SNR Performance Of Automated Geodesic Active Contour Based Liver Segmentation

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Introduction

Assessment of liver volume with MRI has been primarily used for transplant procedures, pathological tracking and providing information about metabolic changes [1]. Most of these techniques however require a degree of manual intervention. To address this, we have developed an automated method to extract the liver region from 3D high-resolution contrast scans that could potentially improve the clinical workflow. However for any such scheme, it becomes imperative to understand the SNR performance. This is especially true, with parallel imaging techniques being increasingly used clinically for MRI scanning of abdominal organs, mostly to reduce the breath-hold times. Since parallel imaging techniques sacrifice SNR for speed, evaluation of SNR performance of the automated segmentation algorithm will indicate its robustness. In this work, we present the preliminary results for SNR evaluation of the automated liver segmentation algorithm with simulated noise data.

Methods and Materials

Figure 1 shows the flow chart for the SNR analysis of liver segmentation algorithm. **MRI Data Acquisition and Analysis:** Five breath-hold 3D liver volumes (LV) were acquired on 1.5T GE Signa MRI scanner with a 8-channel body coil array, using the contrast enhanced, T_1 weighted LAVA sequence. The acquisition parameters varied with volunteers: TE/TR = 1.7-2.1 ms/3.8-4.3 ms, matrix size: 256 x 256 to 320 x 192, slice thickness: 2.6 mm to 4.4 mm. ZIP2 was performed on all data sizes to give a final matrix of 512 x 512 to give voxel size ranging from 0.82 mm x 0.82 mm x 1.3 mm to 0.82 x 0.82 x 2.2 mm. Trained medical personnel manually segmented the portal phase liver volumes on GE Advantage Windows Workstation to generate the liver mask (LM). These LMs were used as the ground truth for evaluating the automatic liver segmentation algorithm. Binary masks (BM) were generated by thresholding these ground truth volumes. **Noise Generation (NG):** SNR was calculated for the entire liver volume as: $SNR = S_{Liver\ Volume} / \sigma_{ROI}$ where $S_{Liver\ Volume}$ is the average signal over the liver volume (obtained using the BM) and σ_{ROI} is the standard deviation (SD) of the background noise prescribed by the ROIs. σ_{ROI} was calculated as: $\sigma_{ROI} = \sqrt{\left(\sum_{1}^{L} (pixelvalue)^2 / 2Ln\right)}$ where L is the number of pixels in the ROI and n is total number of pixels within ROI [2]. Original datasets were noise corrupted (NCV) to obtain SNR levels (also referred to as SNR bins) of 12,11, 10, 9, 8, and 6. The noise obtained from the multiple-coil array root sum-of-square (RSS) magnitude reconstruction has a modified probability distribution function [2]. To simulate this, zero-mean, Gaussian noise, with standard deviation adjusted to obtain the preset SNR level, was injected into the real and imaginary channels. RSS was then performed with the number of coils used to acquire the dataset, and the resulting noise matrix was added to the original data matrix to obtain the noise corrupted volume (NCV). SNR values were again measured as described above for each NCV and corrected for magnitude bias in RSS [2]. The NG unit was implemented with Matlab (v. 7.4).

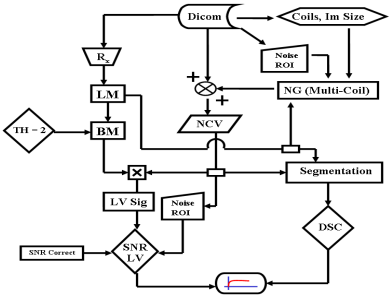

Figure 1. Flowchart for the SNR analysis of liver segmentation algorithm. Please see the text for explanation.

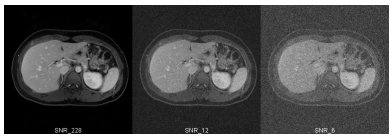

Figure 2. Typical liver images at different SNR (SNR = 228, 12 and 6 from L to R).

