

# ACCELERATING ENCODED SIMULTANEOUS MULTI SLICE MRI WITH COMPRESSED SENSING

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**Introduction:** Simultaneous Multislice Acquisition (SIMA) by Hadamard-encoded excitation [1] has been proposed as an alternative to 3D volume imaging (3DFT) when acquiring fewer than 64 slices to avoid ringing and leakage artifacts. Since all slices are excited simultaneously, SIMA enjoys SNR benefits over slice-by-slice imaging similar to 3DFT. It also has the added advantage of arbitrary slice placement while 3DFT requires the slices to be equispaced. In SIMA, linear combinations of the Fourier coefficients of each slice are measured during data acquisition. Thus, the measurement space is not purely the Fourier space but a hybrid space. In this work, we investigate the use of compressive sampling strategies within the SIMA framework. In addition to Hadamard and complex Hadamard encoding, we introduce the use of Noiselet encoding in SIMA.

**Theory:** Complex exponential modulation of an RF pulse shifts the location of the slice according to the offset specified in the modulation term. By summing together a set of pulses with appropriately chosen frequency offsets, several slices can be excited simultaneously. A 2X2 Hadamard matrix that can be used to encode 2 slices is shown in Fig 1(a). This approach has been used to excite up to 16 slices simultaneously [1]. Complex Hadamard encoding was used in [2] by adding additional phase terms ( $\pi/2$  or  $3\pi/2$ ) to the complex exponential modulation factor (Fig. 1(b)). It is well-known that the usual Fourier measurement and wavelet sparsity bases are not maximally incoherent. Noiselets are a family of functions that are maximally incoherent with the Haar wavelet transform [3]. Thus, they are of interest as a sampling basis in CS. A 2X2 Noiselet transform is shown in Fig. 1(c). The standard Fourier encoding can be represented as  $\mathbf{y} = \mathbf{F} \mathbf{x}$  where  $\mathbf{F}$  is a 2D Fourier operator that maps the image  $\mathbf{x}$  to a set of measurements  $\mathbf{y}$ . Using similar formalism, the Hybrid-Fourier encoding in SIMA can be expressed as  $\mathbf{y} = \mathbf{H} \mathbf{F} \mathbf{x}$ . Here,  $\mathbf{x}$  represents a stack of slices and  $\mathbf{y}$  represents the corresponding measurements. The operator  $\mathbf{F}$  is a 2D Fourier operator acting individually on each slice. The operator  $\mathbf{H}$  generates element by element linear combinations of the resulting Fourier coefficients from each slice.

$$H = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} H_2^c = \begin{bmatrix} 1 & i \\ 1 & -i \end{bmatrix} H_2^n = \begin{bmatrix} 1-i & 1+i \\ 1+i & 1-i \end{bmatrix}$$

Fig. 1: Encoding matrices for a 2 slice simultaneous acquisition scheme: a) Hadamard, b) Complex Hadamard, c) Noiselet

SNR	Hadamard	Complex Hadamard	Noiselet	Sequential
ZF	19.86	19.86	19.89	17.35
CS	23.57	23.61	23.93	18.75
$\Delta$ SNR	3.72	3.73	4.14	1.39

Table 1: Comparing SNR values in images from undersampled SIMA and sequential acquisition data. (ZF: Zero-filled, CS: Compressive Sensing)

100ms, RF duration = 6ms) was used to acquire data with the three SIMA methods. The same sequence was also used to acquire single slice data sets with the truncated sinc pulse using the same parameters for comparison (sequential method). Both the SIMA and the single slice data sets were retrospectively undersampled along the phase-encode direction to simulate accelerated acquisition. The undersampling masks were generated randomly but with a variable density distribution as suggested in [4]. In SIMA methods, undersampling was performed in the hybrid space. The number of encodings steps acquired for each linear combination (i.e. [1 1] vs. [1 -1] in Fig. 1(a)) was kept constant but the undersampling masks differed across different encodings. Parameters  $\lambda_1$  and  $\lambda_2$  were optimized individually for each case and the problem solved using the method in [4].

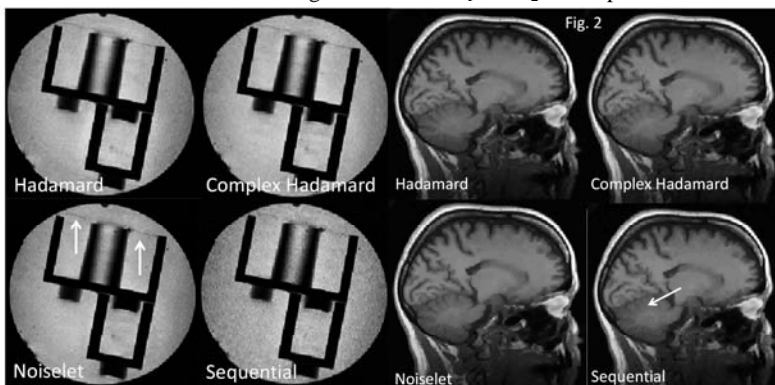


Fig. 2: Reconstructed images from undersampled SIMA and sequential acquisition data using CS: (Right: simulated in vivo data. Left, water + lego phantom)

resolution features as pointed to by the arrows in the figures.

**Conclusion:** Compressive sampling strategies within the SIMA framework were investigated. The inherent SNR and incoherent non-Fourier encoding that can be achieved with the SIMA framework results in higher image quality in CS. The proposed methods are particularly interesting for dynamic imaging applications where the need for high temporal resolution limits the number of slices that can be acquired.

**References:** [1] Souza, S. P., et al., J CAT, 12(6), 1988. [2] Cunningham, C. H., et al., Proc. ISMRM, 2002. [3] Coifman, R., et al., ACHA, 10, 27-44, 2001. [4] Lustig, M., et al., MRM 58(6), 2007.