A Neural Network Approach for Image Reconstruction from a Single X-ray Projection

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Introduction

Radiotheraphy is the one of the most common methods of treating lung cancer patients. It requires clear imaging of patient's anatomy and tumor to precisely radiate cancerous cells. Therefore, before receiving radiotherapy, a series of cone beam computed tomography (CBCT) scans are taken of the patient's thorax. However, the motion blur is prominent in the thorax due to breathing. It is important to eliminate blurring artifacts in 3D images reconstructed from a set of 2D x-ray projected data.

One approach is referred to as 4D-CBCT which groups the CBCT projections into bins (Figure 1) representing different breathing phases and then reconstructs a 3D image for each phase. In Figure 2 it can be seen that the 4D-CBCT mitigates the motion blur in 3D-CBCT, but it does not give complete motion information. Since the resulting image is the average over all instances in each phase, its temporal resolution is rather low. Therefore, it is desirable to develop a method that allows for time-resolved volumetric reconstruction from a single projection image at that instance.

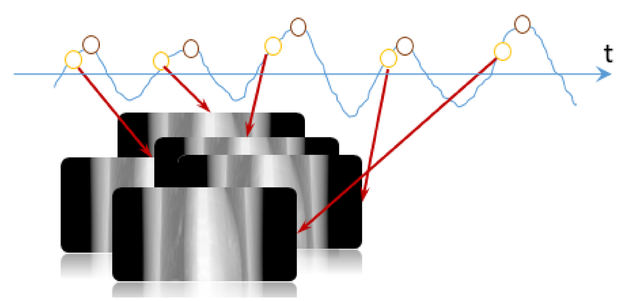


Figure 1: Phase Binning

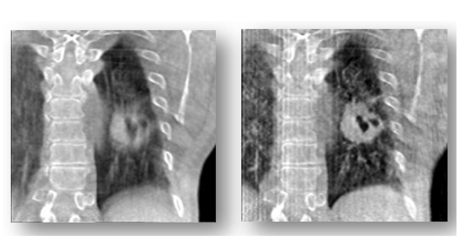


Figure 2: CBCT (Left), 4DCBCT (Right)

We purpose to tackle this problem by building a 3D lung motion model via principal component analysis (PCA) and developing a neural network (NN) to maps patches of the projection image to correspond to the three largest principal components.

Objectives

The three main objectives of our study are:

- Apply the PCA to obtain a low-dimensional lung motion model
- Estimate the model parameters via a neural network approach
- Reconstruct a volumetric image by deforming a reference image with the estimated parameters from NN

Data Set

We generated the data via NCAT phantom and computed the projection image (384x256) for an imager of size 40x30 cm^2 using the Siddon's algorithm. In Figure 3 a sample of one 3D image is given showing each viewing direction.

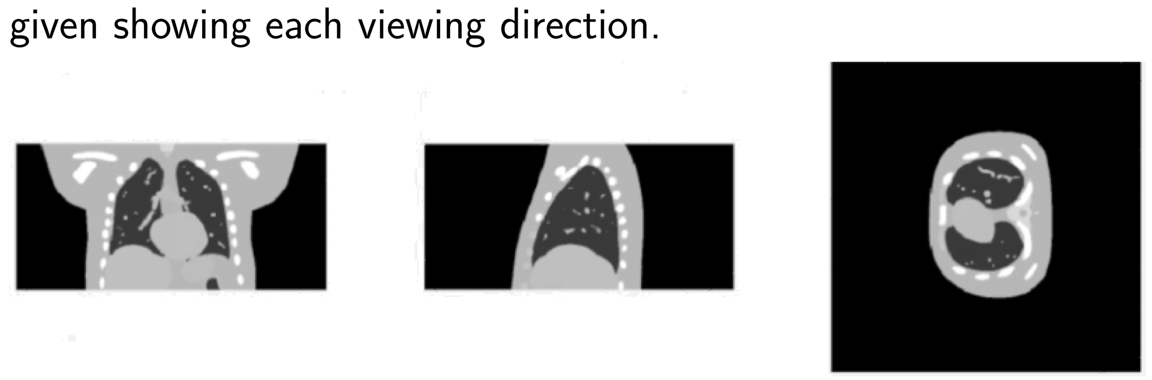


Figure 3: A single slice of generated data set: Front view, Side view, Top-down view

