PE Detection with Dual-Energy CT Data Augmentation

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Editors: Under Review for MIDL 2022

Abstract

3D segmentation U-Nets are trained for pulmonary embolus detection on three different data sets. We investigate the impact of the training data set on the generalization capabilities and use dual-energy CT data augmentation to increase performance.

Keywords: Detection, Segmentation, Pulmonary Embolus, Dual-Energy CT, U-Net

1. Introduction

A pulmonary embolus (PE) is a blood clot in the pulmonary arteries that obstructs blood flow, causing a poor oxygen supply, and can even lead to right heart failure. The development of automatic PE detection systems to support medical diagnosis is highly demanded. To apply these systems in clinical practice, good generalization is necessary. Reliable clinical performance is required under different contrast levels, different types and severity of emboli, even in the presence of comorbidities. In a dual-energy CT (DECT) scan, data from low- and high-energy X-ray spectra are acquired simultaneously which allows to compute

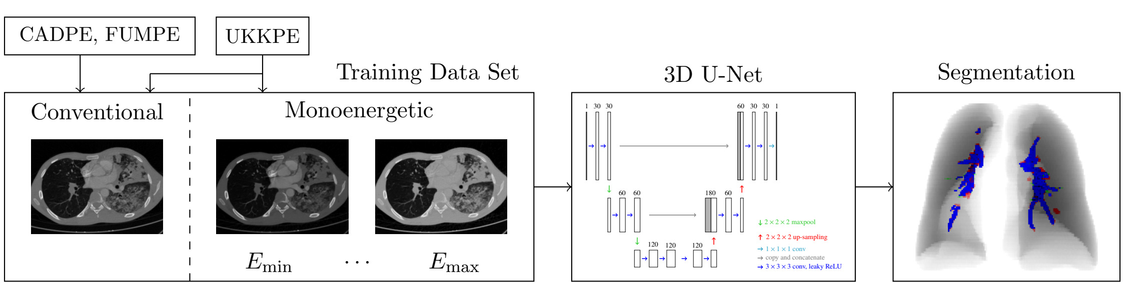

Figure 1: The detection problem is addressed via binary segmentation using a 3D U-Net and subsequent connected components clustering. Training is performed with three data sets: CADPE and FUMPE use conventional images, while UKKPE additionally involves dual-energy CT augmentation with a probability of 50%.

Table 1: Overview of the used data sets, where N is the number of cases, N_{PE} is the number of emboli and V is the embolus volume.

data set	year	N	$\frac{N_{\mathrm{PE}}}{N}$	$\frac{N_{\mathrm{Proxi}}}{N_{\mathrm{PE}}}$ [%]	$\frac{N_{\mathrm{Peri}}}{N_{\mathrm{PE}}}$ [%]	$V_{\min}/V_{\mu}/V_{\max}$ $[\mathrm{cm}^3]$	DECT
UKKPE	2021	114	4.84	24	76	$4.5 \cdot 10^{-3}/1.44/65.24$	yes
FUMPE	2018	35	3.14	61	39	$0.5 \cdot 10^{-3}/4.24/46.27$	no
CADPE	2013/19	91	3.48	37	63	$3.4 \cdot 10^{-3}/4.40/63.65$	no

monoenergetic (monoE) images corresponding to different energy levels. Low-energy images provide high contrast, while simulated high-energy images provide low contrast. Lartaud et al. (2019) used DECT-based augmentation to create contrast-independent aorta segmentation networks. We investigate the generalization of deep learning-based PE detection from CT data in particular the influence of the data set and the role of DECT augmentation.

