## Kinetic Parameter Estimation of Independent Components Derived from Simulated Dynamic Contrast Enhanced Breast MRI Data

## Y. Wang<sup>1</sup>, B. Zhang<sup>2</sup>, S. Roys<sup>2</sup>, N. Correa<sup>1</sup>, T. Adali<sup>1</sup>, and R. Gullapalli<sup>2</sup>

<sup>1</sup>Computer Science and Electrical Engineering, University of Maryland, Baltimore County, Catonsville, MD, United States, <sup>2</sup>Radiology, University of Maryland, Baltimore, Baltimore, MD, United States

Introduction: Dynamic contrast-enhanced (DCE) MRI is presently the best strategy for differentiating between benign and malignant breast lesions.<sup>1</sup> Contrast enhanced MR studies have reported high sensitivity (up to 100%) but a variable range in specificity ranging anywhere from 30-85%. Although a few products are currently available to aid in the diagnosis and interpretation of DCE MRI datasets, the specificity remains low. Recently we demonstrated the feasibility of using independent component analysis in extracting relevant spatial locations and their time courses of contrast enhancement.<sup>2</sup> However there appears to be significant variability in the results which may stem from variable signal to noise ratio between different datasets. This variability in signal to noise may come from variations in MR system calibration or from malfunctioning coil elements. Alternatively the DCE images may suffer from poor signal to noise because the contrast agent was not administered appropriately or the line extravasated during injection. Regardless, both these reasons lead to a poor quality images where the system related issues would increase the noise of the entire group of images in general and the second type of error would provide very little enhancement over the baseline signal for it be diagnostic. It is very important therefore to assess the reliability of the derived independent components and the kinetic parameters that might result



Fig 1. Breast image showing embedded lesions of various size & shape

from such an assessment. Here we report our results on the performance of ICA as a function of noise using actual breast images with various size lesions embedded within the breast. Each of these lesions mimic realistic dynamic contrast enhancement and range from benign to malignant lesions with different wash in and wash out patterns. In addition we also present our findings on the kinetic parameter analysis of the independent components derived from the datasets with varying signal to noise ratio.

Methods: Breast images were obtained from a healthy volunteer on a 3.0 Tesla Siemens Tim Trio system using a 3D-FLASH sequence. The acquisition parameters were FOV=380mm, matrix 304x448, slice thickness=1.25mm for a total of 160 slices covering the entire breast in the axial plane. Seven such sets of images were obtained from the same volunteer to mimic the DCE exam without the contrast injection. The overall signal to noise of these images was about 80:1. Three types of simulated lesions each depicting Type I, II, and III as defined by Kuhl et al.<sup>1</sup> were generated. The size of the lesions varied from 9 pixels to 178 pixels representing a volume of 12µL to 235µL and varied in shape from a tiny square to a star pattern shown in Fig 1. After embedding the lesions, increasing levels of random noise was added to the images providing new sets of images with signal to



0.4 0.2 Type I Curv n Ktrans 0.5 e II Curv n 0.8 0.6 0.4드 0 Type III Curv SNR<sup>10</sup> 5 15 20 Figure 4. K<sup>trans</sup> is stable over a SNR of 10

noise varying from 5-20. Each of the dynamic datasets was then subject to IC analysis using Infomax algorithm.<sup>3</sup> To determine the minimum SNR necessary to see all the lesions, the number of embedded lesions that were detected by the IC analysis was determined for each signal to noise level. This experiment was repeated four times, each time using freshly generated random noise. Similarly, the size of lesion that can be detected at different SNR levels was also determined. Once a threshold of minimum SNR was determined, we used that threshold to determine the robustness of the derived kinetic parameters (K<sup>trans</sup>) using the Tofts Model.<sup>4</sup> Once again this experiment was repeated four times with freshly generated



random noise.

**Results**: Independent component analysis was quite robust in detecting all the lesions at high signal to noise ratios. At an SNR of less than 20 the detection efficiency of ICA declined (Fig. 2). The size of the lesions also was a strong factor in ICA's ability to detect the lesions. Lesions greater than 200µL were seen even at an SNR as low as 5.(Fig. 3). All the three lesion types (I, II, and III) were detected at a SNR greater than 10 but the ability of detection depended on the size of the lesion. Figure 4 shows K<sup>trans</sup> derived from independent components obtained at various signal to noise. The value of Ktrans appears stable up to a SNR of about 10 below which there is considerable variability in its estimation.

**Conclusions**: Our simulations suggest that the optimal SNR required for robust determination of components is about 20. At this SNR the derived kinetic parameters appear to be robust. The size of the lesion plays a major

role in their detestability and may be the limiting factor in determining the quality of the derived kinetic parameters. The normal signal to noise of breast images is about 80:1 at 3 Tesla and it appears that ICA can be used reliably even on DCE images obtained from lower field strength magnets. Acknowledgement: Part of this work was supported by an Intramural grant from the Dept of Radiology, UMB. **Reference**:

- 1. Kuhl CK et al. Radiology 1999;211:101-110
- 2. Zhang et al. Proc Intl Soc Magn Reson Med 14, page 835, Seattle 2006.
- 3. Bell A.J. and Sejnowski T.J, Neural Computation, 1994:1129-1159
- 4. Tofts and Kermode, Magn Reson Med, 1991:357-367