Semi-Automatic Algorithm for Breast MRI Lesion Segmentation Using Marker-Controlled Watershed Transformation

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Introduction

Motivation.

- Accurate segmentation of breast lesions in MRI still remains a challenging problem.
- Considerable variation in terms of shape, size and overlapping area with healthy tissues.

Reference Methods:

- Stochastic watershed for optic disk segmentation [1].
- Drawback: Require post-processing morphological operations such as dilation, erosion and fill-holes to obtain a smooth and continuous lesion boundary.

Goals:

- Novel Marker-controlled Watershed Transformation for semi-supervised breast MRI lesion segmentation.
- Improve lesion segmentation accuracy in breast MRI.

Methodology

Watershed Transformation:

- **Drawback**: Over-segmentation due to several local minima [2].
- **Solution:** Detect markers both within and outside lesions.

Steps:

- Selected 2D subtraction T1-Weighted MRI slice based on ground truth annotation by radiologist.
- ROI drawn around lesions and Contrast Limited Adaptive Histogram Equalization (CLAHE) applied.
- Morphological gradient of the ROI taken out:

$$\boldsymbol{g}(\boldsymbol{f}) = (f \oplus B) - (f \ominus B)$$

- Pixels with higher intensity in the ROI chosen as markers.

$$\boldsymbol{S} = \max(s_1, s_2, s_3, \dots) \in \overrightarrow{\boldsymbol{ROI}}$$

- Watershed transformation uses the markers to guide lesion segmentation.

Number of Makers:

- 45 makers found to be optimal, refer to Fig.1.

Validation:

- 80 female patients T1-Weighted MRI with mean age of 50±13
- 59 malignant and 47 benign lesions

