Automated Analysis of Hepatic MR Elastography Images with Motion Artifacts and Signal Inhomogeneities

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Purpose: Magnetic Resonance Elastography (MRE) is a clinical technique that is being increasingly used to noninvasively diagnose and stage hepatic fibrosis by calculating hepatic stiffness [1]. In MRE, mechanical waves are introduced into the body, imaged with phase-contrast MRI, and the resulting phase images are processed to calculate stiffness images. The image acquisition and stiffness inversion are highly reproducible. However, the selection of an appropriate ROI from which to report the stiffness of the liver is currently done manually and results in inter-reader variability of the stiffness measurements of approximately 20%. We recently proposed a promising, fully automated method for the retrospective analysis of clinical MRE images whose agreement with the readers was superior to inter-reader agreement [2,3]. The algorithm works by defining an initial liver contour via tissue classification, refining it with an active contour, using a confidence map determined during the stiffness inversion to limit the ROI to areas with high SNR and minimal wave interference, and calculating the mean stiffness. A new approach to the initialization stage of this algorithm is presented here that will provide additional stability to the entire algorithm and allow for the automated analysis of images with high intensity inhomogeneity, motion artifact, and poor edge contrast, which are common in clinical MRE magnitude images. Clinicians involved in advanced imaging as well as researchers working on developing automated quantification techniques are the target audience for this study.

Methods: Clinical MRE magnitude images are acquired with a GRE sequence with TR/TE = 50/20 ms. The inherent fat > blood > liver intensity contrast is locally distorted, however, due to intensity inhomogeneity caused by coil sensitivity profiles, and intravoxel phase dispersion due to MRE driver motion. Fat, being closest to the coils and the driver, is most strongly affected by these problems, causing its intensity range to overlap with that of the liver in affected areas. Fat is initially separated from the internal organs by progressively eroding 4 pixel layers from the outside of the body until the layer with minimal SNR, containing the ribs and/or the abdominal cavity, is found. If no distinguishable minimum is found, erosion is stopped 8 pixels after the highest intensity layer, corresponding roughly to the middle of the fat layer. The mean and standard deviation (μ and σ) of the tissue intensities inside this boundary are calculated exclusively from the left half of the image (which contains most of the liver). The fat external to the boundary is then thresholded above the mean of the internal tissues to remove areas where signal is decreased due to intravoxel phase dispersion and low coil sensitivity. The μ and σ of fat are then calculated and used in conjunction with the μ and σ of the internal tissues to construct the intensity membership functions illustrated in Figure 1. These functions are used to classify the internal tissues as background, liver, or fat. The initial liver mask is formed using the internal organs mask in the left half of the image. Voxels in which the sum of all membership functions is below 0.6 are excluded as partial volume or blood vessels (which have intensities between liver and fat). The image intensity is then normalized with the Local Entropy Minimization Scheme (LEMS) [3], and the active contour segmentation as well as confidence map thresholding and outlier removal, are performed as per our previous method [2]. Small blood vessels, illustrated in Figure 2, are not always excluded by the inversion confidence map, but may cause stiffness underestimation, and thus are targeted for removal from the ROI by this segmentation. The new initialization algorithm was tested using a dataset of 500 clinical MRE cases that had stiffnesses analyzed by multiple clinical readers.

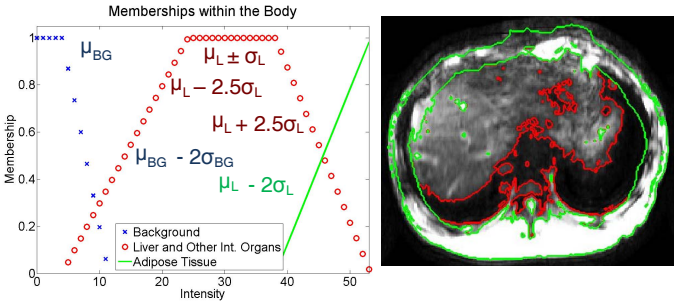

Figure 1: Tissue classification for contour initialization. The membership function used to classify the intensity histogram into liver, background, and fat, as well as the resulting masks overlaid on the original image are shown.