Liver Segmentation: The segmentation algorithm has been designed for extracting liver volumes from single phase (portal) of the contrast enhanced scan. The segmentation algorithm uses a statistically driven, data adaptive geodesic active contour for extracting the organ of choice (liver) from the given volume. The algorithm is evaluated by comparing the automatic segmented (AS) volume to the LM and computing the Kappa statistic $\kappa = 2*\left(|AS \cap LM| / |AS + LM|\right)$, which provides a measure of the overlap between two volumes as well as the sensitivity (how much of the organ can be delineated?) and specificity (how much can organ be delineated without including extra-organ region). A κ value of 0.8 was considered as lower threshold for acceptable segmentation. For each dataset, the algorithm was tuned to provide the highest κ for the original un-corrupted dataset. This value of κ was kept constant for all NCVs derived from that particular dataset. Except for one dataset, the tuning parameter values remained the same across the remaining four datasets. The seeding location obtained from the original un-corrupted volume was used to seed the NCVs derived from the particular dataset. κ, sensitivity and specificity were evaluated for each NCV and compared with the SNR values.

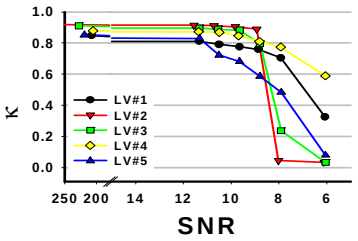

Figure 4. Plot of κ vs SNR for the five datasets.

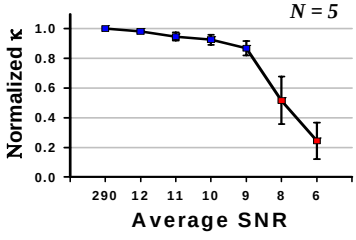

Figure 5. Plot of normalized κ vs SNR. Bars indicate standard errors

Results

Figure 2 shows a slice from the typical dataset used for SNR analysis. The mean SNR for five datasets was 294±177. As seen from Figure 3, the SNR values are tightly clustered for each SNR bin across 5 datasets, suggesting that segmentation results for each SNR bin across five datasets can be easily compared. The mean liver volume for the five datasets was 1987±232 cm^3, while for liver volumes obtained from automatic segmentation algorithm was 2053±490 cm^3, suggesting an overestimation of 14%. The mean κ for the original datasets was 0.88±0.03. As seen from figures 4 and 5, for SNR > 12, the normalized κ changed < 5%, suggesting that SNR of 12 is sufficient for the robust performance of the current algorithm. Thus, going by the MRI scaling relationship for SNR ($SNR \alpha \sqrt{Acq\ Time}$), this will result in ~ 600x gain in acquisition speed. With a lower threshold of normalized κ = 0.8, algorithm performance degrades for SNR< 9 as evident from Figure 5, where the blue boxes indicate acceptable SNR values, whereas the red ones indicate failure. Similar trends were noticed for sensitivity measure, whereas specificity was not much affected by SNR. **Discussion and Conclusion:** The current work suggests that the liver segmentation of MRI datasets with geodesic active contours is fairly robust for SNR upto 9. In present context, where the datasets were acquired with SNR of ~300, the results suggest that it may be possible to achieve considerable time savings by acquiring datasets with parallel imaging techniques for automated liver volume assessment and possibly acquire generic "segmentation scouts" designed to enhance the segmentation accuracy. While the noise from parallel acquisition techniques is spatially varying, depending on the coil g-factor [4] and might alter this curve, the work suggests that the minimum SNR of 9 would likely be the lower SNR cutoff for the current implementation of the algorithm. This SNR requirement is approximately 50% greater than the Rose criteria (SNR > 5) for human vision and applicable to MR images as well [3]. However, given the complexities of the human vision system, the current result seems fairly interesting for machine-based segmentation along with the shorter breath hold times for reduced motion artifacts in abdominal imaging.

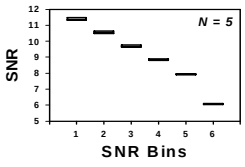

Figure 3. Box plot for SNR values at each SNR bin.

References: [1]. Radiology 2005; 237:322–328 [2]. MRM 38:852-857 (1997) [3]. MRM 48:550-554 (2002) [4]. MRM 54:1439-1447 (2005)