2. Materials and Methods

The training and evaluation are performed on three different data sets: The first (internal) data set UKKPE bundles (spectral) PE cases from UKK Cologne over three years, while the other two data sets (FUMPE (Masoudi et al., 2018) and CADPE (González et al., 2020)) are publicly available, see Table 1 for details. The main difference between the data sets is that FUMPE and CADPE were collected specifically for building a PE detection benchmark, whereas in the retrospectively collected UKKPE data set, pulmonary emboli are mostly contained as comorbidities. We train a 3D U-Net (Ronneberger et al., 2015) on each data set individually and evaluate it on each of the available test data sets. Further, the influence of DECT augmentation on generalization is analyzed. For this purpose, monoE images are generated within different energy intervals during the training, see Figure 1. We evaluate the sensitivity of all networks at five false positives per scan. A predicted embolus is considered a hit if the Dice score of prediction and reference label is at least 20%.

3. Evaluation and Results

The test results of the different training setups are shown in Figure 2. Generalization depends strongly on the data set. Training on CADPE leads to better generalization compared to training on FUMPE, which generalizes worst. The different performance on various data sets indicates that for clinical integration the evaluation should not only be done on one dataset but on several. When evaluating the conventionally trained networks on the monoE images, it is observed that the performance decreases sharply with higher energy level. Thus, generalization on different contrasts is not ensured. Training with DECT augmentation increases generalization. By analyzing the performance on the conventional and monoE images from UKKPE, two statements can be made. Firstly, training with small contrast variations increases performance on the conventional images with a slight improvement in robustness to contrast variations. Secondly, training with strong contrast variations increases the generalization to different contrasts with little decrease in performance on conventional

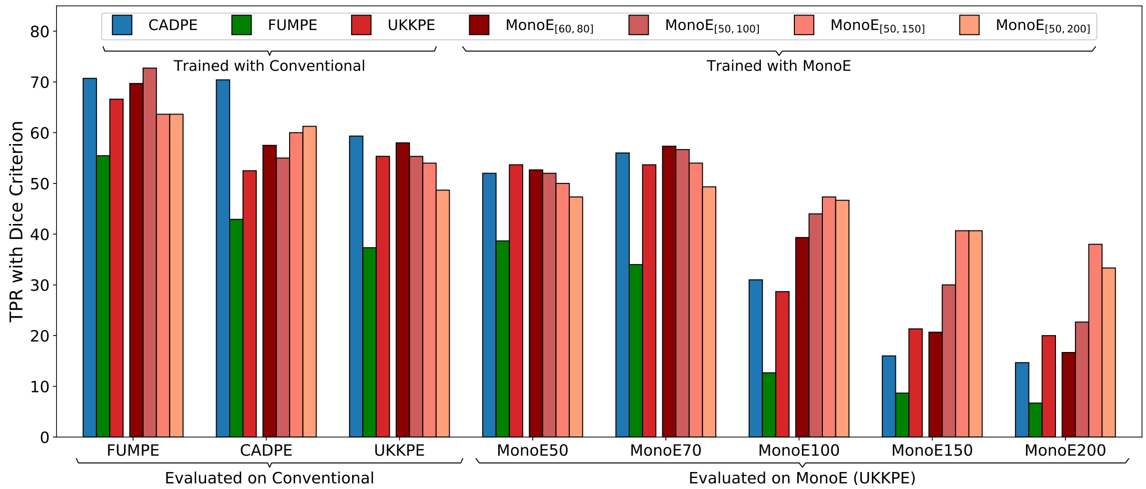

Figure 2: Each of the seven training setups is evaluated once on the conventional images of the three data sets and once on different monoE images of UKKPE. Per data set, 25% of the cases were selected for testing purposes and left out during training.

images. Also on CADPE and FUMPE, DECT augmentation increases performance on the conventional images. On CADPE, all networks with DECT augmentation outperform the network trained without DECT augmentation. On FUMPE, the network trained with monoE images within the interval $[50\,\text{keV}, 100\,\text{keV}]$ even outperforms the CADPE network, which so far generalizes best on the conventional data.

4. Conclusion

We showed that generalization depends strongly on the data set and that it can be increased by dual energy data augmentation so as to become more robust to contrast variations which may enable the transition to non-PE protocols and detection of incidental PE.

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