Our Approach

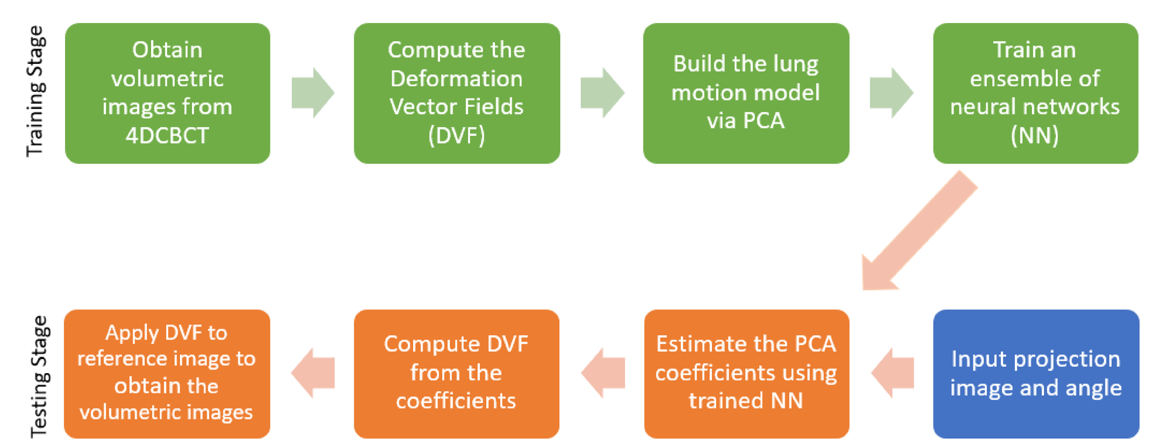


Figure 4: Overview of our approach

Our method consist of two stages, each with three main parts: computing the deformation vector field (DVF), obtaining the PCA principal components, training and testing the neural network. The workflow is illustrated in Figure 4

Computing the DVF

The DVF is the vector field that represents the transformation of an object from a reference configuration to a target configuration as best illustrated in Figure 5. From the set of CBCT images we choose a reference image and then compute DVFs from the reference image to each of other images in the set using Demons Algorithm [1].

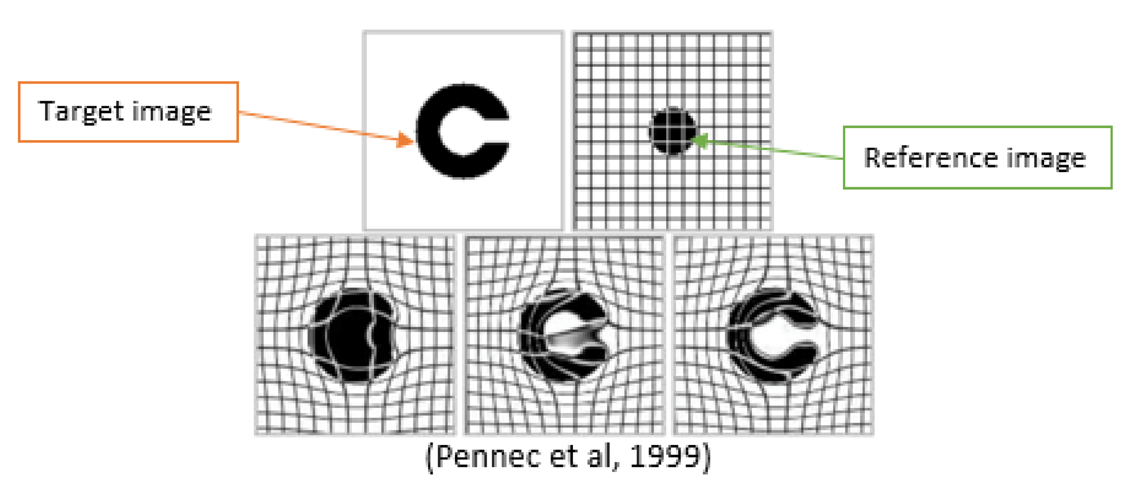


Figure 5: Visualizing Demon's Algorithm: Transforming a dot to a 'C' [2]

Building the PCA Model

Due to the periodic motion of the lungs, these DVFs are highly redundant, which motivates us to apply dimension reduction scheme. We do so by the means of Principal Component Analysis. From the set of DVF, ten registered images are sampled along one breathing cycle. The PCA lung motion model is built from the sampled DVF by centering the sampled DVF, i.e. subtracting the mean of the sampled DVF, and then conducting singular value decomposition on the centered DVF vector. The three largest eigenvectors are taken as the PCA components. No more than three PCA components are needed for the model as it accounts for approximately 95% of the motion [4]. Every instance of the PCA motion model, $\mathbf{x}(t)$ can now be approximated as a weighted sum [?] as show below:

$$\mathbf{x}(t) \approx \bar{\mathbf{x}} + \sum_{k=1}^{k} \mathbf{u}_k w_k(t) \quad (1)$$

where $\bar{\mathbf{x}}$ is the mean DVF, $\mathbf{u}_k$ is the eigenvectors, and $w_k(t)$ is the PCA coefficients.

