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Using very small contour sets to train high-quality deep-learning segmentation models

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Introduction

Deep learning-based auto-segmentation methods have been introduced as effective tools for medical imaging segmentation with reduced human efforts and bias. The amount of the well-curated data available for training is critically important to achieve a high-quality deep-learning(DL) model. However, obtaining manual contours is a time-consuming task and requires considerable expertise. In many clinical applications, the availability of well-curated training data is very limited. Many data augmentation approaches, such as rotation, cropping, or random nonlinear deformation, have been introduced to overcome this challenge. However, these approaches have limited ability to emulate actual patient population variations and can be highly sensitive to the choice of parameters. Further researches are needed to overcome the data sparsity in DL model training.

Aims

This study aims to propose an effective data augmentation method which enables to generate high-quality DL segmentation models when the availability of contoured cases is severely limited (e.g.~10 patients).

Materials and Methods

Dataset

- Thirty head-and-neck CT scans with well-defined contours
    - Templates for generating synthetic CT scans
- Two hundred head-and-neck CT scans without contours

Synthesizing New Examples

Fig. 1 shows the workflow of our proposed method to using principal component analysis(PCA) approach to generate synthetic CT scans, which can simulate realistic patients.

- The 30 head-and-neck CT scans with contours were deformably registered to those 200 CT scans without contours.
- The acquired deformation vector fields (DVFs) were used to train a PCA model for each of the 10 well-contoured CT scans by capturing the mean deformation and the most prominent variations.
- In total, we trained 30 PCA models, where each model can produce an infinite number of synthetic CT scans and corresponding contours by applying random deformations.

Network Training

- A VNET architecture was trained for left and right parotids autosegmentation, using only the synthetic CT scans.
- 300, 600, 1000, and 2000 synthetic CT scans and contours generated from one PCA model were used for training.
- This process was repeated by using the same numbers of training cases generated from 7, 10, 20, and 30 PCA models with the training data distributed evenly between each PCA model.

Evaluation

Calculate Dice similarity coefficients between the auto-generated contours and the physician-drawn contours on 162 independent test CT scans.

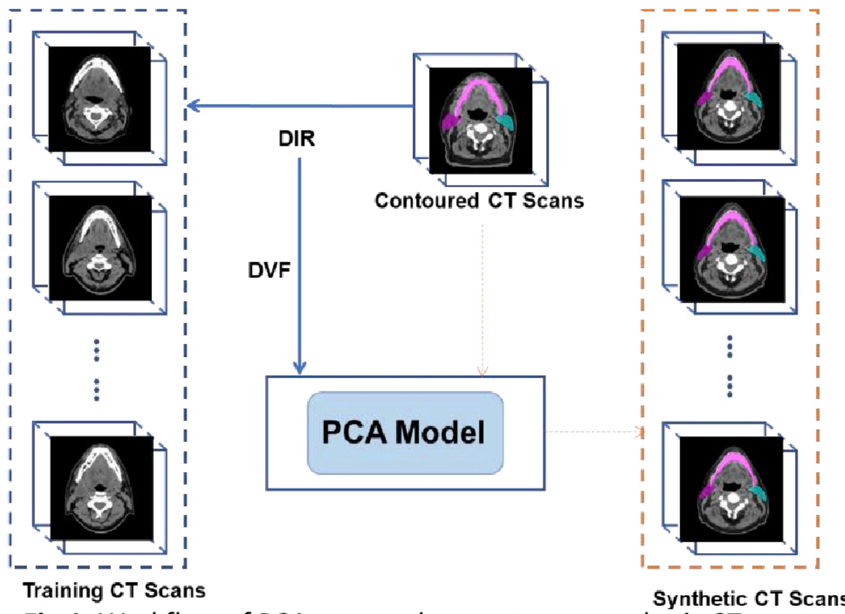

Fig 1. Workflow of PCA approach to generate synthetic CT scans and corresponding contours

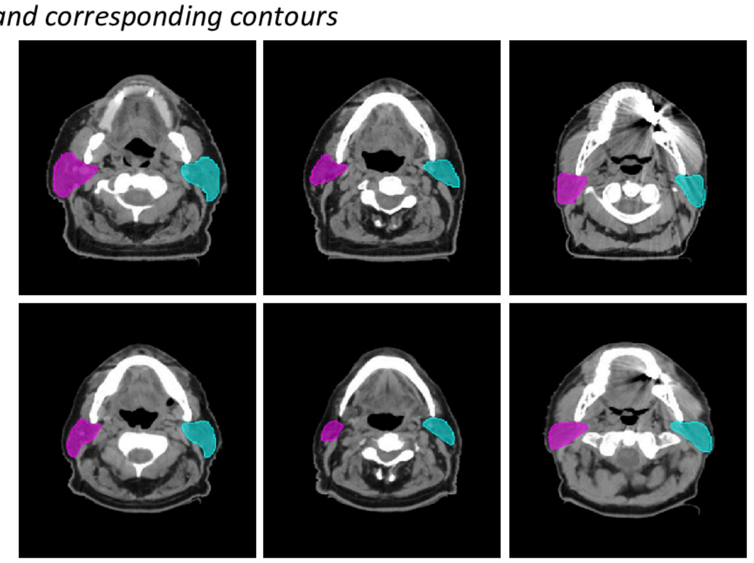

Fig 2. Comparisons between manual and synthetically generated contours. Real (top row) and synthetic(bottom row) CT scans with parotid contours

Results

- Results for left and right parotids segmentation are plotted in Fig. 3 and 4.
- The average Dices for left and right parotids segmentation range from 63.2% to 83.1%, and 61.0% to 82.9%, respectively.
- Average Dice value varies with the number of synthetic CT scans as well as number of PCA models used to train the networks.

