Segmentation of Hepatic Tissue in MRI Using Fuzzy Logic

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INTRODUCTION

Liver segmentation in magnetic resonance imaging (MRI) is a challenging task due to its several acquisition parameters, intricate organ irrigation and variable tissue signal intensity. For these reasons, it lacks in specialized algorithms and public databases. Segmentation isolates the organ, limiting image analysis to a certain region of interest. We propose here a manually initialized algorithm based on fuzzy logic for segmentation of the hepatic tissue in magnitude in-phase (IP) and opposed-phase (OP) MR images, avoiding major internal blood vessels and biliary structures for better fat fraction calculation in the assessment of liver steatosis.

MATERIALS AND METHODS

The scheme is divided in initialization, fuzzy classification and post processing steps, as depicted in Figure 1. Initially, the user inputs seeds over the liver tissue, the brightest and darkest ones are chosen for region growing operations in both images. The average intensity of each resulted area is stored. Then, fuzzy rules are applied to the areas: for OP images, a given pixel is classified as boundary if its intensity is lower than the calculated average, liver if it is the same within a range and vessel if higher. Opposite rules apply for IP images (Figure 2). Aggregation method was `AND`. To each pixel a boolean value is assigned representing “liver” or “not-liver”. Finally, the results from both images are combined using logical `AND`, binary erosion, binary opening and a final region growing based on the initial seeds. The algorithm was tested in 32 pairs of OP/IP images of patients diagnosed with moderate or no significant steatosis. Results were compared to manual segmentation and to other authors using Jaccard similarity coefficient.

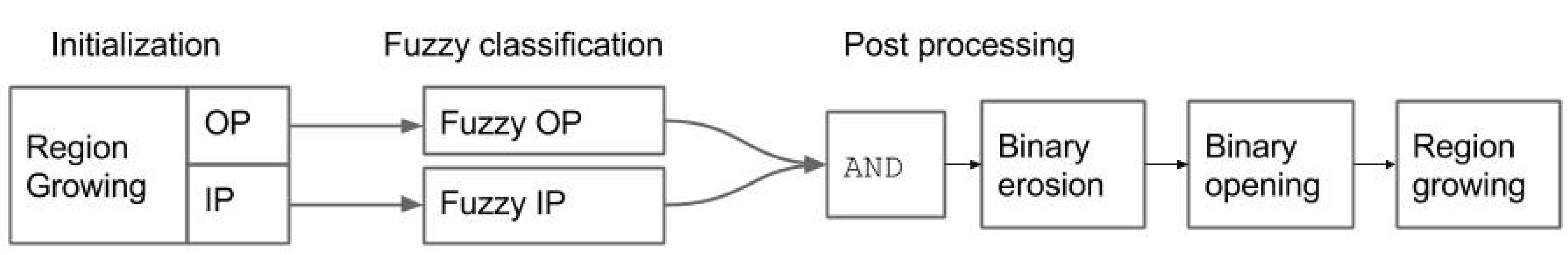

Fig. 1: Three main stages of the proposed segmentation scheme.

