Markerless Tumor Tracking Using Kalman Filter and Deep Learning

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Motivation

According to the Center for Disease Control, more people die from lung cancer than any other cancer in the United States. A complication that arises from lung cancer treatment, radiation therapy, is radiation pneumonitis. **Radiation pneumonitis can be fatal and affects over 23% of patients.**

Figure 1.1: Image of Tumor in the Lungs

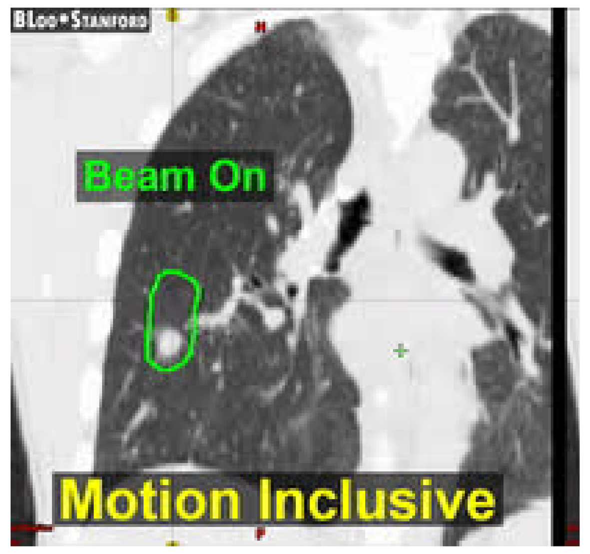


Figure 1.2: Motion inclusive GIF of Tumor in the Lungs

Abstract

Radiating lung tumors requires accurate and real-time localization of tumors during patient treatment. Although tumors can be tracked using template matching, this method is not reliable as tumors can change shape and rotate. In a partnership between UNT, TAMS, REU students, and Loyola Chicago Medical Center, a deep learning method was implemented to handle this issue. The ability to track tumors using deep learning provides access to more accurate and precise lung radiotherapy which can help reduce the amount of radiation damage done to healthy tissue surrounding the tumor. Additionally, because of overlapping bones and organs, it is oftentimes hard to detect the tumor in fluoroscopic images. We utilized the Kalman Filter to combat this issue by improving the accuracy of our results when tumor visibility was low.

Data Augmentation

- First, 100x100 pixel images of the tumor and background were cropped from the original frames.
- Then, we created augmented versions of the cropped images by applying rotation, brightness, and zoom transformations.

