

# Optimization of Breast Tissue Segmentation: Comparison of Support Vector Machine and Fuzzy C-mean Clustering Algorithms

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**Background** We compare two methods of breast tissue segmentation: 1) fuzzy c-mean (FCM) clustering [1], an unsupervised learning method that classifies voxels into a specified number of clusters by iteratively minimizing intra-cluster variation, and 2) the support vector machine (SVM) method [2, 3], a supervised learning method that uses training data to construct hyper-planes to minimize the margin between classes. We also investigate the effect of varying the number of output clusters and the combinations of input image types. Our goal is to segment breast images into fibroglandular tissue, fat, lesions, and skin. Among other uses, segmentation aids magnetic resonance guided high-intensity focused ultrasound (MRgHIFU) therapy by improving the accuracy of proton resonant frequency thermal mapping and improving the modeling of the simulated ultrasound beam patterns.

**Methods** Both algorithms require sets of images with different tissue contrast to classify voxels into clusters that represent different tissue types. In this study, MR images including non-fat saturated (FS) T1-w, FS T2-w, FS proton density (PD)-w and three-point Dixon separated fat-only and water-only images are input into the clustering algorithms. All imaging was performed on a 3T Siemens Trio scanner using a Siemens 4-channel breast coil. With approval by the local Institutional Review Board and informed consent obtained from the volunteer, three subjects were examined using the following sequences: 3D T1-w three-point Dixon (TR/TE1/TE2/TE3=11/4.7/5.7/6.8 ms), 2D FS heavily T2-w (TR/TE = 11s/70ms), and 2D FS PD-w (TR/TE = 11s/7ms). The common imaging parameters were FOV=192x192 mm and matrix size = 192x192x88. Each 1x1x1 mm<sup>3</sup> voxel in the 3D breast volume was classified into one of the tissue types — fibroglandular tissue, fat, lesion, and skin. The impact of the selected combination of image types and the number of output clusters was studied. Using the optimal combination from these tests, a comparison of SVM and FCM was made in terms of the ability to classify the voxels into desired tissue types, with confirmation by an experienced breast radiologist.

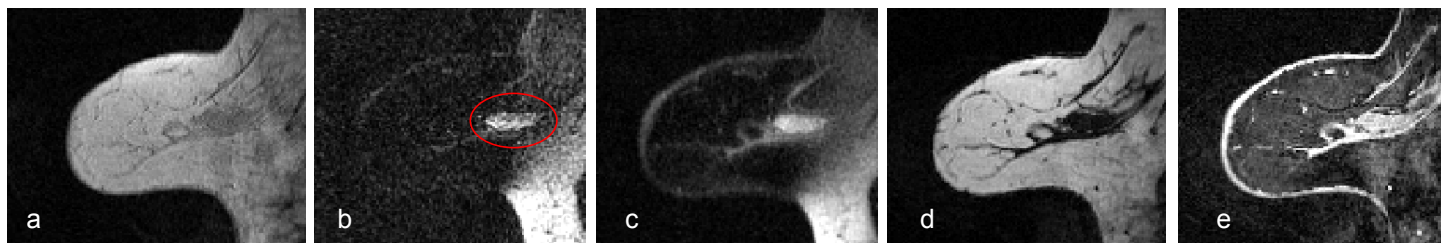


Fig. 1 Representative single sagittal images showing different types of inputs to the segmentation algorithms: (a) non-FS T1-w, (b) FS T2-w, (c) FS PD-w, (d) three-point Dixon fat-only and (e) water-only images. Circled area in image (b) is a fibroadenoma.

**Results** Figure 1 shows images from the various sequences in a patient with a fibroadenoma (circled). Figure 2 (a, b) shows the effect of using different combinations of these images as inputs to the SVM algorithm, comparing the segmentation obtained with the T1, T2 and PD-weighted images with and without the three-point Dixon fat/water images. Inclusion of Dixon images improved accuracy of segmentation, decreasing erroneous assignment of voxels at the interface of fat and fibroglandular tissues (arrow) and the skin boundary detection (arrowhead). The impact of the number of output clusters using SVM is illustrated in Fig. 2(c), where the glandular tissue and the skin components were incorrectly classified into a single cluster when the number of output components was reduced by one. For this patient, six components appear optimal. The performance comparison of SVM and FCM using the identical optimal combination of multi-spectral MR inputs and the number of output clusters is given in Fig. 2(a, d). The figures suggest that SVM outperforms FCM in terms of the accuracy of the segmentation.

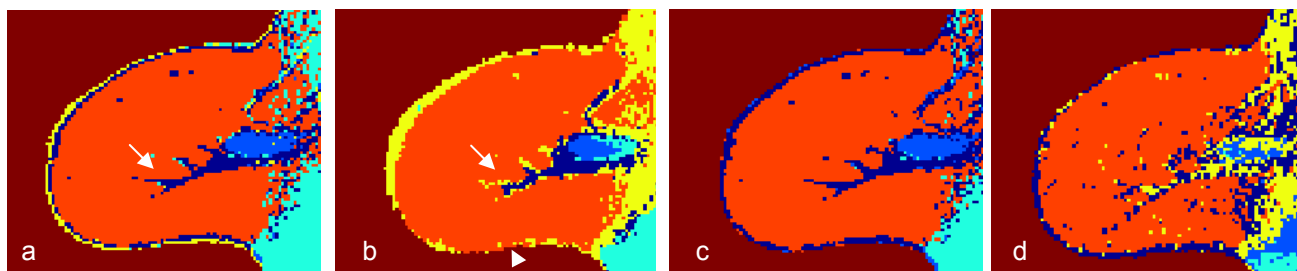


Fig. 2 Segmentation outputs: Fat—orange, fibroglandular tissue—dark blue, fibroadenoma—blue, fat close to the coil—light blue, skin—yellow, background—red. The impact of Dixon fat-only and water-only image on tissue segmentation: (a) with (b) without Dixon images as input. Effect of number of output clusters on segmentation: (a) six clusters (c) five clusters. Glandular tissue and skin were incorrectly classified into one cluster in (b), displayed in yellow. Comparison of (a) SVM and (d) FCM with the same input multi-spectral MR images and the same number of output clusters.

**Conclusion** We have demonstrated that SVM is useful technique that segments breast tissue into fibroglandular tissue, fat, lesions, and skin. Non-FS T1-w, FS T2-w, FS PD-w and three-point Dixon fat-only and water-only images comprise the optimal combination of multi-spectral inputs to SVM. Appropriate selection the number of output clusters is essential for an accurate segmentation.

## References

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