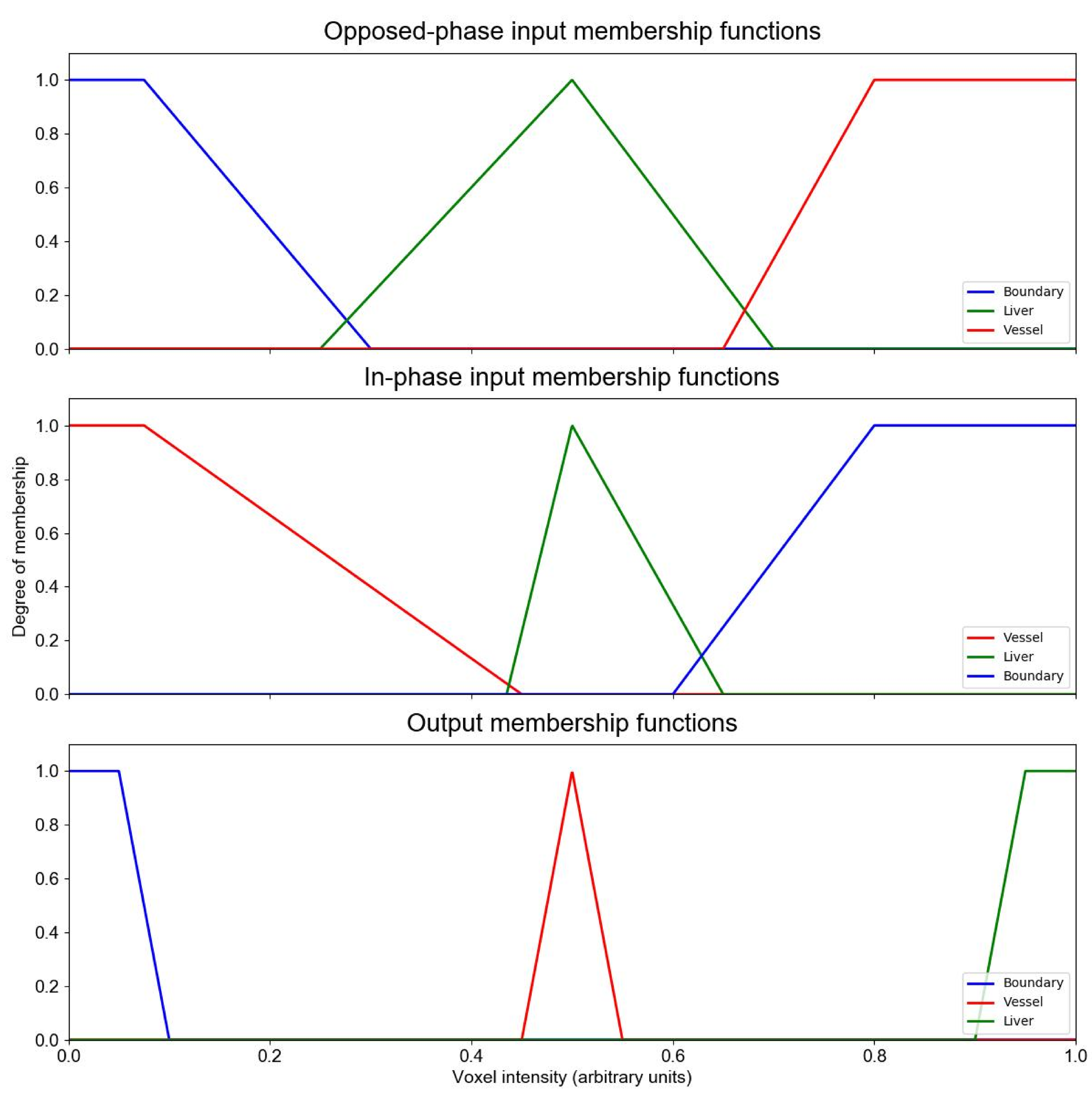

Fig. 2: Membership functions for input fuzzy OP and IP sets and output crisp set.

RESULTS AND DISCUSSION

Figures 3, 4 and 5 shows examples of OP (A) and IP (B) images, their manual (C) and computerized (D) segmentations. In Figure 3, great similarities can be observed both in outer and inner boundaries, demonstrating the efficiency of the adopted scheme (Jaccard coefficient 0.89). Figure 4 has respiratory artifacts causing changes in signal intensity, which was overcome by the multiple-seed initialization, however misregistration between OP/IP images impaired results (Jaccard coefficient 0.86). Figure 5D shows the results for unfortunate choice of the seeds leading to under segmentation as the algorithm did not correctly identify the increase in signal caused by the proximity of the abdomen coil as part of the liver (top left lobe, fig 5A). The `AND` operation used to join OP and IP image results also means that well segmented boundaries in will lose area when joined. That is a compromise we decided to take instead of an OR operation that would preserve borders but wipe internal structures.