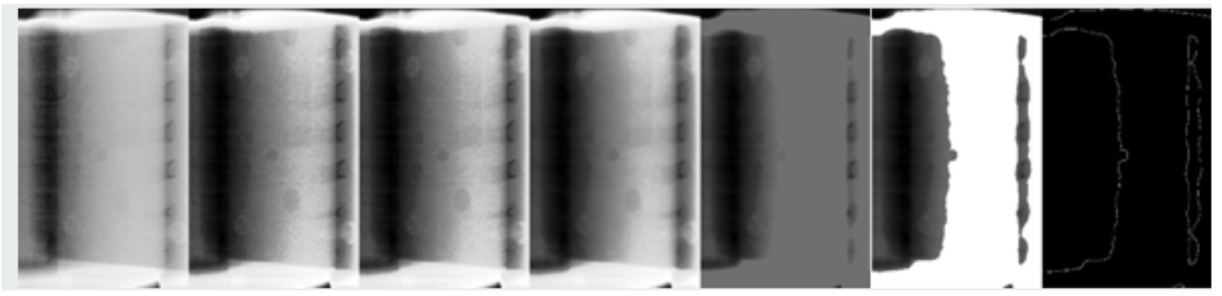


Figure 2: Image Processing

Template Matching

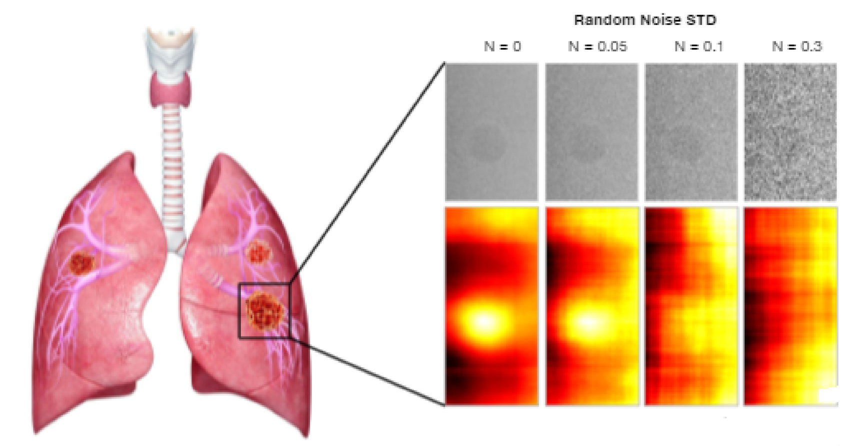


Figure 3: Effect of noise on the visibility of the tumor. Second row provides the corresponding similarity map provided by template matching. Sourced from Abolfazl Meyarian, Himan Namdari

- Template matching looks for a specific target by using a template image and comparing it to an inputted image
- The score of the match is the sum of absolute differences between the target and template area
- This method is not reliable because once the tumor deforms it no longer matches the template image

