Symmetrical Cluster Analysis for Thermographic Breast Cancer Detection

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OBJECTIVE

This study aims to develop an algorithm that can effectively and accurately distinguish between tumor-affected and normal breast tissue. This is being achieved by performing statistical and cluster analyses on the existing dataset to identify key characteristics of tumor-affected tissues.

INTRODUCTION

Thermographic Imaging utilizes an infrared thermal camera to capture the skin temperature, and potentially indicate tumorous regions of interest based on the skin temperature patterns. Prior research indicates that tumorous regions are warmer than normal breast tissue, and that tumorous tissue cools at a slower rate than normal breast tissue [1].

MATERIALS & METHODS

- Patients and Volunteers were imaged over the course of 15 Minutes with an N2 Infrared Camera with Thermal Resolution of 50 mK / Digital Count.
- Image Analysis, Processing, and Algorithm Development were completed in MATLAB.

Image Analysis was carried out with two mechanisms:

(1) Statistical Analysis of tumorous regions as indicated by truth data.

(2) Cluster Isolation and Symmetric Removal to identify potential tumorous regions.

Statistical Analysis was carried out on both Tumorous and Normal tissue by comparing the Region of Interest and the Opposing Region. Each region was identified using the truth data given and user manual selection of patient nipples as reference points. The pixel intensity levels of each region in the first and last image of the series were statistically analyzed. Based on these data, a pixel intensity threshold was set and spatial clusters were formed using the Density Based Spatial Clustering Method [2]. Clusters were then isolated using a symmetrical analysis algorithm to identify clusters of clinical value.

RESULTS

Confirmation of Theoretical Data

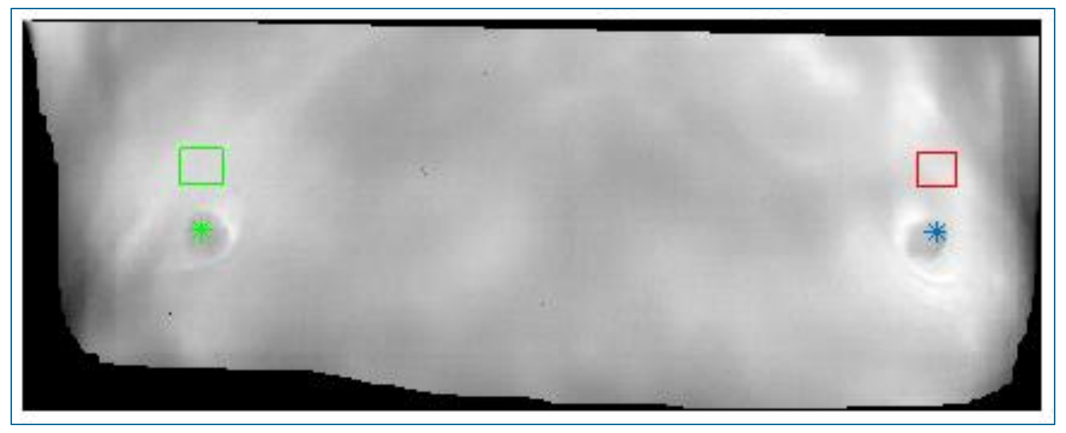


Figure 1: Patient 11 with Region of Interest (Red) and Opposite Region (Green) highlighted.