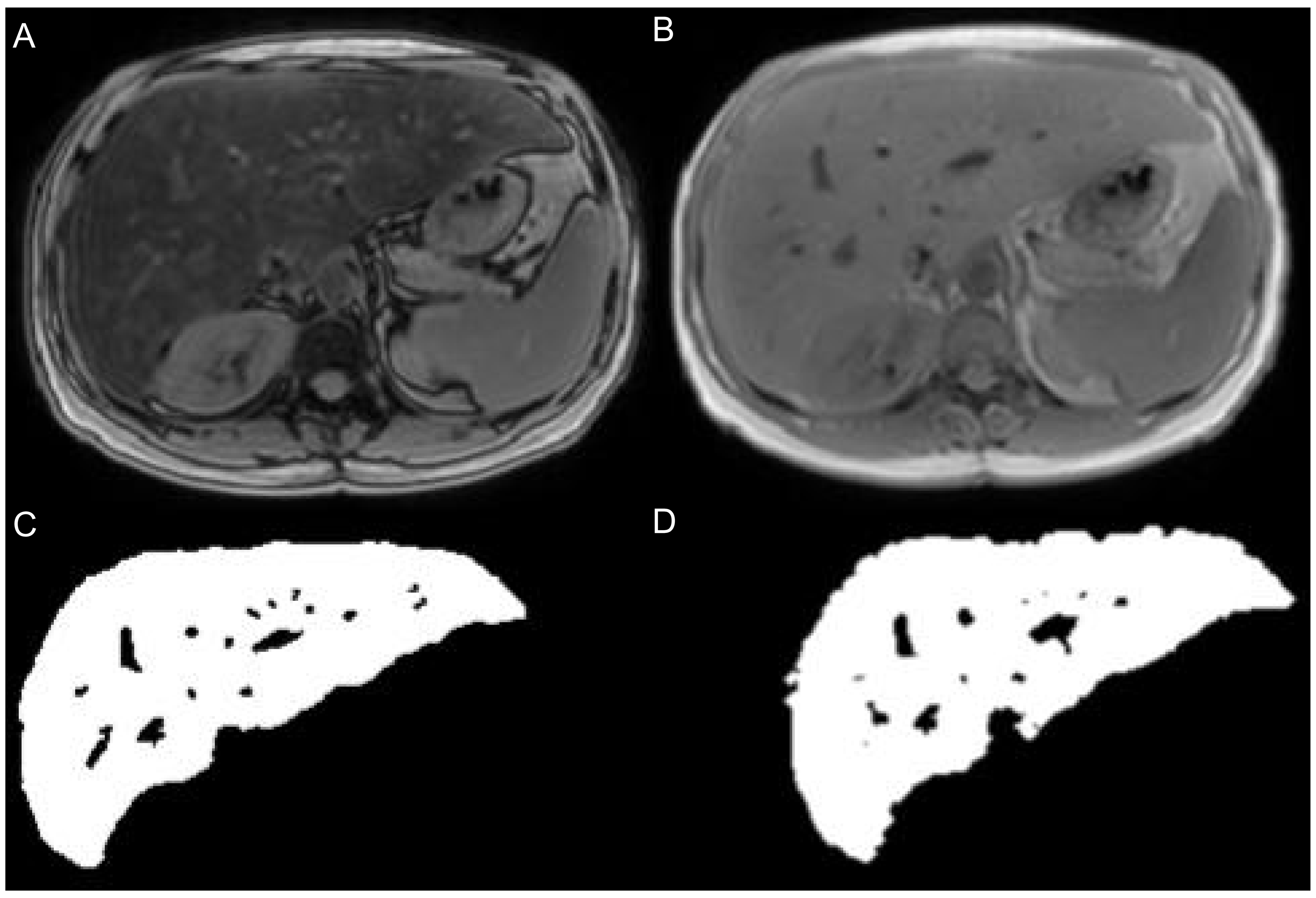

Fig. 3: Example of segmentation result with Jaccard coefficient = 0.89.

