Learning Patient Rotation Using Synthetic X-ray Images from 3D CT Volumes

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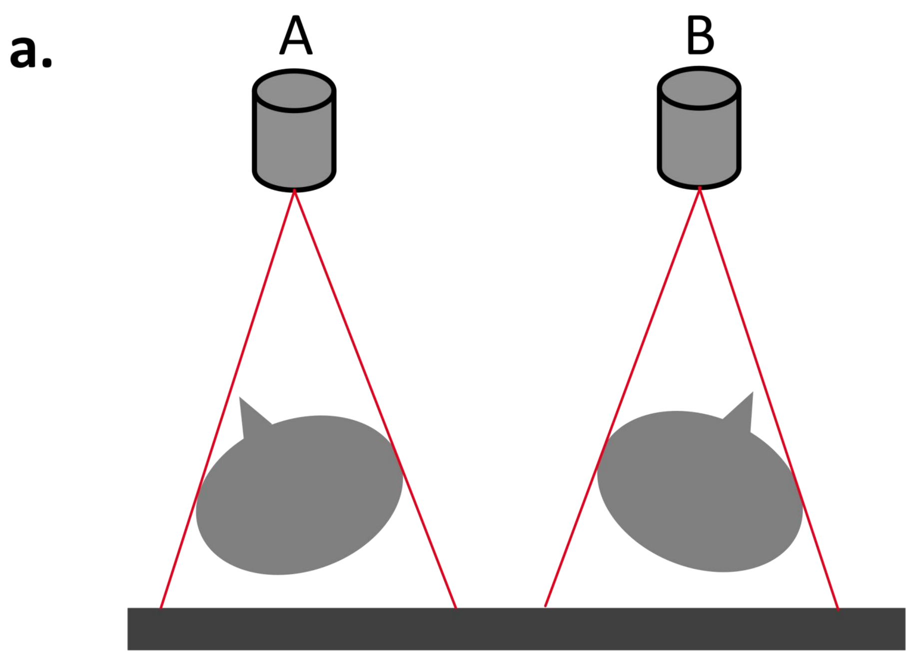
Disclaimer: The work presented in this paper is not commercially available.

Abstract

- Curation of large-scale annotated clinical data for DL is challenging due to **scarcity** or **ethical issues**.
- **Synthetically generated data** could **supplementary** be used with real data to train AI models.
- We can forward project 3D **photon-counting CT** volumes to 2D **synthetic chest X-rays (CXRs)**.
- Downstream task: Use DenseNet-121 to **quantify internal patient rotation**.
- **Good correlation** between true and predicted α, with $R^2 = 0.992$, with 95% confidence level of ≈ ±2°.

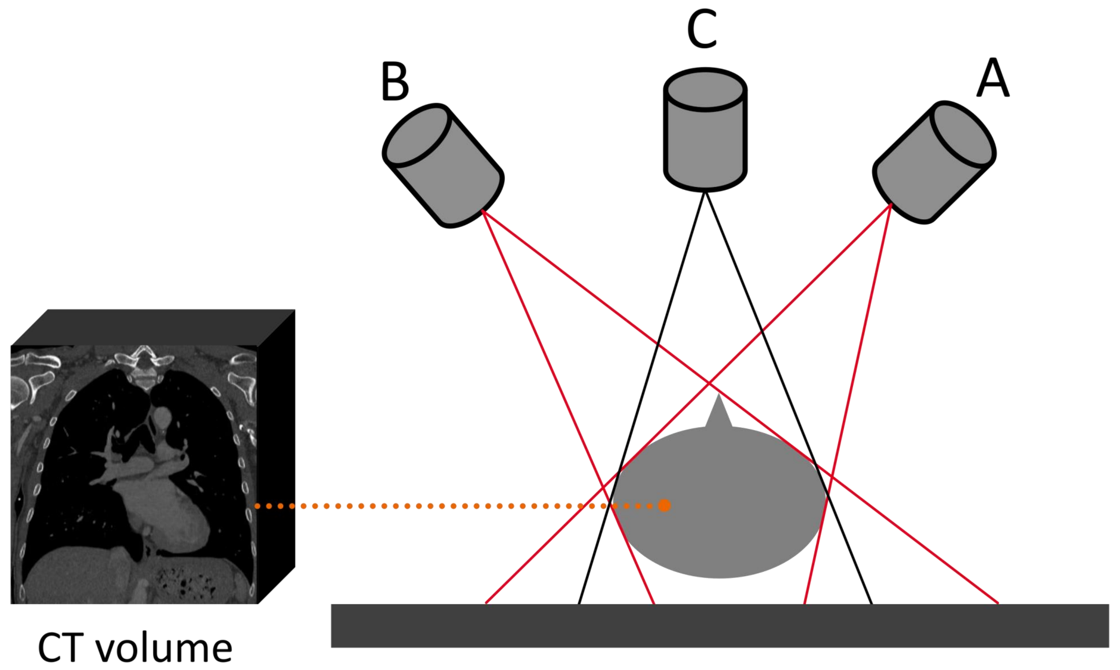
In anteroposterior (AP) CXR:

a.



Patient Malpositions

b.



CT volume

Proposed Simulated Views

Background

- **AP CXRs** is susceptible to **patient rotation** due to illness or medical instruments (Fig. a).
- Currently, cardiothoracic ratio or clavicle-spine distance are used to determine if a CXR is rotated
  - **require clinical expertise** and **hinder clinical workflow**.
- Therefore, an algorithm **to quantify internal patient rotation** is desired, which can automatically inform the technician **if and how the re-exposure** is needed.

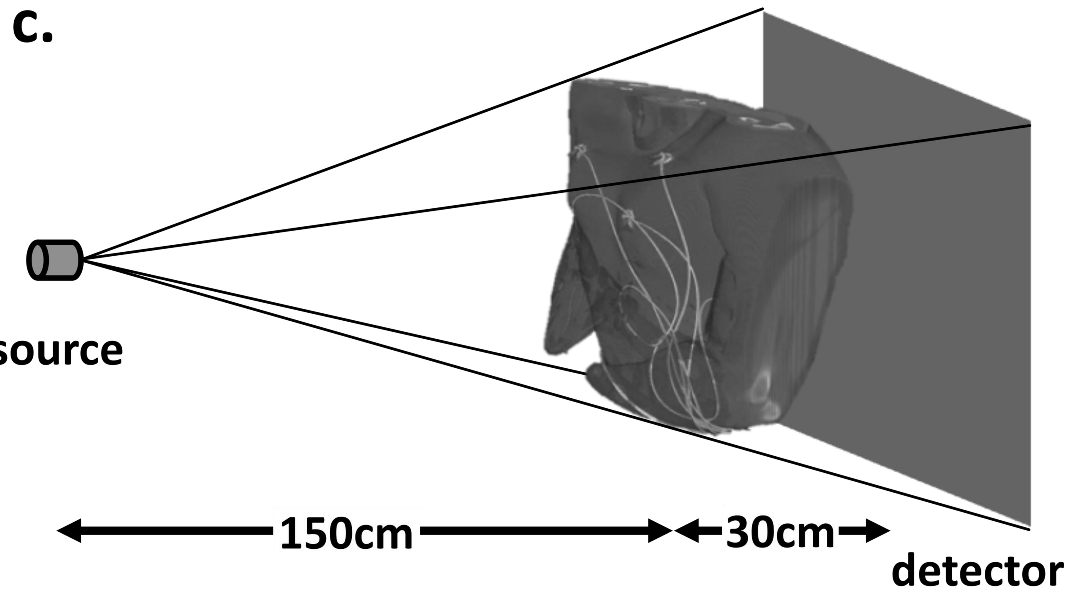
Motivation

- Emerging usage of realistic synthetic data for machine learning in medicine [1-3].
- **Synthetic X-rays** were used as training data for learning airspace **quantification** [4] lesion **segmentation**, landmark or surgical tool **detection** [5].
- We hypothesize that the trained model would implicitly **learn features in chest rotation without the need for annotations** such as cardiothoracic ratio or clavicle-spine distance (Fig. b).