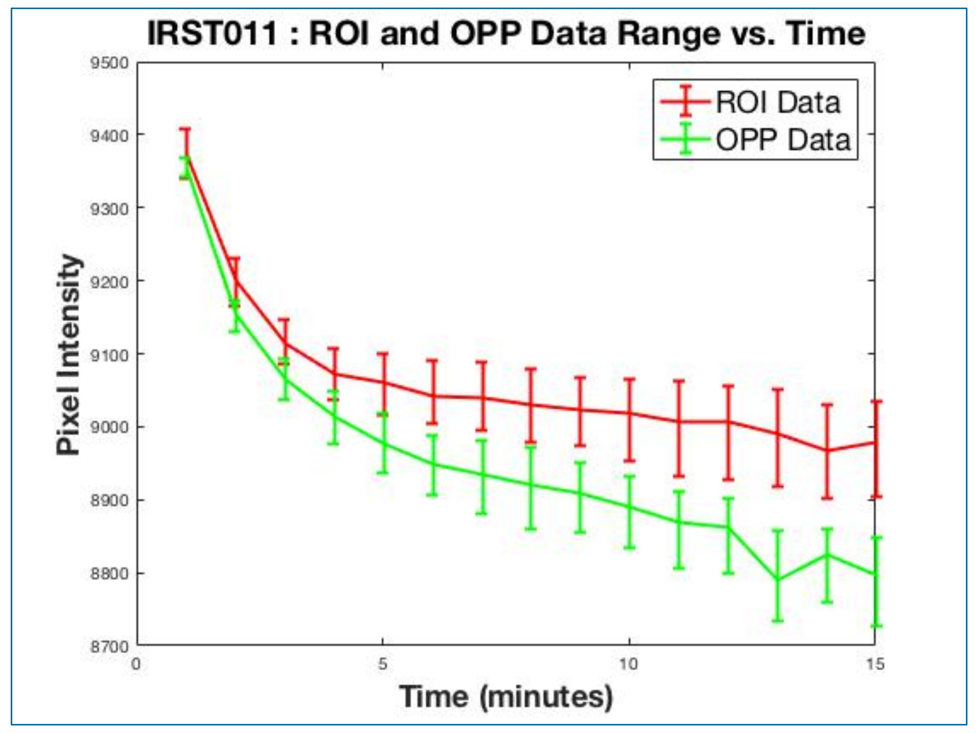


Figure 2: Mean Intensity and Intensity Range of ROI and OPP throughout imaging window.

Application of Cluster Isolation Algorithm

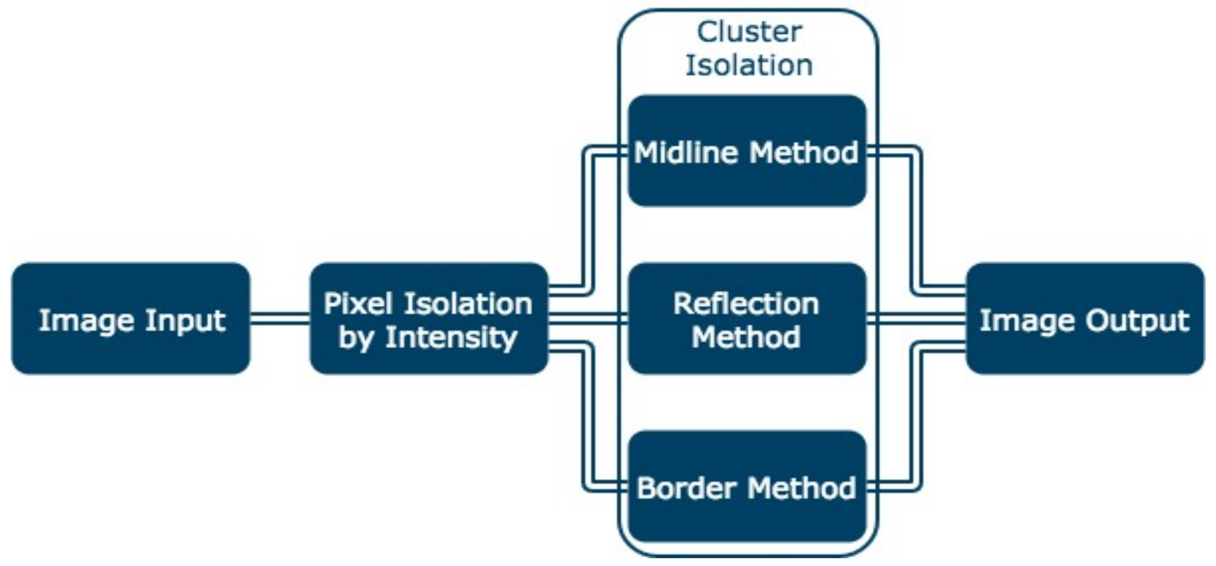
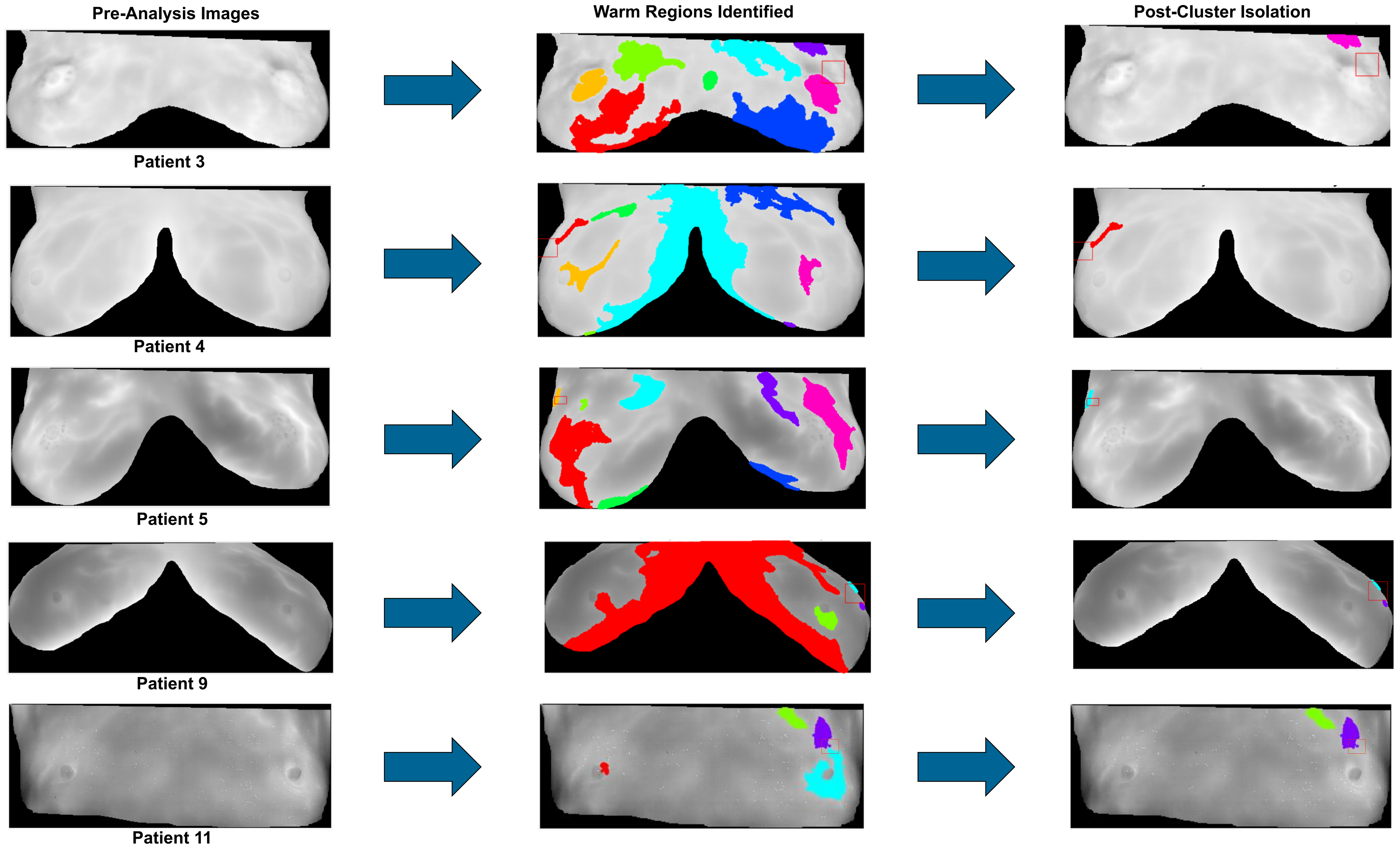


