

# Maximal contrasts using MR complex data: with an application to visualise cortical structure

Z. Chen<sup>1</sup>, L. A. Johnston<sup>2</sup>, and G. F. Egan<sup>3</sup>

<sup>1</sup>Florey Neuroscience Institutes, Carlton, VIC, Australia, <sup>2</sup>Electrical and Electronic Engineering, University of Melbourne, <sup>3</sup>Centre for Neuroscience, University of Melbourne

**Introduction:** Recent developments in MR phase imaging enable analyses of MR signals in the complex domain [1-3]. However, in clinical diagnoses and anatomical studies, it is necessary to objectively map complex MR signals to a one-dimensional signal for visualisation. The Susceptibility Weighted Imaging (SWI) method [4] uses the phase image to calculate a phase mask that is multiplied with the magnitude image to enhance the contrast caused by tissue susceptibility. SWI has demonstrated great advantage in contrast enhancement for various applications. In this work, we introduce a new method called Maximum Contrast Image (MCI) to further improve the image contrast from complex MR signals. Enhanced image contrasts obtained with the new method have been demonstrated using a 3T dataset of a cortical brain section. Furthermore, in contrast to the nonlinear operation in SWI, the MCI method uses a linear operation, which permits meaningful quantification of the MCI signals.

**Theory of Maximum Contrast Image (MCI):** Consider three MR tissue signals,  $\vec{x}, \vec{y}, \vec{z}$ , measured in the complex domain, for example, the cortical white matter, grey matter and CSF. In a T2\* weighted gradient echo acquisition, the magnitude of the complex signal represents the T2\* spin magnetization, and the phase captures the local field difference caused mainly by the susceptibility differences amongst tissues. The contrast between tissue  $\vec{x}$  and  $\vec{y}$  can be defined as:

$$C(\vec{x}, \vec{y} | \vec{r}) = \|\vec{x} - \vec{r}\| - \|\vec{y} - \vec{r}\| \quad (1.)$$

where  $\vec{r}$  is the reference spatial point used to observe the contrast. If we chose  $\vec{r}$  to be the origin, (0,0), of the complex domain, Eq. (1) will result in the magnitude contrast for tissues  $\vec{x}$  and  $\vec{y}$ . For a given pair of tissue signals of interest, the observed contrast depends on  $\vec{r}$ , and the optimal observing point  $\vec{r}_{opt}$  locates where the contrast defined in (1) is maximised ( $C^*$ ). Mathematically, we have the following:

$$C^*(\vec{x}, \vec{y}) = \arg \max_{\vec{r}} C(\vec{x}, \vec{y} | \vec{r}) = \arg \max_{\vec{r}} \|\vec{x} - \vec{r}\| - \|\vec{y} - \vec{r}\| \quad (2.)$$

The solution of Eq. (2) is  $C^*(\vec{x}, \vec{y}) = |\vec{x} - \vec{y}|$  and is achieved when  $\vec{r}$  locates in the line formed by  $\vec{x}$  and  $\vec{y}$ . Figure 1 provides an intuitive example of the process. Similarly, for a third tissue type ( $\vec{z}$ ) the maximal contrast between  $\vec{x}$  and  $\vec{z}$  is  $C^*(\vec{x}, \vec{z}) = |\vec{x} - \vec{z}|$  when  $\vec{r}$  locates in the line formed by  $\vec{x}$  and  $\vec{z}$ .

Based on these results, we now consider the contrasts between  $\vec{x}$  and two other tissue types, which is defined as:

$$\overline{C}(\vec{x} | \vec{r}) = C(\vec{x}, \vec{y} | \vec{r}) + C(\vec{x}, \vec{z} | \vec{r}) \quad (3.)$$

and the maximal contrast is given by

$$\overline{C}^*(\vec{x}) = \arg \max_{\vec{r}} (C(\vec{x}, \vec{y} | \vec{r}) + C(\vec{x}, \vec{z} | \vec{r})) \quad (4.)$$

Clearly,  $\overline{C}(\vec{x} | \vec{r})$  is maximal when  $C(\vec{x}, \vec{y} | \vec{r})$  and  $C(\vec{x}, \vec{z} | \vec{r})$  are maximised simultaneously. Following the results above, the solution of Eq. (4) is obtained when  $\vec{r}$  locates at the intersect of line  $\{\vec{x}, \vec{y}\}$  and line  $\{\vec{x}, \vec{z}\}$ . This leads to  $\vec{r} = \vec{x}$ , and the results can be readily generalised to more than 3 tissue signals of interest. In this work, the noise power in real and imaginary channels are assumed to be identical, denoted as  $\sigma$ . Under this condition, it can be shown that the observed noise power is independent of  $\vec{r}$ .