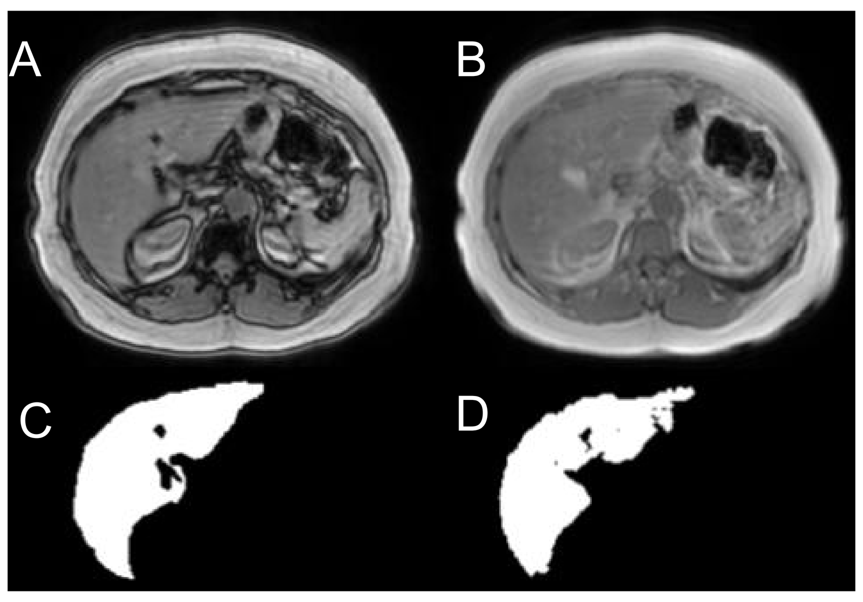

Fig. 4: Example of segmentation in image with respiratory artifacts (arched lines) and misregistration. Jaccard coefficient = 0.86.

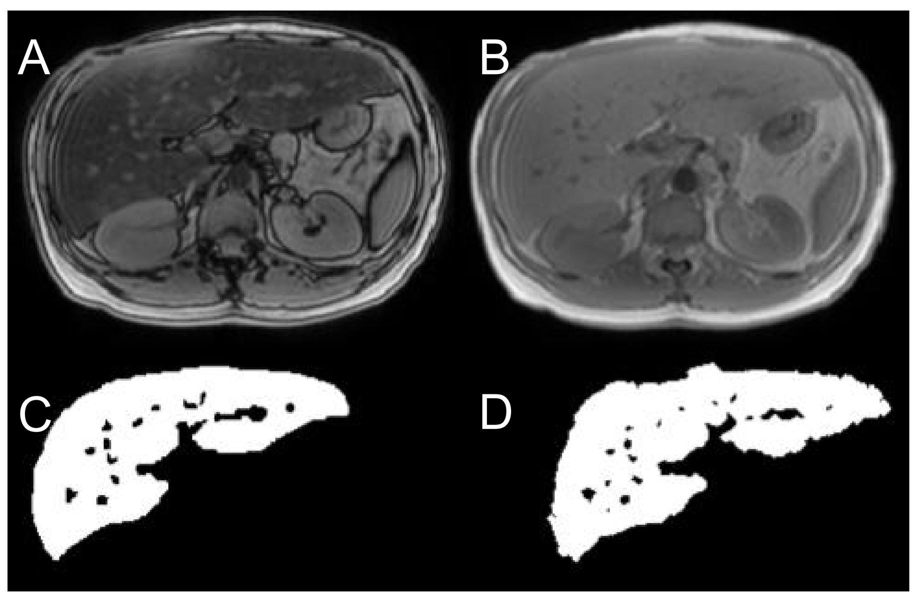

Fig. 5: Example of under segmentation (top left in 5D) caused by inhomogeneity in signal due to coil proximity. Internal structures are preserved. Jaccard coefficient = 0.86.

Average results for 32 pairs of images were: Jaccard coefficient of 0.85, accuracy of 0.99, sensitivity of 0.93 and specificity of 0.99. Other authors who recently performed abdominal organ segmentation in the same type of IP/OP images achieved Jaccard coefficients of 0.75 [1] and 0.89 [2].

CONCLUSION

The proposed method achieved results slightly higher than literature and excluded internal structures of the liver, a desirable feature for fat fraction calculation as their presence may impair the results. Lower coefficients were found either in regions with B1 field inhomogeneities artifacts due to coil proximity or when images were misregistered.
The algorithm is open to contributions at https://github.com/livertools/fuzzyliver.

REFERENCES

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