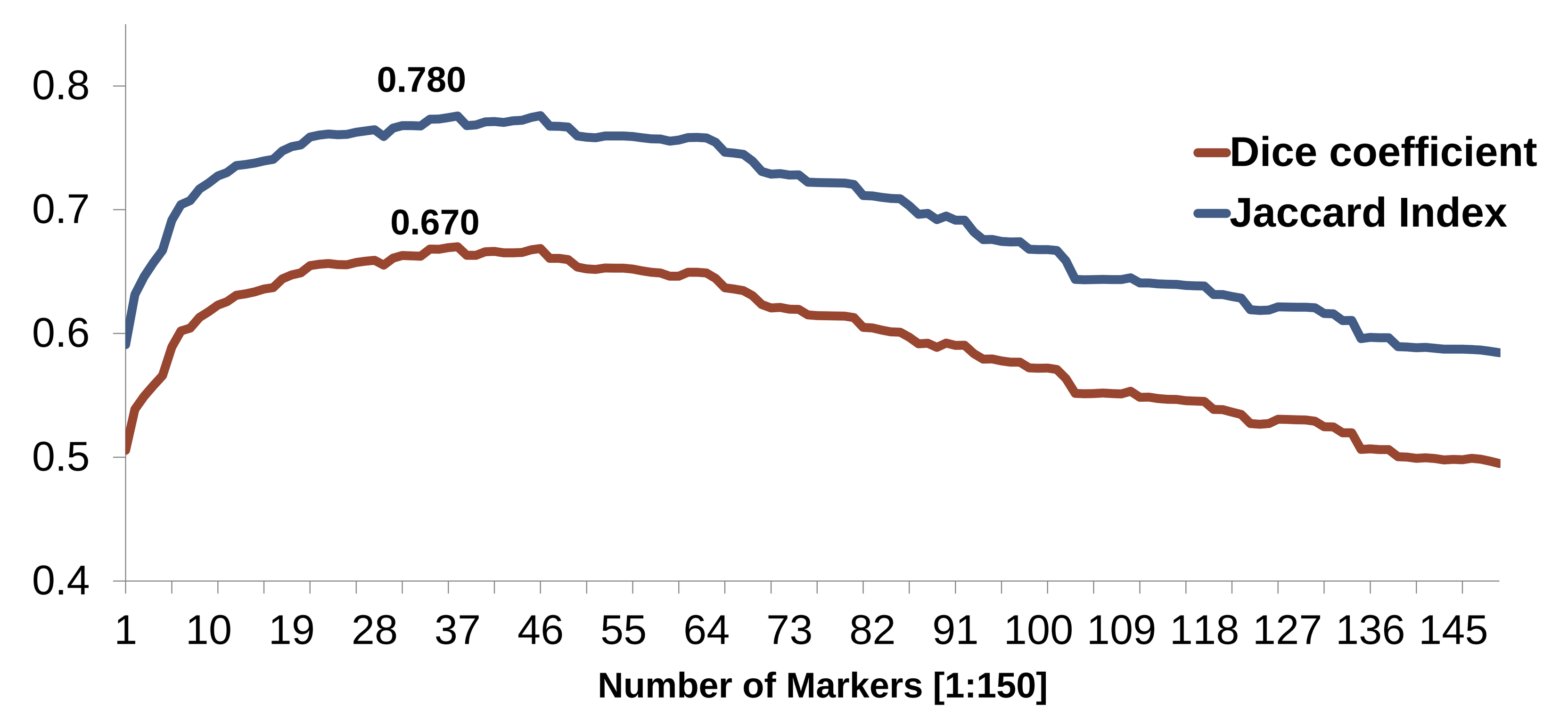

Figure 1: The mean of total lesions for Dice coefficient and Jaccard index with different number of markers.

