

CT Thermometry for Cone-beam CT Guided Ablation

Zachary DeStefano, Nadine Abi-Jaoudeh, Ming Li,
Bradford J Wood, Ronald M Summers, Jianhua Yao
National Institutes of Health

Introduction

Monitoring temperature during ablation procedures is important for prevention of overtreatment and undertreatment. In order to accomplish ideal temperature monitoring, a thermometry map must be generated. In particular, this must be possible for Cone-beam CT (CBCT) scans. This possibility was explored with CBCT scans of a pig shoulder phantom being ablated [1]. We are extending this work by using CBCT scans of real patients. Additionally, we are employing various image refinement techniques to improve the thermometry map.

We used a data set of CBCT scans taken during 13 ablation procedures performed between September 2013 and June 2015. For each ablation procedure, there were between 1 and 4 ablations done. With each ablation, a baseline scan was taken followed by 1-4 comparison scans at different time points. Each of these time points had the ablation needle at different temperatures. We thus wanted to generate a thermal map at each of these time points in order to know how much tissue has been affected.

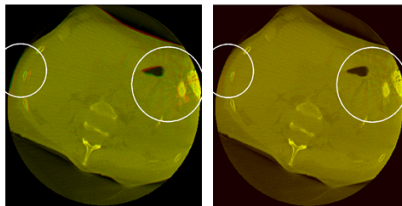
For each comparison scan, the following was done to generate a thermal map:

1. Register the comparison scan to the baseline scan
2. Filter both images and calculate the difference
3. Find the Region of Interest (ROI) manually or via automated Detection
4. Calculate the Sliding Window RMSE value for the ROI
5. Correlate values from (4) in the temperature zones with the temperature data
6. Use regression from (5) to generate thermal map for entire ROI

Pipeline

Image Registration

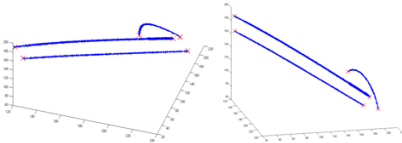
Each comparison scan was registered to the baseline scan. Affine and Deformable Registration were performed using NiftyReg [2].



Baseline (green channel) and Comparison (red channel) Image superimposed on one image before registration (left) and after registration (right)

ROI Detection

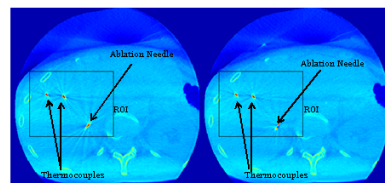
The HU values of the needle and thermocouple is much higher than normal tissue. Thus we can isolate those points. We find the Connected Components and then run PCA on each component to locate the endpoints.



Needles and Thermocouples (blue) and their endpoints (red) detected using PCA

Change Detection

These images have a low signal to noise ratio as well as beam hardening artifacts. Because of this, a simple difference image is quite noisy. We decided to use an averaging filter to obtain or verify the Region of Interest (ROI) that contained the ablation zone. We then calculate a Spatial Offset RMSE value for each pixel in the ROI.



Slice in Baseline Scan where Ablation occurred

Slice in Comparison Scan where Ablation occurred

The panel to the left shows different ways of comparing the ROI, including:

1. Raw Subtraction (top)
2. Average Filtered Image difference (middle)
3. Sliding Window method difference (bottom)

Raw Subtraction

1. Let A be baseline image
2. Let B be comparison image
3. Each pixel $f(i,j)$ in result image is as follows: $A(i,j) - B(i,j)$

Average Filtered Image difference

1. Let C be baseline image after applying an averaging filter
2. Let D be comparison image after applying an averaging filter
3. Each pixel $f(i,j)$ in result image is as follows: $C(i,j) - D(i,j)$

Spatial Offset RMSE Method

For each pixel $f(i,j)$ in result image:

1. Let U be neighborhood around $f(i,j)$ in the baseline image
2. Let V be neighborhood around $f(i,j)$ in the comparison image
3. Calculate the following^{*}:

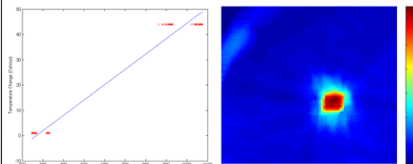
$$RMSE = \sqrt{\frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} (U(k+i, j) - V(k+i, j))^2}$$

^{*}U,V are $n \times m$ matrices and the missing values of U are obtained as follows:

$$U(k+i, n+m) = U(k, i)$$

Regression

We then took the sliding window RMSE value and calibrated it using the measured temperature change at the needle through a regression model. We used the model to calculate a thermal map in the ROI. This thermal map was used to obtain an approximate mean temperature around the needles and thermocouples.



