to consider. First of all, it should be possible to generate arbitrary number of ellipsoid (parameter *numObjects*) in a single phantom image. Each of those ellipsoids is generated with random size, rotation, placement within the field of view, and intensity. It is possible to specify a minimal radius (*minRadiusPixel*) to avoid degenerated ellipsoids in form of a line with a width of a single pixel. Similarly, the minimal intensity (*minValue*) can be specified as well. This can be useful to limit the dynamic range. The case that multiple ellipsoids overlap each other can be handled in two ways that are specified with the *allowOcclusion* parameter. Thus, image intensity within the intersection is either summed up or dominated by the ellipsoid with the highest intensity. Lastly, it is ensured that no ellipsoid intersects the image border, which can be even further amplified by enforcing an empty margin at the border (*pixelMargin*).

II.II. Vessel phantoms

The vessel phantoms are procedurally generated from a given start point, orientation, and diameter. There is a certain probability that the vessel either changes its orientation (*changeProb*) or splits into two segments (*splitProb*). The maximal angular change (*maxChange*) and allowed number of splits (*maxNumSplits*) can be limited as well. After a split, the further generation of both vessels is then recursively invoked with a decreased diameter (*splitDiameterChange*). The generation of a single vessel offshoot will eventually stop when it reaches the image boundary.

III. Results and discussion

The proposed generators are capable of producing large collections of diverse image phantoms (see Figure 1). Whether these phantoms are good representations for anatomical structures is difficult to assess. However, the ellipsoid generator has already been used to train a neural network for automatic image reconstruction, which successfully managed to generalized to actual measurements of a distinctly different distribution [8].

IV. Conclusion

We introduced a Julia package that provides a simple yet expressive interface for synthesizing vast amounts of phantom images. The generated phantoms appear to represent anatomical structures reasonably well and are thus suited for the training of various machine learning tasks. This package should be considered as a good starting point for collaborative extension to include a variety of clinically encountered structures.

Author's statement

Conflict of interest: Authors state no conflict of interest.

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