Training the NN

We begin generate training data by sampling along the spline and adding Gaussian noise. These are the principal coefficients of the training example. We then reconstruct the corresponding deformation vector fields using the weighted sum of the principal components and applying the deformation to our reference image, yielding a new volumetric image. Finally, we simulate a projection of that volume at a randomly chosen angle by using Siddon's ray tracing algorithm to compute the line integrals. This process is repeated 5000 times to generate our full training set.

We use the training data to train an ensemble of neural networks (Figure 6), each on a different patch of the projections selected from a grid and the projection angle, to predict the principal coefficients of the deformation vector field that maps the reference image to the volumetric image whose x-ray contains the patch that was given to the neural network. The networks are trained using batch gradient descent with momentum and L2 regularization.

Struture of the Neural Network

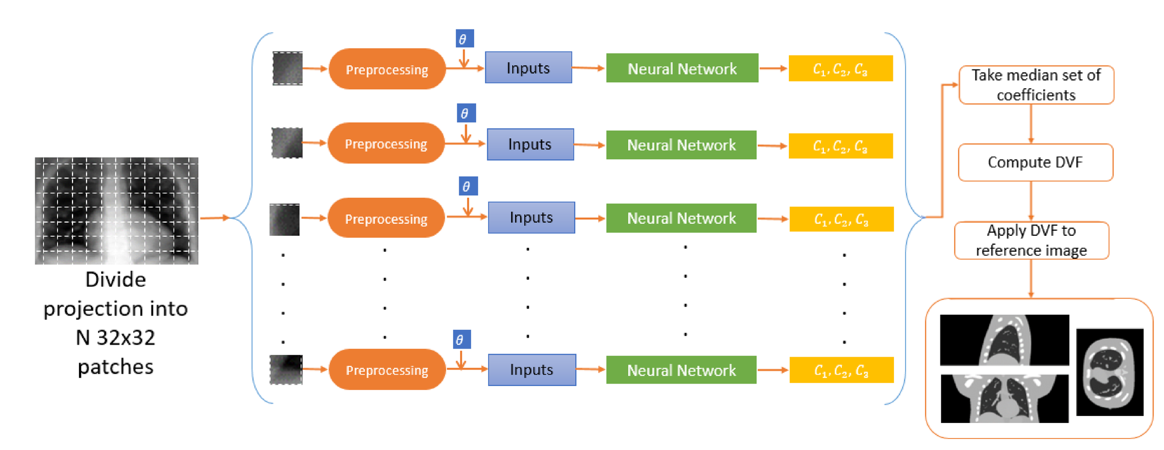


Figure 6: Ensemble of Neural Networks

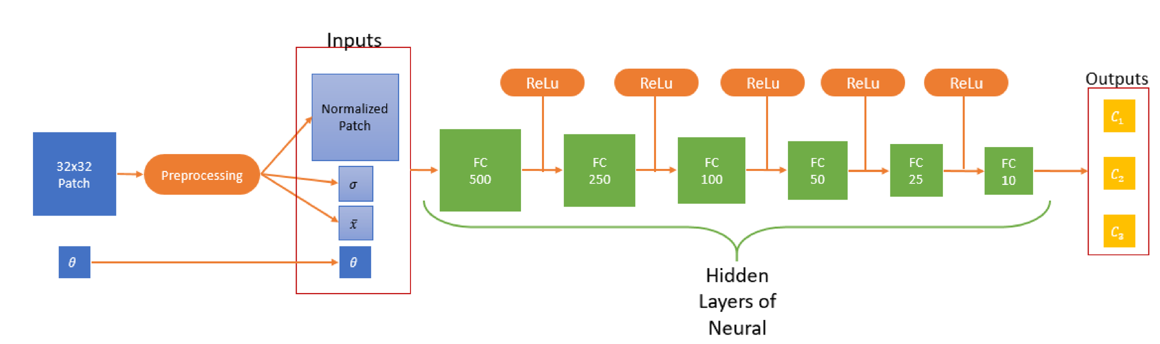


Figure 7: A single Neural Network showing hidden layers

Our neural network consists of two types of layers.

- Fully Connected: each unit of the previous hidden layer is connected to every unit in next hidden layer
- Rectified Linear Unit: a threshold operation, where any input value less than zero is set to zero: $f(x) = \max(0, x)$

Testing the NN

Once trained we can now use the NNs to estimate the model parameters. Same as training, we break a single X-ray projection into a set of 32x32 patches. After the same preprocessing, each patch is then passed through the NN along with the angle of the projection (Figure 7). The NN then outputs three estimated coefficients that are used to compute a new DVF. This estimated DVF is then applied to the reference image to reconstruct a volumetric image corresponding to this projection.

Results

We evaluate our algorithm via relative error between the ground truth and the estimated volumetric images. For our simulated data in the worst case the relative error was 5.5% which is an improvement compared to the work by Li et. al. 2011, a basis for our study. In conclusion, we obtained some promising results with the simulated data. Our future work is to test on real patient data.