**Materials and Methods:** A 3T MRI dataset of a cortical brain section was acquired using a Tim Trio Siemens system (Siemens Medical Solutions, Erlangen, Germany) equipped with a Siemens 12 channel Head Coil Matrix coil. A young healthy volunteer participated in the scan. An oblique axial 2D Gradient Echo sequence was used in the scan with the following parameters: TE = 45 ms, TR = 1100 ms, flip angle = 30°, Field of View = 188 × 240 mm<sup>2</sup>, Matrix size = 352 × 448, in-plane resolution = 0.5 × 0.5 mm<sup>2</sup>, slice thickness = 2 mm. MR channel data were stored and combined using a complex image optimised SENSitivity Encoding (SENSE) reconstruction method [3]. Magnitude images were taken from the magnitude of the reconstructed complex images. The phase term of the reconstructed complex images was unwrapped and filtered to remove the background phase signal due to the imperfect shimming of the main field. Susceptibility Weighted Images (SWI) were produced according to [4]. Specifically, we calculated both positive and negative phase masks and multiplied each of them with the magnitude image four times to obtain the two types of SWI, denoted SWI+ and SWI-, respectively. Maximum Contrast images (MCI) were calculated as follows. The joint magnitude and phase histogram of a selected cortical region was first obtained. The complex means of the grey matter (GM) and the whites matter (WM) were obtained from the centroids of the identified clusters. The MCI-GM was obtained from the magnitude of the complex images subtracted by the complex mean of GM. The MCI-WM was obtained from the magnitude of the complex images subtracted by the complex mean of WM. The contrast to noise ratio (CNR) between two tissue types were computed from their mean value difference divided by the joint standard derivation. The sum of squares variance (also known as Contrast [5]) was calculated based on the co-occurrence method [5]:  $s = \sum_{i,j} (i-j)^2 p_{i,j}$  where  $p_{i,j}$  is the histogram count for image intensities  $i$  and  $j$ .

**Results and discussion:** The resultant images from different methods are shown in Fig. 2 where the displayed dynamic range of each image is optimised according to the full width of the intensity histogram. The statistical comparisons of CNR and sum of squares variance are shown in Table 1. Visually, the MC images in Figs. 2 E and F show improved overall contrast compared with other images, especially in Fig. 2 E where GM is used as the reference tissue. The use of GM as reference in MCI provides a good separation of WM, GM and CSF. Table 1 shows that MC images provide improved overall CNR and the sum of squares variance. Furthermore, the MCI method uses only linear transformation of the complex data, and hence the physical parameters of the MR signals are preserved, which enables the meaningful quantification directly from the MC images.

**Reference:** [1] Duyn, J.H., et al., PNAS, 2007, 104(28):11796-801.

[2] He, X., et al., PNAS, 2009, 106(32):13558-63. [3] Chen, Z., et al. NeuroImage, 2009, early view.

[4] Haacke, E.M., et al., MRM, 2004, 52(3):612-8. [5] Haralick, R.M., et al., IEEE J SMC, 1973, 3:610-21.

Table 1: statistical measurements

	CNR (GM to WM)	CNR (CSF to GM)	Sum of squares variance
Magnitude	11.91	10.77	722
Phase	5.19	6.04	953
SWI-	12.23	7.93	734
SWI+	5.46	10.71	780
MCI-GM	12.05	10.87	971
MCI-WM	12.04	10.65	907

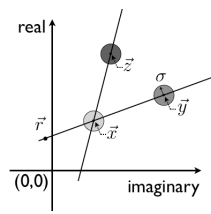


Fig 1: MCI scheme

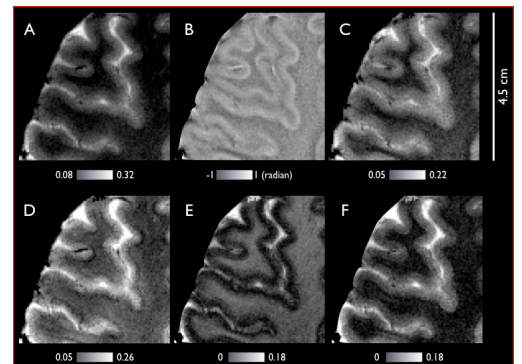


Fig 2: A,magnitude; B,phase; C,SWI-; D,SWI+; E,MCI-GM; F,MCI-WM