Simulation analysis of region-of-interest measurement errors on parameter maps derived from Dynamic Contrast-Enhanced MRI and T1 mapping of small volume breast cancer

Moira C Schieke[1]
[1]Lakeshore, Milwaukee, WI, United States

Introduction:
Detection of small tumors and post-treatment tumor changes in small volumes using Dynamic Contrast-Enhanced MRI (DCE-MRI) and T1 mapping requires an understanding of multiple complex sources of measurement error. Analysis of these independent errors is difficult in highly heterogeneous patient and animal model tumor tissue. Computer-generated models of MRI tumor images allow for simplifications to filter for sources of measurement error such as signal-to-noise ratio, contrast-to-noise ratio, region-of-interest size and shape, tumor size and shape, and partial volume effects. In this study, simulations using simplified and homogenous computer-generated models of MRI tumor images are used to explore the influence of these variables on small volume measures of small breast cancer tumors for T1 mapping measures and DCE-MRI measures of the forward leakage rate constant (K^{trans}).

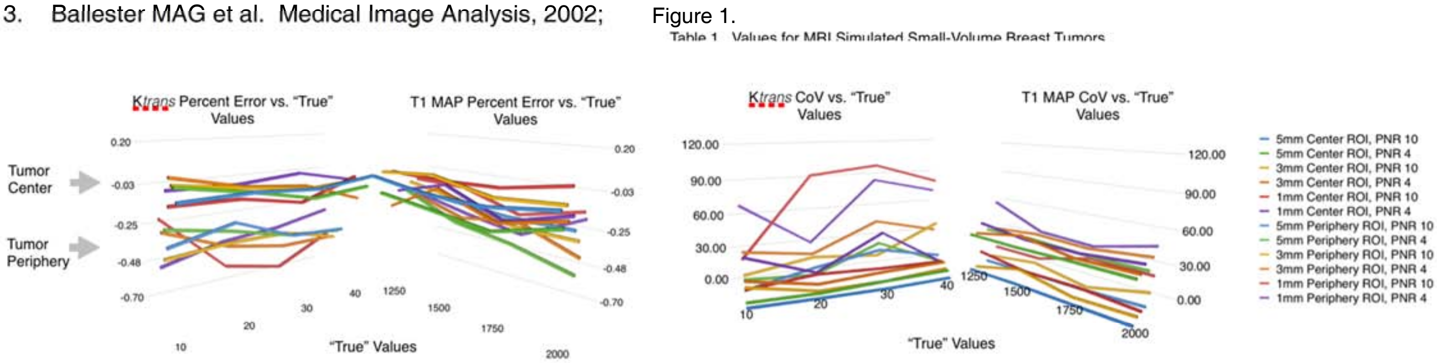
Materials and Methods:
A plug-in for open source MIPAV software (CIT, NIH, Bethesda, MD, USA) that creates computer-generated models of MRI tumor images was used for this study. Simulations were conducted by first creating models of small volume breast tumors with a range of values for “true” tumor tissue values, “true” normal tissue values, an index of SNR, and resolution (table 1). “True” values for MRI tumor and normal tissue values were based on published literature results in breast cancer at 1.5T.[,2] Partial volume effects were modeled by using a subsampling algorithm to model changes in MR signal due to partial voluming from two separate tissues on standard MR sequences described in published literature.[3] The plug-in initially generated isotropic high resolution (0.125mm) spherical tumors with diameter 10mm which produced a final resolution of 1mm and diameter of 10mm after subsampling. SNR effects were modeled using a gaussian noise profile and entering a “parameter noise ratio” (PNR) = parameter value/standard deviation. For each generated tumor model, three separate sets of small-volume region-of-interest (ROI) (diameter 5mm, 3mm, and 1mm) were used to measure values at the center of the tumor (n=5 per set) and at the periphery in a region containing approximately 50% tumor (n=5 per set). Percent error (as compared to the entered “true” value) was determined for the average measure for each set.

Results:
Results are shown in figure 1. Graphs show percent error as a function of “true” parameter values using 5mm ROI, 3mm ROI, and 1mm ROI for K^{trans} at the center and periphery of the tumor, T1 map values at the center and periphery of the tumor. Coefficient of variance (CoV) for repeat measures was graphed against “true” values for both the K^{trans} and T1 map values. Partial volume errors had a greater impact on percent error of tumor measures than SNR across the range of values in this study. K^{trans} percent errors were higher than T1 mapping errors for periphery ROI in areas of partial voluming secondary to differences in contrast-to-noise ratio (CNR). CoV was greatest for periphery ROI. Impact of SNR on CoV increased as ROI size decreased, with large CoV for 1mm ROI at the tumor periphery.

Discussion:
Computer-generated tumor models of homogenous small breast cancer tumors demonstrated the impact of CNR versus SNR on percent error and CoV of small-volume ROI measures. Although model simplification improves independent variable analysis, it also limits direct clinical applicability. Additional variables would be expected to influence MRI measurement errors and future simulations will address these limitations. Improved understanding of the impact of complex sources of error obtained through simulations will help optimize strategies for detecting small tumors and to detect small volume tumor changes.

References:
1. Broadbent D. et al. Proceedings of ISMRM, 2011.
2. Huang W. et al. Radiology, 2011; 261:394-403
3. Ballester MAG et al. Medical Image Analysis, 2002;

Figure 1.



6:389-405.