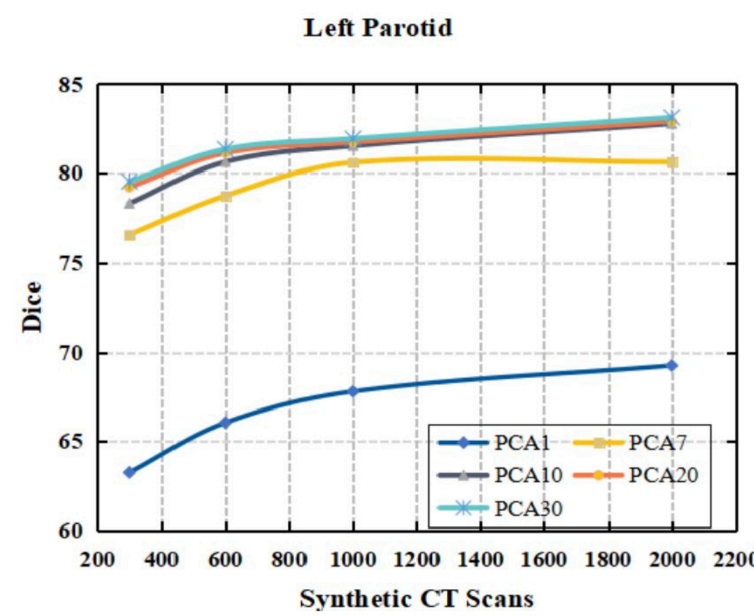

Fig 3. Dice results for left parotid

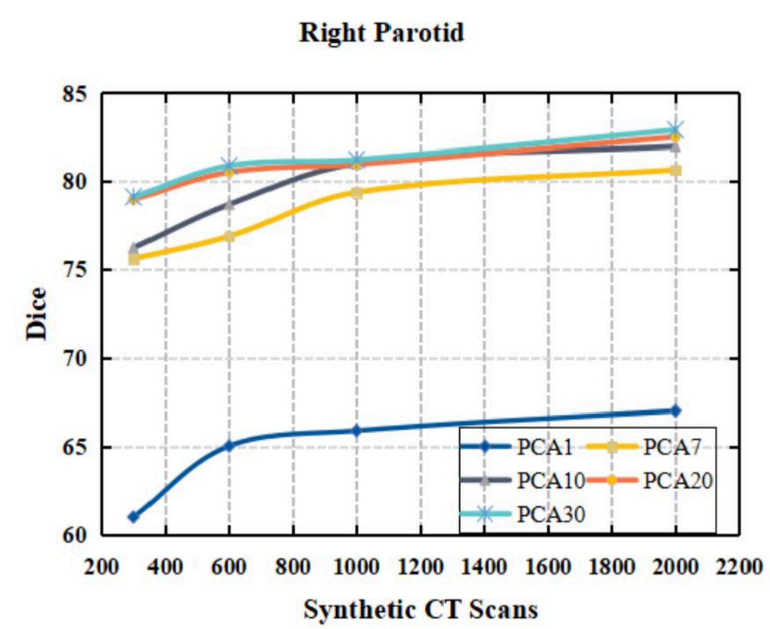

Fig 4. Dice results for right parotid

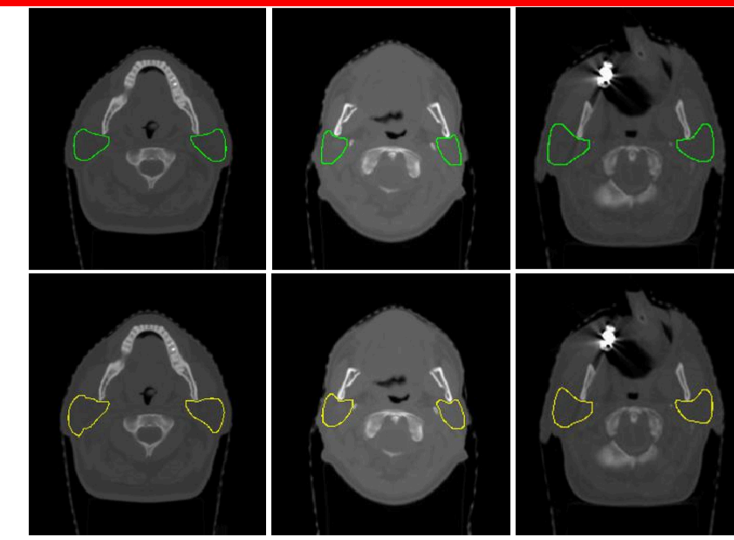

*Fig 5. Visually inspection of the autosegmentation results. Physician drawn contour in **green**. VNET-generated contour in yellow. All auto-generated contours were predicted by the VNET model trained on synthetic CT scans generated from 10 PCA models.*

- Using only 10 well-curated patients for training, we were able to achieve a segmentation accuracy of 82.8% and 82.0% for left and right parotids, which are comparable to the results of the state-of-art autocontouring approach.
- Improvement is marginal using more than 10 PCA models or creating more than 2000 synthetic CT scans.

Conclusion

- We demonstrated an effective data augmentation approach to train high-quality deep-learning segmentation models from a very limited number of well-contoured patients.
- This work could potentially greatly reduce the effort in data curation for deep-learning based autosegmentation.

References

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2. Rhee, D. J., Cardenas, C. E., Elhalawani, H., McCarroll, R., Zhang, L., Yang, J., ... & Court, L. E. (2019). Automatic detection of contouring errors using convolutional neural networks. Medical physics, 46(11), 5086-5097.

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