# Iterative Learning for Joint Image Denoising and Motion Artifact Correction of 3D Brain MRI – *Supplementary Materials*

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In what follows, we provide more details regarding the iterative learning algorithm, competing methods, and discussions on the computation costs.

## I. Iterative Learning Algorithm

The detailed implementation of the proposed iterative learning algorithm is shown in Algorithm 1, with the flowchart illustrated in Fig. 1 (a) of the main text.

**Algorithm 1** Proposed Iterative Learning Algorithm of JDAC

**Require:** Denoising model $\mathbf{f}_D$, Anti-artifact model $\mathbf{f}_A$, Noise estimation $\mathbf{f}_N$, Input $\mathbf{y}$, Learning rate $\delta$, Max iterations $K$, Early-stop threshold $\Delta$
**Ensure:** Denoised and motion corrected MRI: $\hat{\mathbf{x}}$

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Initialization: x^0 = v^0 ← y, u^0 ← 0
for k = 0 to K − 1 do
    x^k = x^k × (1 − δ) + v^k × δ
    ṽ^{k+1} = x^k + u^k
    σ_e^k = f_N(ṽ^{k+1})
    v^{k+1} = f_D(ṽ^{k+1}, σ_e^k)
    x̃^{k+1} = v^{k+1} − u^k
    x^{k+1} = f_A(x̃^{k+1})
    u^{k+1} = x^{k+1} − v^{k+1}
    σ_e = f_N(x^{k+1})
    if σ_e < Δ then
        return x̂
    end if
end for
```

## II. Details of Competing Methods

The detailed parameter setting and implementation of the competing methods are shown as follows:

(1) **DRN-DCMB** [1]: The DRN-DCMB is a residual CNN with densely connected multi-resolution blocks to predict a residual image and reduce motion artifacts in T1-weighted MRIs acquired at different imaging planes. Since DRN-DCMB is a 2D-based model, we train this model with randomly selected slices of MRIs in MR-ART with motion artifacts and simulated Gaussian noise. The trained model is applied to MRI volumes slice-by-slice during inference.

(2) **SUNet** [2]: The SUNet is an efficient retrospective 2D method using stacked UNets to address the problem of rigid motion artifacts. Specifically, it first employs a UNet to learn structural details from adjacent slices for prediction and then uses another UNet to preserve spatial structure details and refine the pixel-to-pixel prediction. Similar to the 2D DRN-DCMB method, we train and test the model in the same way as DRN-DCMB.

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(3) **BM4D**: BM4D is a 4D implementation of the popular denoising model BM3D [3] based on [4] to reduce additive spatially correlated stationary Gaussian noise for 3D volumetric data. We use a Python package of BM4D binaries[1] for implementation and directly apply BM4D to test MRIs for comparison.

(4) **UNet3D** [5]: The UNet is one of the most popular architectures in medical image denoising [6], anti-artifact [7], and restoration [8], [9]. In the experiments, we use the 3D implementation of UNet from MONAI[2] as the baseline of 3D deep learning models.

(5) **nnUNet** [10]: The nnUNet is similar to UNet3D, but has a modified network architecture. Following [11], the nnUNet uses trilinear upsampling instead of deconvolution upsampling and batch normalization rather than instance normalization for artifact reduction. The nnUNet is trained following the strategy used in the previous study [11].

(6) **FONDUE** [12]: The FONDUE is a deep CNN model designed for denoising multi-resolution structural MRI. This method is trained with diverse MRIs from different datasets and has resolution-invariant capabilities. Considering the parameter scale of FONDUE and the limitation in our GPU memory, we download the pre-trained model following instructions of the open source code on GitHub[3] and fine-tune it on the MR-ART dataset.

## III. Computation and Time Cost Analysis

We further calculate the computation costs of our JDAC and all competing methods using the Flopth toolbox , and report the average time spent processing each test MRI in Table SI. Owing to GPU memory constraints, the time cost is recorded based on the same CPU platform (Intel(R) Core (TM) i7-8700K CPU @ 3.70GHz). It can be seen from Table SI that the parameter scales and FLOPs of all the five 3D models are usually higher than that of 2D-based methods (*i.e.*, DRN-DCMB and SUNet), while 2D-based methods are more time-consuming during inference because they need to process 3D data slice-by-slice. The FONDUE and BM4D methods have the highest test time costs since they require data sampling repeatedly during processing. *On the other hand*, Table SI indicates that although JDAC necessitates longer training time compared to UNet3D and nnUNet, it manages to attain a comparable test time cost (*i.e.*, 5.80 seconds) to that of the two 3D models (*i.e.*, 3.30 seconds for UNet3D and 3.02 seconds for nnUNet). The possible reason is that while JDAC, as an iterative framework, generally demands more training time, it typically needs only 1-2 iterations during inference, thanks to the proposed early stopping strategy.

[1] https://pypi.org/project/bm4d/
[2] https://docs.monai.io/en/stable/networks.html#basicunet
[3] https://github.com/waadgo/FONDUE

TABLE SI: Time and computation cost. For JDAC, a+b denotes the numbers for the denoising model and the anti-artifact model. M: Million; GMac: Giga multiply-accumulate operations; H: Hour; S: Second.

| Method | #Parameters (M) | FLOPs (GMac) | Training Time (H) | Test Time (S) |
|---|---|---|---|---|
| DRN-DCMB | 0.11 | 1.86 | 6.67 | 27.03 |
| SUNet | 4.08 | 25.73 | 13.43 | 81.74 |
| BM4D | - | - | - | 109.63 |
| UNet3D | 3.33 | 130.86 | 4.99 | 3.30 |
| nnUNet | 3.75 | 132.47 | 7.44 | 3.02 |
| FONDUE | 2.16 | 69.10 | - | 227.33 |
| **JDAC (Ours)** | 2.92+2.92 | 149.41+149.34 | 13.19+9.32 | 5.80 $\sim$ 15.50 |

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