**Introduction:** Parallel imaging and constrained image reconstruction are two popular approaches that enable sub-Nyquist MRI experiments. This work explores the combination of parallel imaging with low-rank matrix modeling of local k-space neighborhoods (LORAKS) [1,2]. LORAKS, a recent constrained image reconstruction framework originally designed for single-coil data, makes use of linear dependencies in k-space that are present for images that are support-limited and/or have smooth phase. It was shown that LORAKS imposes support and phase constraints in a fundamentally different way from previous constrained reconstruction methods, can yield substantial improvements in reconstruction quality, and is flexible enough to be used with calibrationless k-space trajectories [1,2].

**Theory and Methods:** The LORAKS framework is based on the fact that low-rank matrices with Hankel-like structure can be constructed from the fully-sampled k-space data of images with limited spatial support and/or slowly varying phase. Specifically, C is a LORAKS matrix formed from k-space samples such that, if B is a small N x N 2D k-space kernel and b is its vectorized representation, then bB implements the 2D convolution of B with the k-space data. It has been shown that C has low-rank when the image has limited support [2]. G and S are similar k-space convolution LORAKS matrices that collect information from opposite sides of k-space (based on known k-space symmetry relationships), and are low-rank when the image has smooth phase [1,2]. This matrix representation is powerful because compressed sensing approaches exist for reconstructing low-rank matrices [3], and LORAKS-based reconstruction can yield better results than traditional sparsity-based compressed sensing [2].

In parallel imaging, we observe k-space data dᵢ simultaneously from i different receiver coils. The proposed P-LORAKS method extends LORAKS by building large matrices according to Cₓᵢ = [C₁, C₂, ..., Cᵢ]. Gₓᵢ = [G₁, G₂, ..., Gᵢ], and Sₓᵢ = [S₁, S₂, ..., Sᵢ], where Cᵢ, Gᵢ, and Sᵢ are the LORAKS matrices for ℓth coil. It is observed that Gₓᵢ, Sₓᵢ, and Sₓᵢ will not only have nullspace vectors corresponding to the LORAKS constraints, but will also have nullspace vectors corresponding to any linear dependence relationships between the different coils. Note that widely-used methods like GRAPPA and SPIRiT depend on the existence of such relationships between the data from multiple coils [4,5]. Also note that P-LORAKS using the Cₓᵢ matrix is nearly identical to the SAKE method [6], though was derived in a different way. P-LORAKS based on Gₓᵢ and/or Sₓᵢ is distinct from previous methods. P-LORAKS reconstructions from undersampled data are obtained by minimizing ∑ᵢ [‖Fkᵢ - dᵢ‖² + λₖ(Cₓᵢ) + λₙ(d(Gₓᵢ) + λₚ(Sₓᵢ))] with respect to the unknown complete k-space vectors kᵢ, ℓ = 1, 2, ..., L. In this expression, F is a Fourier-domain subsampling matrix, λₖ, λₚ, and λₚ are regularization parameters, and J(·) is a nonconvex penalty function that encourages the matrices to have low-rank structure based on prior knowledge of the approximate matrix rank [2]. Optimization is performed using an efficient majorize-minimize algorithm that alternates between computing truncated SVDs and solving simple least-squares problems [2].

**Results:** Figure 1 compares the normalized singular values of the LORAKS matrices to the normalized singular values of the P-LORAKS matrices for fully-sampled k-space data. The fact that the P-LORAKS singular values decay much more rapidly than the LORAKS singular values indicates that the P-LORAKS representation more effectively compresses this data, and should be more effective than the LORAKS representation for multi-coil MRI applications. A comparison between SPIRiT and P-LORAKS is shown for 8-channel data in Fig. 2. We observe that P-LORAKS can achieve accurate reconstructions from limited data, with advantages over SPIRiT. We also observe that P-LORAKS using phase information (Sₓᵢ) is more effective than SAKE/P-LORAKS using support information (Cₓᵢ), which is consistent with previous LORAKS results [2].

**Conclusions:** P-LORAKS is a new kind of constrained parallel image reconstruction approach that merges LORAKS constraints with parallel imaging, and has certain advantages over existing methods. P-LORAKS can be used with calibrationless k-space trajectories (not shown due to space constraints), and is easily used in combination with other regularized reconstruction methods. We expect the approach to be useful in a range of different accelerated MRI experiments.