## 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 y = F x where F is a 2D Fourier operator that maps the image x to a set of measurements y. Using similar formalism, the Hybrid-Fourier encoding in SIMA can be expressed as y = HFx. Here, x represents a stack of slices and y represents

the corresponding measurements. The operator 
$$F$$
 is a 2D Fourier operator acting individually on each slice. The operator  $H$  generates element by  

$$H = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix} H_2^c = \begin{bmatrix} 1 & i \\ 1 & -i \end{bmatrix} H_2^n = \begin{bmatrix} 1-i & 1+i \\ 1+i & 1-i \end{bmatrix}$$
element linear combinations of the resulting Fourier coefficients from each slice. Representing the sparsity basis as  $\psi$ , the unconstrained convex optimization problem for SIMA CS can be written as

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

SNR	Hadamard	Complex	Noiselet	Sequential
		Hadamard		
ZF	19.86	19.86	19.89	17.35
CS	23.57	23.61	23.93	18.75
ΔSNR	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)

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arg min  $\| \mathbf{HFx} - \mathbf{y} \|_{2}^{2} + \lambda_{I} \| \mathbf{\psi} \mathbf{x} \|_{1} + \lambda_{2} \| \mathbf{x} \|_{TV}$ 

Methods: Image slices (previously obtained using a 3D SPGR sequence) were combined to simulate SIMA acquisitions. Complex white Gaussian noise was added in k-space and the k-space data was undersampled at different rates to simulate accelerated acquisition. The SIMA methods were then implemented on a Bruker Biospec 7T scanner. A truncated sinc pulse with 1.35 kHz bandwidth was modulated to create the desired pulses used for each SIMA encoding methods. Pulses for 2, 4, and 8 slice excitations using Hadamard, complex

Hadamard, and Noiselet encoding were created. A Cartesian FLASH sequence (FOV of 4cm, 256 x 256 data size, 1mm slices, TE = 7.427ms, TR =

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.

Results: For the phantom study, when fully sampled SIMA images were compared to their single slice counterparts, the expected  $\sqrt{N}$  increase in SNR (where N denotes the number of slices) was observed. Table 1 shows the SNR of the reconstructed phantom images for 4-slice encoding and 50% undersampling. In the table, ZF denotes the zero-filled reconstructions and CS denotes the reconstructions using the nonlinear conjugate gradient method. Table I shows that the SNR of the SIMA methods are higher compared to sequential acquisition. More importantly, the SIMA methods provide a greater increase in SNR due to CS reconstruction compared to the sequential acquisition. This difference is attributed to increased acquisition SNR and improved incoherence properties. For visual comparison, sample images (both from simulations and acquired data) are shown in Fig. 2.It can be observed that the SIMA CS also allows recovery of high

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.