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Results

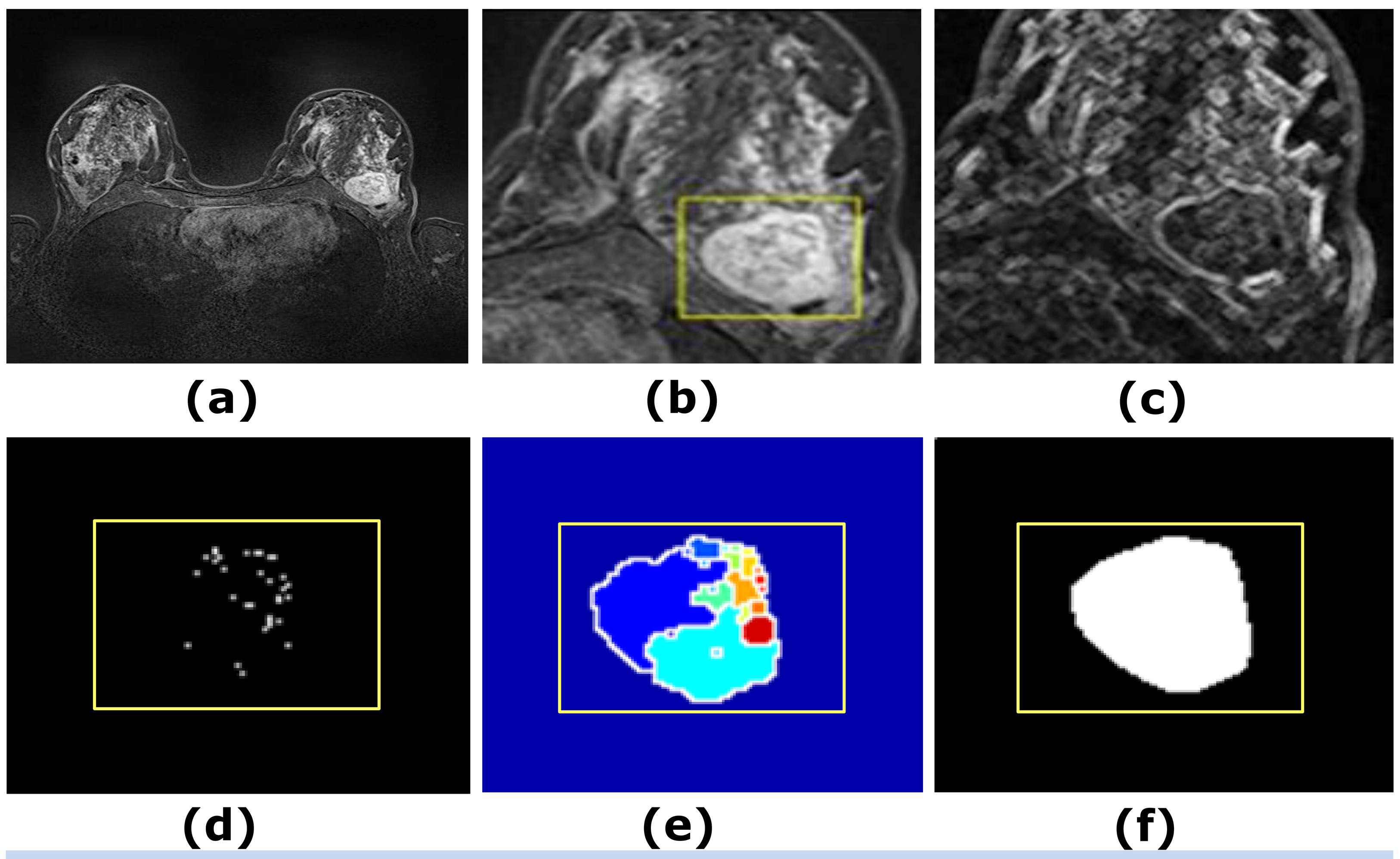

Figure 2: Steps involved in segmentation pipeline: (a) MRI 2D slice. (b) Contrast enhancement using CLAHE. (c) Image gradient. (d) Highest pixel intensities as markers. (e) Watershed transformation applied. (f) Segmentation mask.

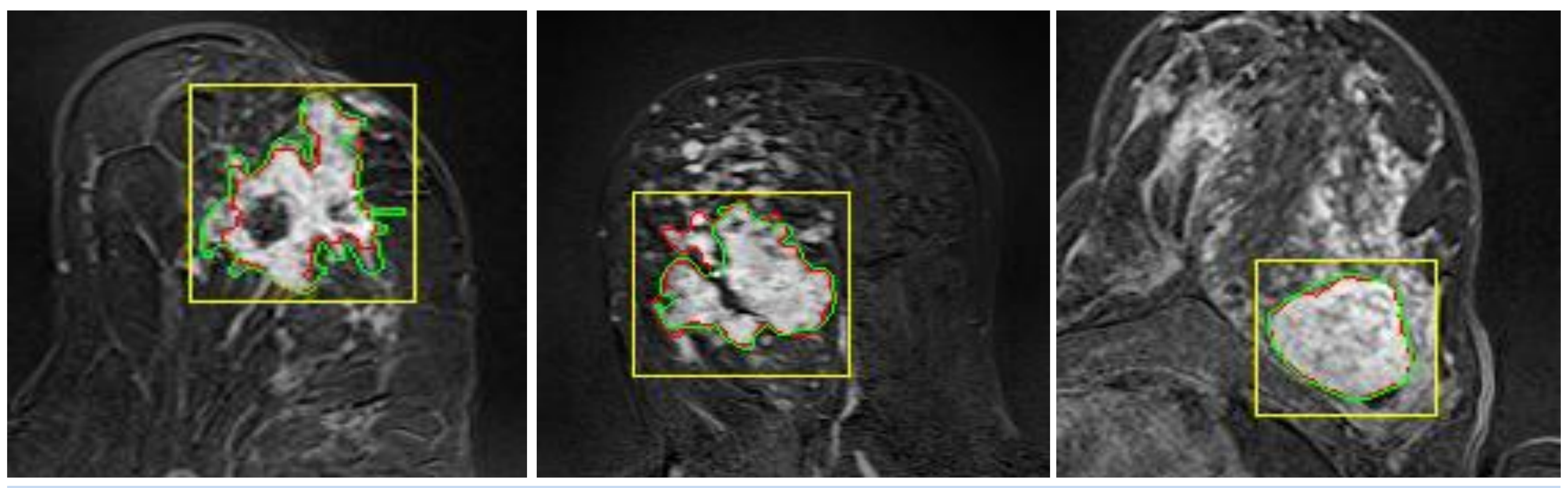

Figure 3: Malignant tumor in the left and middle images, benign tumor in the right. The yellow bounding box represents the ROI, ground truth tumour outlines are shown in green and our results in red.

Method	Dice coefficient	Jaccard Index
Proposed (45 Markers)	**0.780±0.172**	**0.670±0.216**
GMM Clustering	0749±0.178	0.627±0.195
K-Means Clustering	0.745±0.1182	0.623±0.195

Table 1: Dice coefficient and Jaccard index (mean ± std) for the different methods.

Discussion and Conclusions

- The proposed method outperform better in comparison to the GMM and K-means clustering.
- Pixels with high intensities chosen as markers.
- **Fewer features, robust and fast approach.**
- High segmentation accuracy for the medium-to-large lesions.
- Useful pre-processing step for classification of breast lesions.

Limitations:

- Segmentation accuracy is low in the case of disjointed lesions.

References

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