Figure 3: Block Diagram for Cluster Isolation Algorithm



DISCUSSION & FUTURE WORK

Results from the ROI and OPP Region Analysis confirm findings from prior research that tumor-affected breast tissue is warmer than normal tissue.

For each patient evaluated, the tumor region identified by the truth data was significantly warmer than the corresponding region on the opposite (unaffected) breast with a 95% confidence level. The tumorous region remained warmer than the normal tissue over the entire period of imaging.

When set at an appropriate intensity threshold for a given patient, the cluster isolation algorithm is able to remove all symmetric clusters and identify a single warm region on or directly next to the tumorous region.

As more patients are added to the data set, we will continue to train the algorithm and improve our region identification accuracy. The goal is to provide information for adjunct usage with mammography that may improve the overall accuracy of early breast cancer diagnosis.

CONCLUSION

Given the available data from the 14 patients imaged thus far, our research indicates that the tumorous breast tissue is noticeably warmer than normal breast tissue. This is evident through the comparison of the tumor-affected tissue with the corresponding region on the opposite breast, which acts as patient-specific baseline. Additionally, these results allow us to train the Cluster Isolation algorithm to identify regions of clinical importance. Current results indicate high validity, but more data is needed for further algorithm development.

REFERENCES

[1] Li Jiang, et al., Phys. Med. Biol. 56 (2011). 187–202

[2] S.M.K. Heris, “Implementation of DBSCAN Clustering in MATLAB”, (2015).