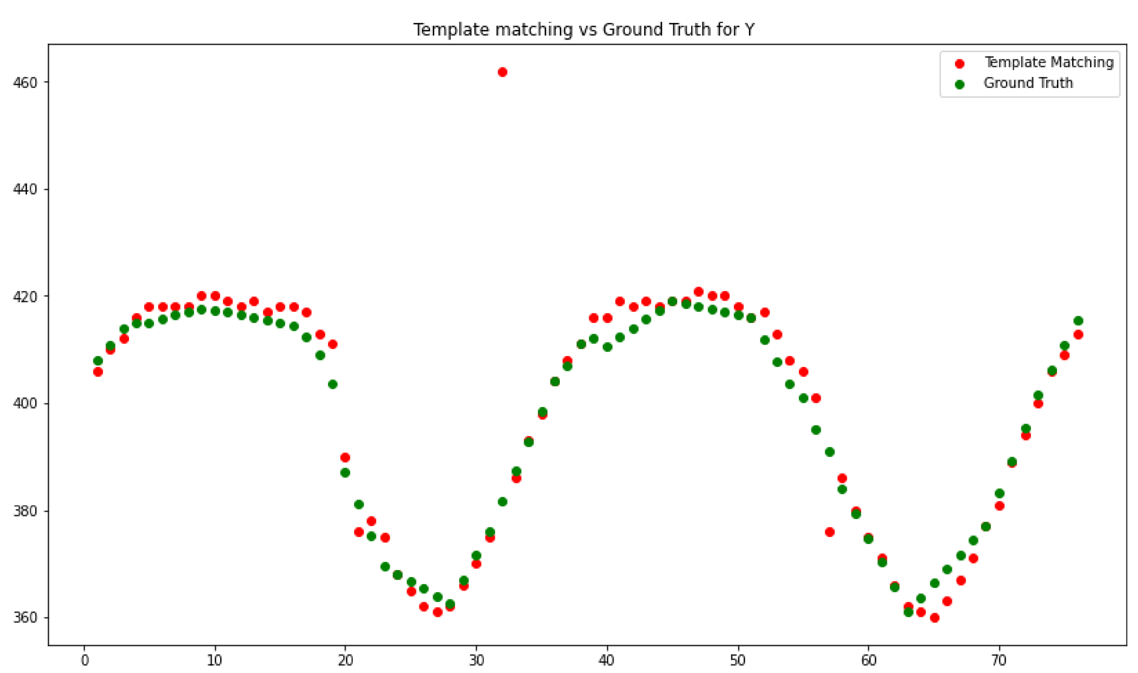


Figure 4: Ground truth and template matching comparison

Kalman Filter

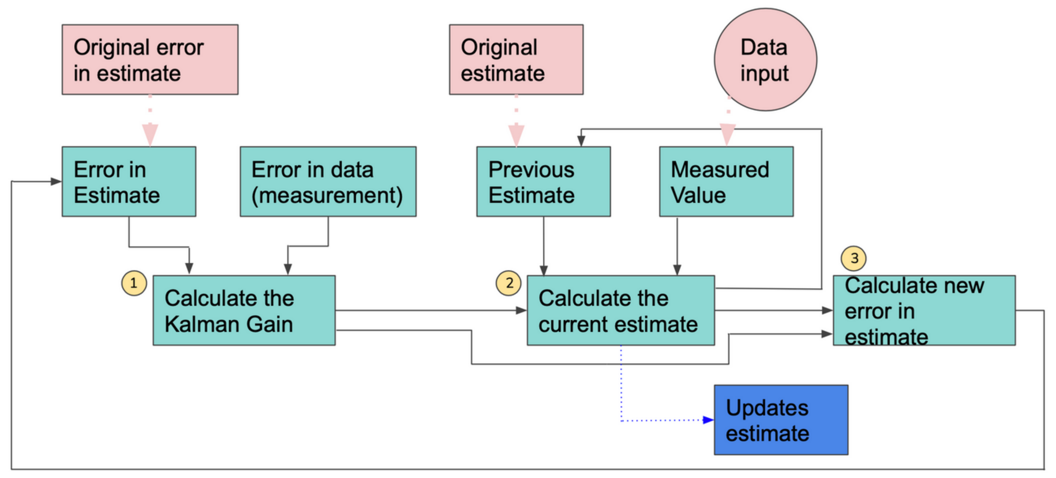
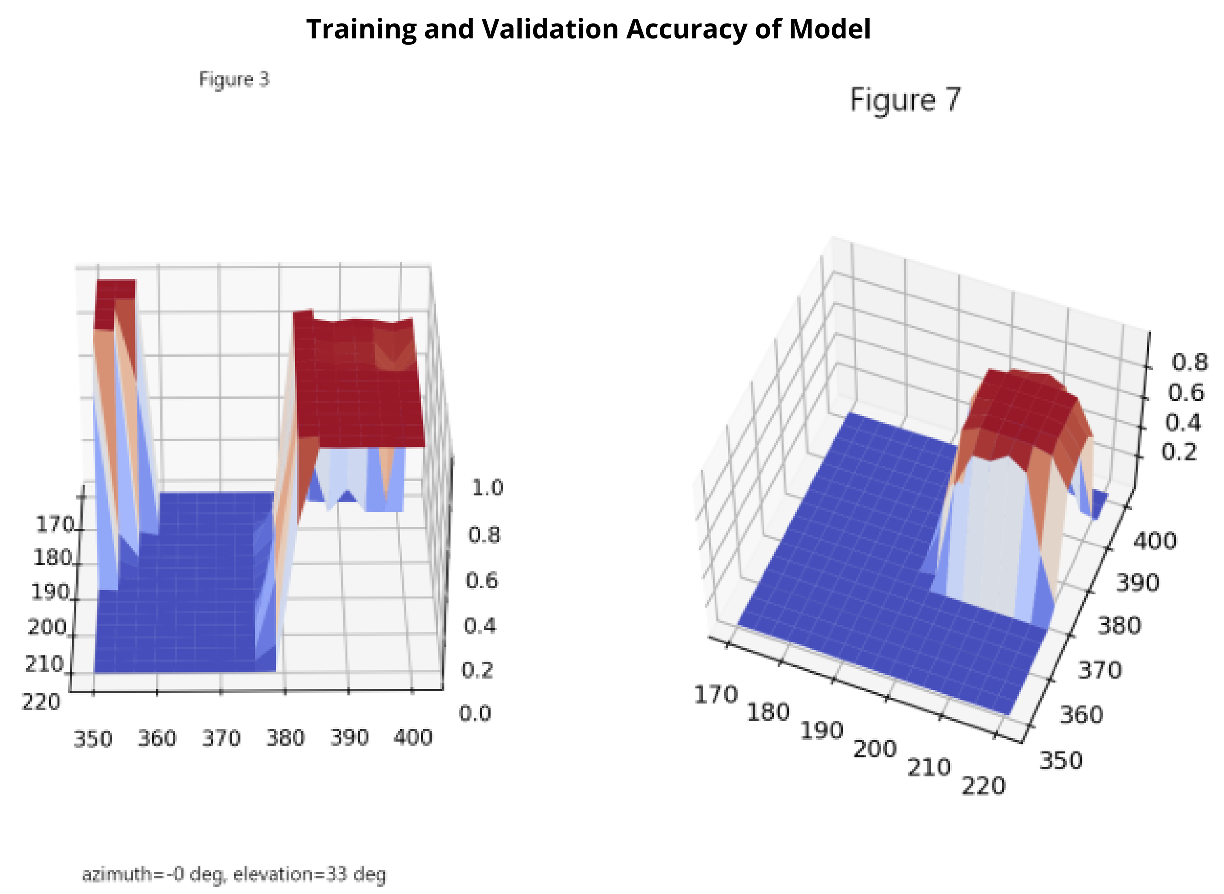