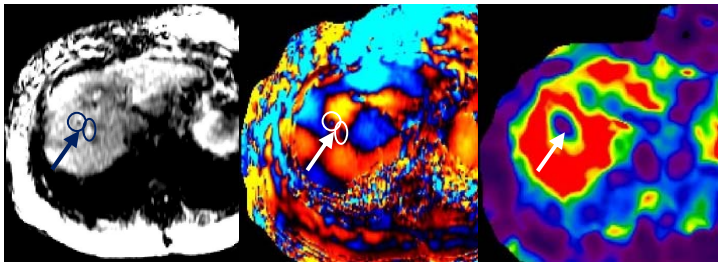

Figure 2: Focally decreased stiffness due to a hepatic blood vessel. Magnitude, motion-encoded phase, and stiffness images are shown.

Results: The algorithm successfully analyzed all 500 clinical cases, 9% of which were previously considered to have failed due to having initializations in nonliver tissue. Examples of difficult cases are shown in Figure 3. The Bland-Altman confidence interval for the difference between the stiffness measurement by the algorithm and the readers was -1.4 ± 25.8 % (mean ± 1.96 standard deviation) across all cases.

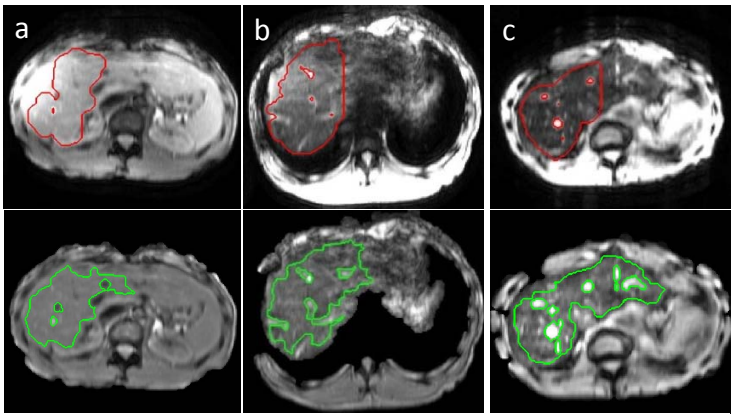

Figure 3: Initializations and segmentations in difficult cases. The images are affected by: a) inhomogeneity, b) motion artifact, and c) reduced signal due to iron overload. Initial contours constructed by taking the internal organ masks in the left half of the image are shown in red. ROIs segmented by the active contour, overlaid on the inhomogeneity-corrected images, are in green. Blood vessels are largely excluded successfully.

Discussion: The model-less classification proposed here led to successful initialization in all 500 cases and thus proved to be highly versatile with respect to intensity variations within and between images. The removal of the background and regions affected by intravoxel phase dispersion, combined with the intensity correction step, allowed the contour to segment without leaking, even in cases with low edge contrast. Blood vessels were excluded successfully in many cases, though additional classification after the intensity correction may yield further improvement. The discrepancy between the algorithm and the readers was comparable to the discrepancy between readers as determined by our previous study.

Conclusions: These results demonstrate an improvement to a fully automated algorithm for reading clinical hepatic MRE cases that is able to determine appropriate ROIs for the stiffness measurements across a wide range of cases, including those with motion artifact, iron overload, and intensity inhomogeneity.

References: [1] Yin, M., et al., Assessment of hepatic fibrosis with magnetic resonance elastography. Clin Gastroenterol Hepatol, 2007; 5: 207-1213. [2] Dzyubak, B., et al., Proceedings of the ISMRM; 2012 May 5–11; Melbourne, Australia. [3] Dzyubak, B., et al. Automated Liver Stiffness Measurement with Magnetic Resonance Elastography. JMRI. 2012. [4] Salvado, O., et al., Method to correct intensity inhomogeneity in MR images for atherosclerosis characterization. IEEE Trans. on Medical Imaging 2006; 25: 539-552.