Methods - Dataset

- 80 **photon-counting CT** datasets. Each with voxel size 0.5×0.5×0.7mm3, ≈1000 slices
- Forward projected by **ray tracing**, which takes into account the cone-beam geometry of the system (Fig. c).
- Projected with angle **α in range of [-20°, 20°], with a step size of 2°** and the central projection at 0° (Fig. d).
- Standard radiographic image post-processing and cropping to the lung region were applied.

c.



X-ray Simulation Setup

d.

α=-20° α=0° α=+20°

Training Data and Labels

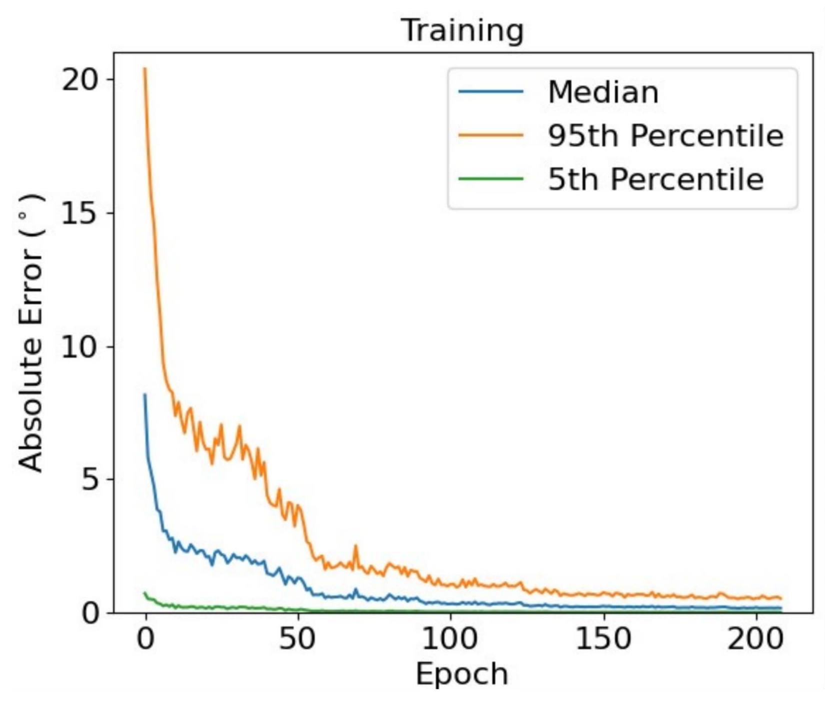
Methods - Training

- Training: 1176 images, validation: 252 images, testing: 252 images.
- Pre-processing: resized to 256×256 pixels, intensities normalized to [0, 1].
- Architecture: DenseNet-121.
- To preserve the sign as our target labels which consist of negative and positive values: hyperbolic tangent function (Tanh) as the activation function in the final output layer.
- Output values are mapped to the range of [-20, 20].
- MSE loss, Adam optimizer (lr=0.01), batch size = 16, Nvidia RTX A40 GPU.