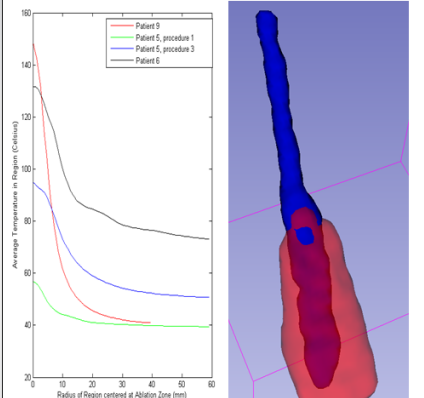
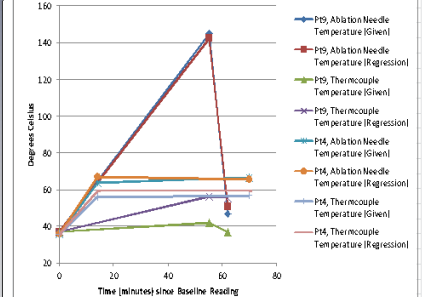
Plot of Sliding Window RMSE vs Temperature Change

Thermal Map generated from Sliding Window RMSE values and regression curve. Temperature in Celsius.

Results

Pt Num	4	5	5	6	8	9
Pt Num	1	1	3	1	1	1
Pt Sex	M	M	M	F	F	F
Pt Age	54	48	43	65	59	61
Baseline Temps	36/36	35/35	38/36	31/31/30	36/37	37/37
Pixel size (mm)	0.3823	0.3823	0.3823	0.3823	0.6549	0.6549
Neighborhood Radius (mm)	1.9646	1.9646	1.9646	1.9646	1.3098	1.3098
Temps (Given)	64/56	58/38	48/83	132/124/45	100/37	145/42
Temps (From Regression)	67.2/59.6	64.2/45.4	50.9/62.2	128.4/108.9/81.0	111.0/36.6	142.6/56.5
Time Since Baseline (min)	34	30	30	7	5	55
Temps (Given)	67/57	66/58	52/95	126/70/36	52/38	47/37
Temps (From Regression)	65.5/59.2	66.0/46	66.3/94.7	126.7/110.0/103.1	65.2/36.5	50.7/55.6
Time Since Baseline (min)	70	22	23	13	13	62
Given & Regression Temp RMSE	2.752	7.7	12.847	16.389	8.636	11.997
Error (RMSE) (Given Temp Range)	8.83%	24.84%	21.77%	15.67%	23.96%	11.11%

Temperatures are in Celsius. Temps (From Regression) is the average temperature in the neighborhood around the needle or thermocouple (with radius specified by Neighborhood Radius) in the thermal map calculated from regression.



This is a graph of mean temperature in the ablation neighborhood versus radius of the neighborhood. This can be used in future works to approximate the size of the ablation zone.

This is a 3D Visualization of the Needle (blue) and the Ablation Zone (red) for Patient 8. Both were obtained through registration by thresholding in ITK-SWAP. For the needle, the HU unit of each voxel was thresholded (>1200 HU). For the ablation zone, the Sliding Window RMSE value in the ROI was thresholded (>72).

Conclusions

As can be observed, for some of the patients, our temperatures after regression were quite accurate while for others, the error was higher. The higher error was the result of a high residual value in the linear regression. This was likely caused by image noise, registration error, or user error when selecting the ROI.

For the patients where the error was low, the methods we employed have the potential to provide useful thermal maps during ablation procedures. These thermal maps can then be used to approximate the size of the ablation zone. Additionally, there is the potential to generate a 3D visual representation of the ablation zone.

In the future, we hope to use a data set where multiple imaging modalities were employed. That way we can test our thermal map against one generated by a modality that is known to generate accurate thermal maps. We also want to incorporate Metal Artifact Reduction into the pre-processing steps.

Acknowledgments

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Bibliography

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