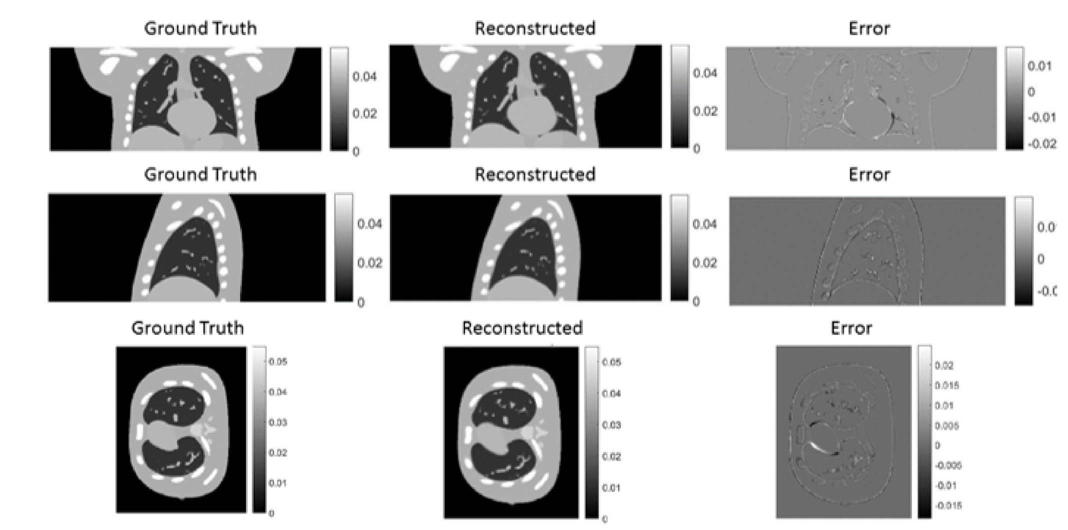
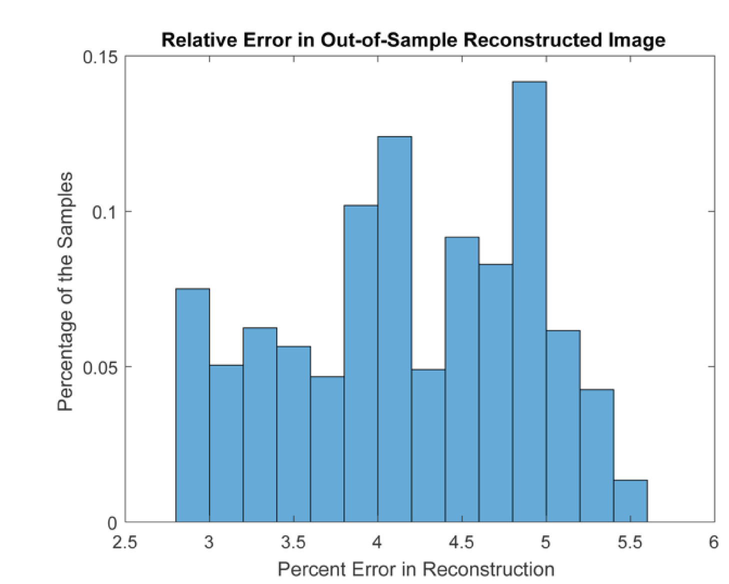


Figure 8: Reconstruction Results (Front, Side, Top-down view)



Conclusions

- With a PCA-based lung motion model, we developed an ensemble of localized NNs to reconstruct time-resolved volumetric CBCT images.
- The proposed method gave 5.5% relative reconstruction error in the worst case on the simulated data, which is an improvement over the state-of-the-art.
- We are currently validating the method on real patient data.

References

[1] J. P. Thirion *Fast non-rigid matching of 3D medical images.* INRIA. RR-2547 (1995), 37.

[2] Pennec X., Cachier P., Ayache N. *Understanding the Demons AlgorithmĂl: 3D Non rigid Registration by Gradient Descent* MICCAI (1999) . Lecture Notes in Computer Science, vol 1679. p 597-606. Springer, Berlin, Heidelberg

[3] R. Li, J. H. Lewis, X. Jia, X. Gu, M. Folkerts, C. Men, and S. B Jiang,*3D tumor localization through real-time volumetric x-ray imaging for lung cancer radiotherapy.* Med Phys. 38 (2011), 2783–2794.

[4] R. Li, J. H. Lewis, X. Jia, X. Gu, M. Folkerts, C. Men, and S. B Jiang,*3D tumor localization through real-time volumetric x-ray imaging for lung cancer radiotherapy.* Med Phys. 38 (2011), 2783–2794.