# Adaptive-BLIP for Magnetic Resonance Fingerprinting

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***Abstract*—We present an improved version of the BLoch response recovery via Iterative Projection (BLIP) algorithm for Magnetic Resonance Fingerprinting (MRF), that drastically reduces the computation time using an adaptive dictionary. At each iteration, the BLIP dictionary is updated through a clustering technique in the quantitative parameter space based on the fingerprint distribution across all voxels. Similar to a random tree, new parameter sets are selected around these clusters, making it possible to obtain a higher resolution than the original dictionary. Without loss of accuracy in reconstruction, simulations with a numerical phantom demonstrated that the computation time and the required memory to store the dictionary is significantly reduced in comparison to a dictionary with finer but fixed resolution.**

## I. Introduction

Inspired by the recent growth of Compressed Sensing (CS) techniques in MRI, the Magnetic Resonance Fingerprinting (MRF) was introduced to accelerate the quantitative imaging [1]. However, the exact link to CS was not made explicit. More recently, a full CS strategy was formulated in [2] including a random pulse excitation sequence following the MRF technique, a random Echo-Planar Imaging subsampling strategy, and an iterative projection algorithm that imposes consistency with the Block equations, namely BLoch response recovery via Iterative Projection (BLIP). The algorithm is given by

$$X^{(n+1)} = \mathcal{P}_{(R_{+}\mathcal{B})^N}\left[X^{(n)} + \mu h^H\left(Y - h\left(X^{(n)}\right)\right)\right], \quad (1)$$

where $X \in \mathbb{C}^{N\times L}$ represents the magnetization response of the image with $N$ voxels, $Y \in \mathbb{C}^{M\times L}$ corresponds to the measurements, $L$ is the excitation sequence length, $h$ is an operator that describes the undersampling in k-space, $n$ stands for the recursion index, and $\mu$ is a stepsize, which is selected adaptively. $\mathcal{P}_{(R_{+}\mathcal{B})^N}$ is the voxelwise projection on to signal model $(R_{+}\mathcal{B})^N$ approximated by the dictionary $D$. The projection for the voxel $i$ can be computed as $\hat{k}_i = \arg\max_k \mathrm{real}\langle D_k, X_{i,:}/\rangle||D_k||_2$, where $X_{i,:}$ is the magnetization sequence of the voxel $i$, $D = [D_1, ..., D_d] \in \mathbb{C}^{L\times d}$, $d$ is the size of the dictionary. It has been shown that BLIP outperforms the MRF technique proposed in [1] especially with a shorter magnetization sequence. Nevertheless, the computation time increases linearly with the size of the dictionary which needs to be big for high quality reconstructions, becoming a trade off between speed and accuracy.

## II. Adaptive-BLIP

In order to address this problem, we propose to project onto an adaptive dictionary that is updated in each iteration, namely Adaptive-BLIP. The number of tissues to be imaged in MRI is usually small compared to the number of voxels in the image, we use this as prior to update the dictionary. To begin with, a coarse dictionary is first defined using a fixed grid. After the projection, quantitative parameters $\theta_c$ are clustered by K-means based on the fingerprint distribution across all voxels. The number of clusters $n_c$ can be defined proportional to the number of expected tissues in the volume to be imaged. For each computed cluster, $n_r$ new parameter sets are chosen randomly using a Gaussian distribution with standard deviation $\sigma_{T_1}$, $\sigma_{T_2}$ and $\sigma_{\text{off}}$ defined according to the $T_1$, $T_2$ and off-resonance intervals. All of the these parameter sets help to generate the new adaptive dictionary using the Bloch equation. The Bloch equation manifold is thus explored in a similar way to a random tree, allowing the algorithm to have a better resolution than the original dictionary, and resulting in a much smaller dictionary that is updated in each iteration.

## III. Simulations

We provide a comparison between the proposed method and BLIP on the same numerical phantom used in [2]. BLIP is tested with two different size dictionaries and the parameters for Adaptive-BLIP is set as $n_c = 10$ and $n_r = 10$, resulting in $d = 110$, the maximum number of iterations is set to 20. Two experiments are given in Figure 1 and 2. They evaluate the performance of the algorithms in terms of the sequence length and input SNR respectively.

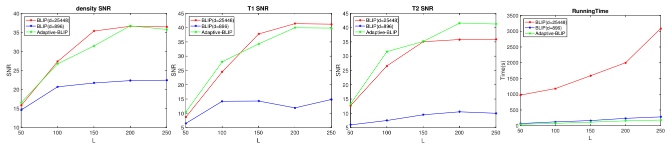



Fig. 1: Reconstruction performance as a function of L

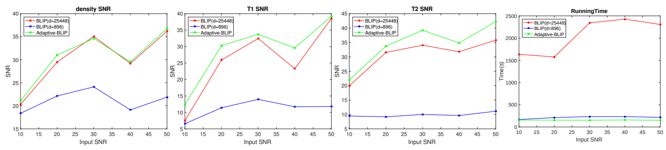
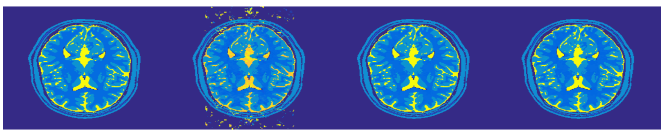



Fig. 2: Reconstruction performance as a function of the input SNR

In order to get a visual indication of the performance of algorithms, we provide also images of $T_1$ map for $L = 200$ with input SNR of $40dB$ in Figure 3. We may remark from the figures that the Adaptive-BLIP can achieve high quality reconstruction with significantly less processing time. Our future work will include more simulations and real data reconstructions.



(a) Original (b) $d = 896$ (c) $d = 25448$ (d) A-BLIP

Fig. 3: A visual comparison of the $T_1$ map estimates

## References

[1] D. Ma, V. Gulani, N. Seibelich, K. Liu, J. L. Duerk, and M. A. Griswold, "Magnetic resonance fingerprinting," *Nature*, vol. 465, pp. 187–192, 2013. [Online]. Available: http://dx.doi.org/10.1038/nature11971

[2] M. Davies, G. Puy, P. Vandergheynst, and Y. Wiaux, "A compressed sensing framework for magnetic resonance fingerprinting," *Siam journal on imaging sciences*, vol. 7, no. 4, p. 2623, 10 2014.