Figure 4: Kalman Filter diagram

Testing the Deep Learning Model

- As seen below, Figure 3 originally also predicted the top left corner of the image, and it was more confident in that coordinate versus the actual tumor, it predicted that point instead of the tumor
- After modifying the code, we were able to get the model to accurately identify the tumor in Figure 7.
- Originally the model was getting the same values for x and y, and it stood constant, after fixing the values it predicted the tumor accurately



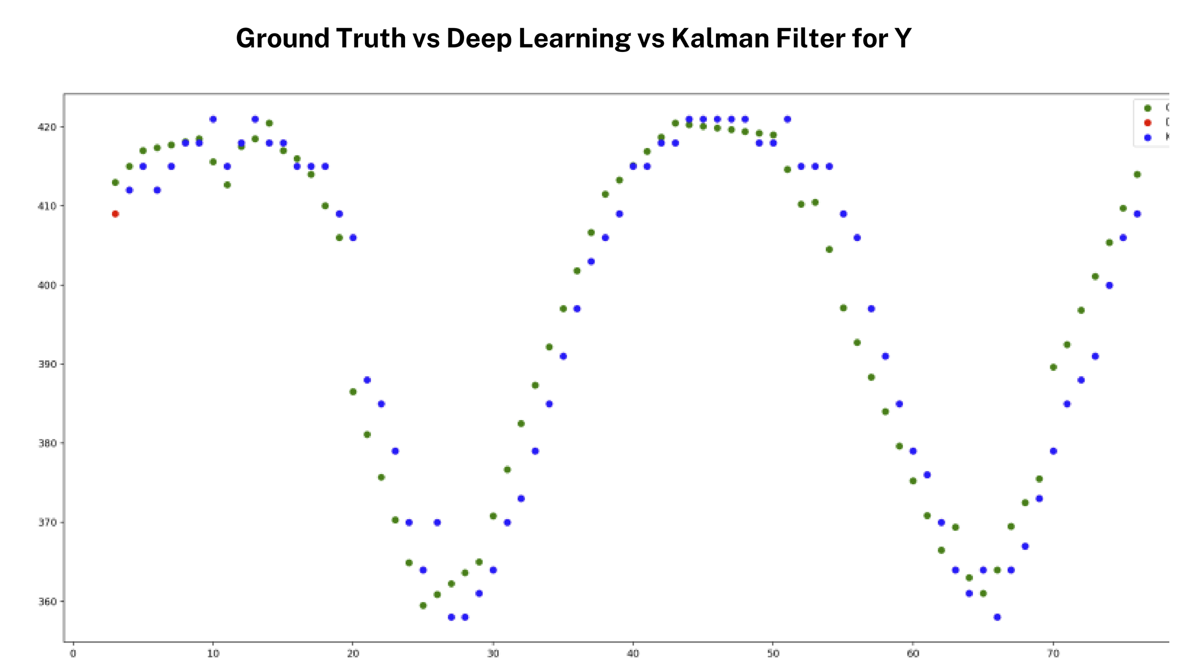


Figure 6: Ground truth, deep learning, and Kalman Filter comparison

- Using images that were acquired from a fast-kV switching real-time fluoroscope, a deep learning model with a Kalman Filter was created to track a tumor.

