# Radial CAIPI-CS for simultaneous multi-slice cardiac perfusion imaging

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**Introduction:** Myocardial perfusion imaging offers unique and invaluable information about the health of the myocardium. Complete coverage without sacrificing the temporal dynamics of rapid first pass perfusion or in-plane spatial resolution is desired. Most of the methods that have been developed to achieve the desired goal undersample the k-space data for each time frame and use advanced reconstruction methods like Compressed Sensing (CS) [1-4] to remove the undersampling artifacts. Recently a simultaneous multi-slice imaging technique termed CAIPIRINHA [5] (or CAIPI) was proposed to achieve increased coverage without losing time and image quality. Multiple slices are simultaneously excited with a phase modulation to minimize the amount of spatial overlap and to effectively exploit coil sensitivity differences to separate the acquired k-space data into multiple slices. The concept was applied to myocardial perfusion imaging with Cartesian k-space sampling [6,7]. CAIPI for radial acquisition has been shown to outperform Cartesian CAIPI in phantom and in-vivo brain images [8]. Here we combine the advantages of radial CAIPI with compressed sensing and show promising results for myocardial perfusion imaging.

**Methods:** Reconstruction from radial CAIPI data was performed by iteratively minimizing the cost function $C$ in (1).

$$C = \sum_{i=1}^{nc} \left\| \left( \sum_{j=1}^{ns} \emptyset_j \left( E S_{ij} \tilde{m}_j \right) \right) - d_i \right\|_2^2 + \alpha_t \sum_{j=1}^{ns} TV_t\left(\tilde{m}_j\right) + \alpha_s \sum_{j=1}^{ns} TV_s\left(\tilde{m}_j\right) \quad -(1)$$

In (1) the first term on the right hand side ensures data fidelity, where $d_i$ is the acquired radial CAIPI data for coil $i$, $nc$ is the total number of receiver coils, $\tilde{m}_j$ is image data corresponding to slice index $j$, $ns$ is the total of simultaneously acquired slices, $S_{ij}$ is the coil-sensitivity for coil $i$ and slice $j$, $E$ is the inverse gridding operator to map image data to radial k-space data and $\emptyset_j$ phase modulates k-space data for slice j. $TV_t$ is the temporal total variation constraint [2] and $TV_s$ is the 2D spatial total variation constraint [2]. $\alpha_t$ and $\alpha_s$ are weighting factors for temporal and spatial $TV$ constraints respectively. ECG-gated radial myocardial perfusion data using a saturation recovery turbo-FLASH sequence without CAIPI was acquired on a Siemens 3T Verio scanner with a 32-channel cardiac coil. The acquisition parameters were TR=2.2 msec, TE=1.2 msec, FOV=260 mm$^2$, matrix size=144 x 40. Time delay after saturation pulse for each slice was 100 msec and golden ratio based angle spacing [9] was used. CAIPI data with a CAIPI factor of two was simulated by adding the acquired radial data for two slices after phase modulation so that adjacent rays corresponding to second slice have their phase alternating between 0 and $\pi$. NUFFT [10] was used for gridding and inverse gridding radial data and the coil sensitivities were estimated using non-CAIPI images by combining last 15 time frames in the dynamic sequence. Reconstructions from (1) were compared with non-CAIPI multi-coil CS reconstructions for each slice done independently with temporal and spatial total variation constraints as described in [2] but using coil sensitivities in the data fidelity term.

**Results:** Figure 1 compares the image quality for the proposed CAIPI-CS reconstruction with direct CS reconstructions. The difference images show few structures in the heart region implying minimal loss in spatial resolution. Peak signal intensity in the difference images is 20% of the peak signal in CAIPI-CS images. Also the mean intensity time curves after pre-contrast signal subtraction in the LV blood pool and myocardial regions match closely. CAIPI-CS reconstructions converged within 50 iterations. On a standard CPU without parallel processing and each iteration took about 2.7 minutes with NUFFT operations consuming bulk of the time to perform gridding and inverse gridding operations for 32-channel data for two slices with 30 time frames each and <7 secs for the computation of constraints.

