Deep learning field map estimation with model-based image reconstruction
for off resonance correction of brain images using a spiral acquisition

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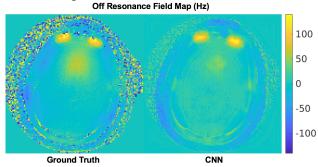[2]Biomedical Engineering, University of Michigan, Ann Arbor, M, United States

Introduction: Off-resonance artifacts in magnetic resonance imaging (MRI) lead to geometric distortions and blurring for non-Cartesian acquisitions. Model-based image reconstruction (MBIR) using accurate field maps can correct for these effects[1], but these field maps conventionally require a two-echo acquisition. For dynamic imaging such as fMRI, having a field map for every timepoint could improve image quality, especially in moving subjects (or drifting B_0 fields) where a single initial field map may not be sufficient for correcting all timepoints in the image series. However, conventional two-echo field maps are infeasible as they would double the total scan time. Prior work has shown deblurring on a single echo image using an entropy metric[2], a piecewise linear estimate[3], or more recently with convolutional neural networks (CNNs)[4]. Here we use a CNN to directly estimate a field map from a single echo time image, and then generate a corrected image using model-based reconstruction.
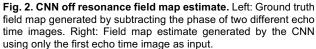
Methods: <u>MRI Acquisition:</u> We acquired 70 slices of 2D 4-shot spiral-out images on a 3T scanner, with volume FOV=240×240× $140mm^3$, resolution=1.9×1.9×2.0mm^3, FA=10°, TR=22ms, $T_{readout}$=15.1ms, with two echo times of TE_1=2.6ms and TE_2=5.1ms, resulting in ΔTE=2.5ms. We acquired data from two subjects, with 50 and 15 volume timepoints for subj. 1 and subj. 2, respectively.

<u>Deep learning field map estimation:</u> From the reconstructed MR images, we calculated target field maps using the relative phases. We then trained a residual CNN to estimate the field map from only the first TE_1 image. The CNN structure is based on the Off-Res Net method[4], having 8 convolution layers with three residual connections (Fig. 1). We used 5×5 convolutional filters and trained using a mean absolute error loss function and the Adam optimizer. We trained the network using 43 slices from the first subject and 40 volume TRs, leading to 1462 image and field map pairs for training and 258 for validation. We applied a random constant phase to each image to avoid the network learning the structure of our training subject. The FOV was also rotated throughout the scan using the MRI system gradients and the subject was asked to move slowly to augment the data (with a slice acquisition time of 84 ms, we did not notice any within-slice artifacts due to this slow motion).

<u>Model-based image reconstruction:</u> We then reconstruct the TE_1 image with the CNN field map to correct for off-resonance[5]. This approach greatly limits potential network hallucinations affecting the image by using a physics-based reconstruction as the final step.
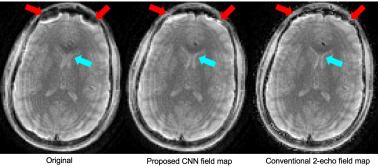

Fig. 1. Field map estimation network. The first echo time image is input to the network as two channels (real & imaginary components) to include phase information, and the network target is the corresponding field map calculated using the first and second echo time images.

Fig. 2. CNN off resonance field map estimate. Left: Ground truth field map generated by subtracting the phase of two different echo time images. Right: Field map estimate generated by the CNN using only the first echo time image as input.

Results: Fig. 2 shows off-resonance field maps generated by a conventional two-echo method and the proposed CNN estimation method, tested on data from subject 2 (not included in training). The network estimates the off resonance in this slice superior to the sagittal sinuses, but underestimates the off resonance in certain areas. The mean absolute error in the brain was 13.6 Hz. Fig. 3 shows off resonance corrected images using the reference field maps from Fig. 2. The proposed CNN method shows similar improvements in distortion correction of the frontal cortex (red arrows) and deblurring of the ventricles (blue arrows) compared to the conventional method.

Fig. 3. Off resonance corrected images. Left: Original image with artifacts in the frontal cortex due to field inhomogeneities. Middle: Image corrected using the CNN field map. Right: Image corrected using a conventional 2-echo field map.

Discussion & Conclusions: We have demonstrated the potential to rapidly estimate a field map from a single echo time image using a CNN. Using the CNN field map estimate with MBIR can correct for off-resonance while avoiding ML artifacts in the final image. We expect this method to have applications in dynamic field map estimation of fMRI images[6], especially in moving subjects where the field map can change as a subject breathes and moves through the FOV. Future work will include training the network on more subjects and with longer echo time data (suitable for fMRI BOLD contrast), as well as incorporating the CNN in an unrolled optimization.

References: [1] K. Sekihara, *et al. Phys. Med. Biol.*, 29(1):15-24, 1984. [2] D. C. Noll, et al. *MRM*, 25(2):319-333, 1992. [3] T. B. Smith *et al.*, *MMR*, 69(1): 82-90, 2013. [4] D. Y. Zeng *et al.*, *MRM*, 82(4):1398-1411, 2019. [5] J. A. Fessler, "Michigan Image Reconstruction Toolbox." [Online]. https://web.eecs.umich.edu/~fessler/code. [6] B. P. Sutton, *et al.*, *MRM* 51(6):1194-1204, 2004.