Conclusion

To conclude, we created two datasets (50x50 and 100x100 pixel images) by augmenting cropped images from the original frames. Then, we split each dataset into a training, validation, and holdout test set. We trained each dataset using a CNN model and found that the 100x100 pixel image dataset produced better results since the images more clearly showed the difference between tumor and background. We worked on getting a prediction for every x and y coordinate. We also worked on measuring the peak to peak uncertainty. Adjusting the x, y, and z values we were better able to train the model We were able to adjust the code to have the model accurately predict the tumor in its spot and fixed the problem where it was predicting other spots in the background. This led us to better accuracy of our model during training and validation. we plan on getting a Gaussian distribution from the points and get our uncertainty off this information. Using the peak of a gaussian distribution to form a covariance matrix we will be able to better measure our uncertainty

$$\operatorname{corr}(\mathbf{X}) = \begin{bmatrix} 1 & \frac{E[(X_1-\mu_1)(X_2-\mu_2)]}{\sigma(X_1)\sigma(X_2)} & \cdots & \frac{E[(X_1-\mu_1)(X_n-\mu_n)]}{\sigma(X_1)\sigma(X_n)} \\ \frac{E[(X_2-\mu_2)(X_1-\mu_1)]}{\sigma(X_2)\sigma(X_1)} & 1 & \cdots & \frac{E[(X_2-\mu_2)(X_n-\mu_n)]}{\sigma(X_2)\sigma(X_n)} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{E[(X_n-\mu_n)(X_1-\mu_1)]}{\sigma(X_n)\sigma(X_1)} & \frac{E[(X_n-\mu_n)(X_2-\mu_2)]}{\sigma(X_n)\sigma(X_2)} & \cdots & 1 \end{bmatrix}$$

Figure 8 : Covariance Matrix

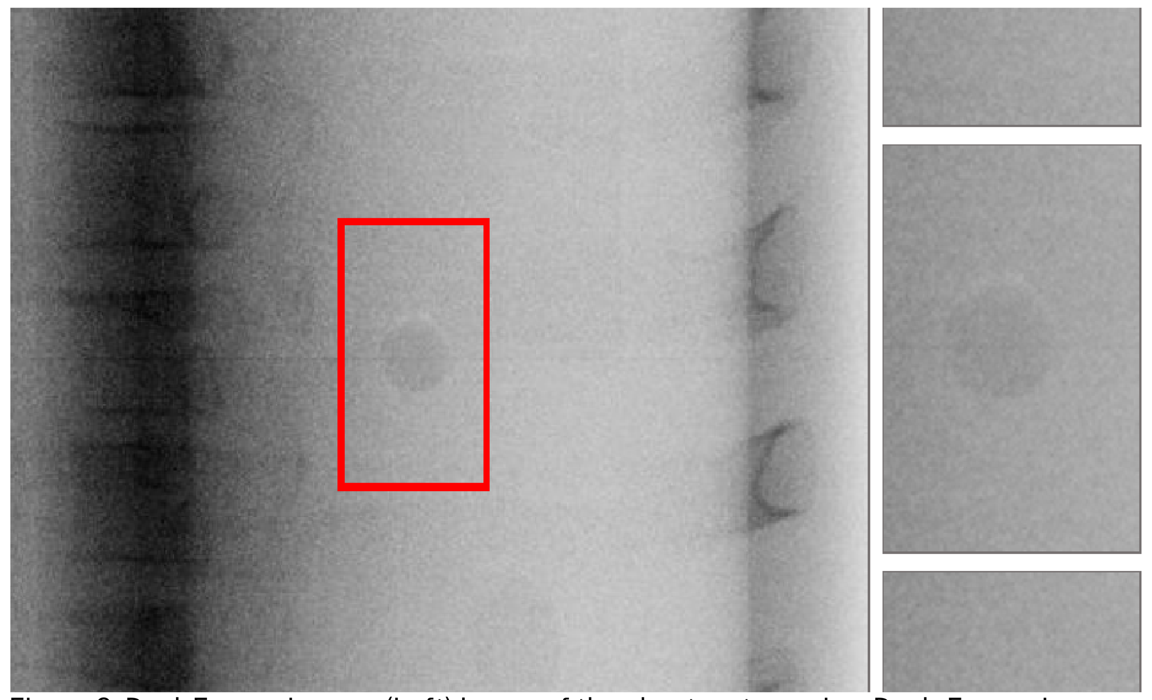


Figure 9: Dual-Energy images (Left) Image of the phantom tumor in a Dual- Energy image (Right) Zoomed-in image of tumor in the top, middle and bottom of the selected area.

References

A. Meyarian, H. Namdari, X. Yuan, M. V. Albert, and J. C. Roeske, “Phantom Tumor Tracking in Dual-Energy Fluoroscopy using a Kalman Filter,” *2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 2020.