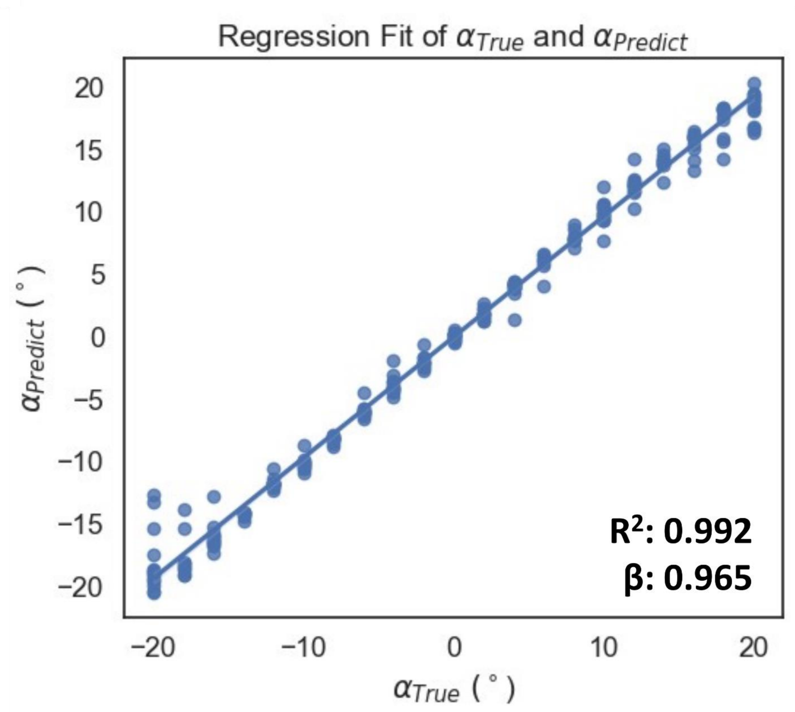
Results & Discussion

- Fig. e: After ≈ 150 epochs, the median, 5th and 95th percentile of absolute error between $\alpha_{predict}$ and α_{true} level off around zero.
- Fig. f: Regression fit shows range of prediction, diagonal line and **R^2 = 0.992** indicate good correlation.
- Fig. g:
  - Red dashed line indicates **mean difference = 0.0385°** → close to the zero line, indicates there is **no bias**.
  - Gray dotted lines indicate **95% confidence interval** (mean ± 1.96 × standard dev. of the differences) → **−2.25° to 2.33°**, which **agrees well** as our synthetic X-ray images were simulated with a **2° step size**.
- Evaluation on real CXR will be the next step.

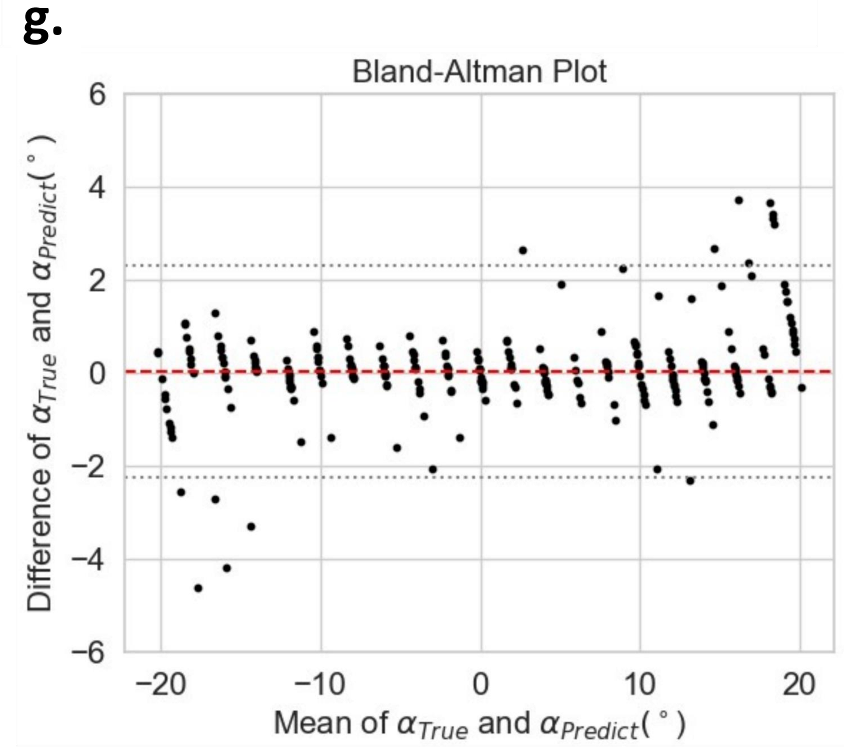
e.



f.



g.



Conclusion

We leveraged synthetically-generated images for learning the quantification of internal patient rotation in CXR, as originally limited by the availability of rotated and labelled CXR.

References

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