

A 2.5D Approach for Breast Lesion detection in 3D Ultrasound

Arathi Sreekumari, Liye Pei, Rakesh Mullick and K S Shriram

Abstract— Lesion detection on 3D Breast Ultrasound volumes is computationally expensive when performed in 3D. Alternatively, 2D slice-by-slice lesion detection loses the context provided by 3D acquisition. We propose an intermediate 2.5D approach by consolidating multi-slice information using a Minimum Intensity Projection (MinIP) onto a single 2D image. We demonstrate the superiority of 2.5D detection over slice-by-slice 2D detection while offering the same computational and memory footprint advantage.

Clinical Relevance— CAD on 3D breast Ultrasound significantly reduces the throughput burden on the clinician. Efficient deployment of Deep Learning based CAD models can reduce memory and computation requirements.

I. INTRODUCTION

3D Breast Ultrasound is a non-invasive and a comfortable modality for screening breast cancer. The clinician must interpret detailed 3D views and sift through hundreds of slices to spot a potential lesion. CAD is therefore an essential first reader narrowing the focus towards plausible lesions.

Deep Learning (DL) based CAD when performed in 2D [1] misses out on 3D patterns, while, 3D detection [2] is memory and compute expensive. We propose an intermediate 2.5D approach that combines the suppleness of a 2D detector with the context available to a 3D model. Since lesions in Ultrasound appear darker than their surroundings, we consolidate information over multiple 2D slices using a Minimum Intensity Projection (MinIP) and proceed to detect them in a 2D fashion.

II. METHODS

The MinIP taken across multiple axial slices generates the 2.5D slice. The lesion is darker than its surroundings and appears more stable and pronounced in the MIP image (Fig 1). We considered only axial slices and their stacks since that is the primary direction of acquisition in 3D Breast Ultrasound. An overlap between adjacent stacks for MinIP computation ensures spatial continuity in 2.5D space.

Our method uses a standard Mask R-CNN architecture [3] for lesion detection. Mask R-CNN is trained both on individual 2D slices and on 2.5D images (derived from different stack sizes). The probability values on each of the inferred slices are stacked back to create a 3D prediction volume. For 2.5D slice input, predictions are not available at every axial location. An interpolation step fills the gaps yielding a complete 3D volume of predictions. Dice overlap in 3D between the ground truth mask and predicted lesion candidates quantifies the detection performance.

Arathi Sreekumari is with Advanced Technology Group, GE Healthcare, Bengaluru, 560066 India, e-mail: arathi.sreekumari@ge.com).



Figure 1. Comparison of Intensity profiles of lesion – over a 2D slice and a Minimum Intensity Projection (MinIP) over 10 slices. Intensity values show greater stability in the MinIP image compared to a individual 2D slice

III. RESULTS

Our experiment utilized 3D breast scans from 183 subjects (Multiple views/volumes per subject) with biopsy-proven breast cancer. A total of 406 cancerous regions were marked by a clinician; 151 volumes without any abnormal finding from 24 subjects were included as control.

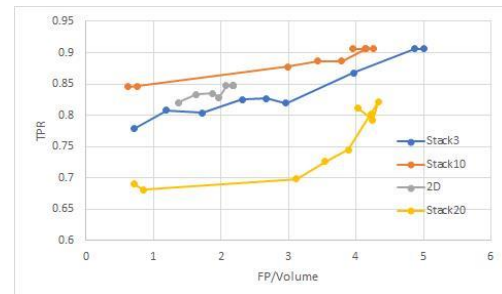


Figure 2. FROC curve comparing lesion detection performance on 2.5D MinIP stacks (3 slices, 10 slices and 20 slices) with 2D slices.

During inference on 60 subjects (155 volumes), detections with Dice overlap ≥ 0.25 with ground truth were deemed as true positives. Lesion detection performance on 2.5D stacks (3, 10 and 20 slices) were compared with individual 2D axial detections as an FROC curve (Fig 2). The 2.5D MinIP consolidation over 10 slices (5 mm in physical space) seems optimal and outperforms 2D slice-by-slice detection. Larger stacks fare worse as lesion signature gets diluted.

IV. DISCUSSION & CONCLUSION

We have presented a 2.5D lesion detection method that exploits the 3D context, with the efficiency of 2D detection.

REFERENCES

- [1] C. Muramatsu, et al, "Mass detection on automated breast ultrasound volume scans using convolutional neural network," 2018 International Workshop on Advanced Image Technology (IWAIT), 2018, pp. 1-2.
- [2] T. -C. Chiang, et al, "Tumor Detection in Automated Breast Ultrasound Using 3-D CNN and Prioritized Candidate Aggregation," in IEEE Trans on Medical Imaging, vol. 38, no. 1, pp. 240-249, Jan. 2019.
- [3] K. He et al, "Mask R-CNN," 2017 IEEE International Conference on Computer Vision (ICCV), 2017, pp. 2980-2988.