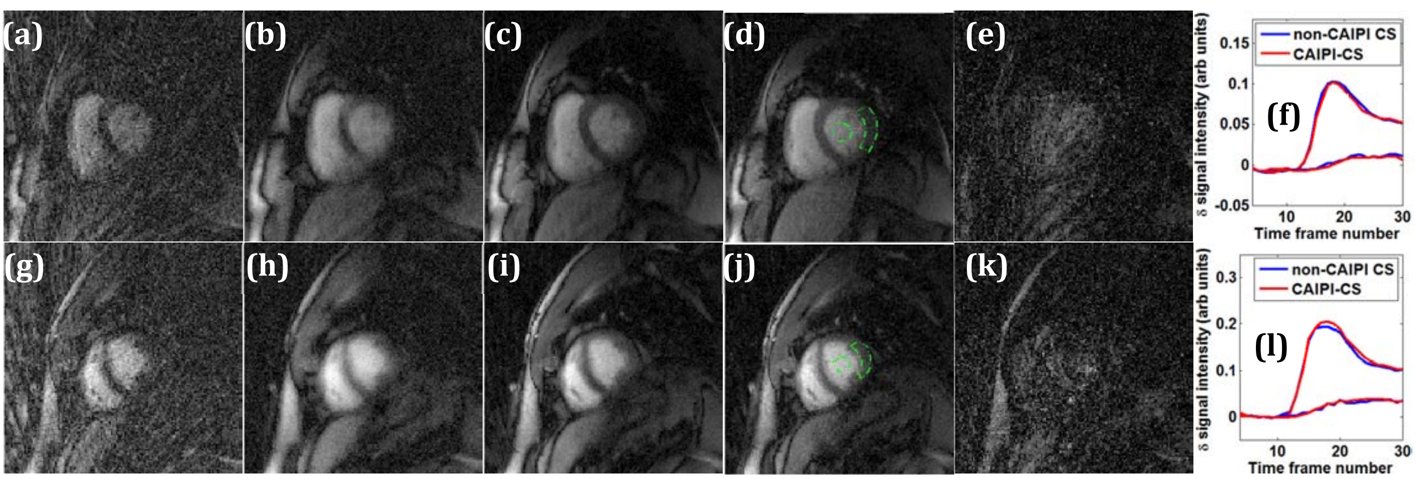


***Figure 1:*** ***(a, g)*** *Two simultaneously excited slices after phase-demodulation and reconstruction using NUFFT [10].* ***(b, h)*** *Corresponding images reconstructed with CAIPI only and without CS [8] by minimizing C in (1) but without TV constraints.* ***(c, i)*** *Corresponding images reconstructed with CAIPI-CS.* ***(d, j)*** *Corresponding non-CAIPI acquisitions reconstructed using multi-coil CS.* ***(e, k)*** *Absolute difference images between (c-d) and (i-j).* ***(f, l)*** *Comparison of mean intensity time curves for the regions of interest in the LV and myocardium shown in (d, j) after pre-contrast signal subtraction.*

**Discussion & Conclusions:** Radial CAIPI with compressed sensing is a promising approach to increase coverage in myocardial perfusion imaging without sacrificing temporal and spatial resolutions. Unlike [7], in which CS was applied first on undersampled CAIPI data followed by a GRAPPA reconstruction to separate the slices, here we do a full iterative joint CS reconstruction by applying TV constraints on both slices independently while preserving fidelity to the acquired CAIPI data. Coil compression [11, 12] and parallel computing using GPUs for NUFFT can help reduce the reconstruction times [13] of the proposed method.

**References:** [1] Otazo et al MRM 64:767-76, 2010. [2] Adluru et al JMRI 29:466-72, 2009. [3] Lingala et al PMB 58:7309-27, 2013. [4] Pendersen et al MRM 62:706-16, 2009. [5] Breuer et al MRM 53:684-91, 2005. [6] Stab et al, MRM 65:157-164, 2011. [7] Stab et al, epub JMRI 2013. [8] Yutzy et al MRM 65:1630-37, 2011. [9] Winkelmann et al. IEEE TMI 26:68-76, 2007. [10] Fessler et al IEEE TMI 51:560-574, 2003. [11] Adluru et al JCMR 14:P242, 2012. [12] Zhang et al MRM 69:571-82, 2013. [13] Stone et al J Parallel Distrib Comput 68:1307-1318, 2008.