Towards real-time cine-MRI reconstruction using meta-learning

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Purpose. Recently, Implicit Neural Representation (INR) have been successfully applied for the undersampled reconstruction of cardiac cine imaging [1], [2]. Although implicit regularisation is a powerful generalisation tool, these methods still present two major disadvantages: (1) training times are significantly longer than with traditional deep learning (DL) methods and (2) they lack the ability to extract information from additional training samples. In this work we propose a general framework for meta-learned initialisations using Reptile [3] that effectively tackles these two problems. Furthermore, we tested our method with the recently proposed neural fields cardiac MRI (NF-cMRI) reconstruction [2], achieving state-of-the-art performance for the self-supervised reconstruction problem.

Methods. Similarly to undersampled reconstruction, in few-shot learning problems, a new task is learned from only a few available observations. Reptile, a computational efficient gradient-based method, approximates a weights distribution by gradient descent over the meta-gradient between the initial weights and the optimised-solution for a training set of tasks (Fig. 1). This formulation was extended for the self-supervised problem in NF-cMRI during the inner loop, by including the task specific data consistency loss and by fixing the previous spatio-temporal encoding.

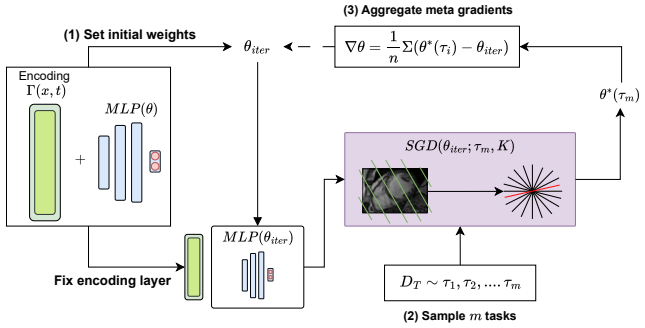

Figure 1: Reptile training with self-supervised data consistency loss.

The framework was tested using a subset of 89 patients from the publicly available dataset [4] of in-vivo subjects. The samples were acquired with a radial bSSFP sequence in a 3T MRI scanner with retrospective ECG-triggering. The fully sampled acquisitions were undersampled in a pseudo-golden-angle manner using different acceleration factors for each testing scenario. Additionally, during the meta-training phase, only 100 randomly selected spokes are taken from each of the sampled tasks.

For comparison, three baselines were considered: GRASP [5], a state-of-the-art non-INR method; a random-initialised NF-cMRI, a state-of-the-art INR method; and a mean-initialised NF-cMRI, a common baseline for few-shot meta-learning problems. Tests were performed under 17x and 26x acceleration factors, in an isolated subset of 15 patients.

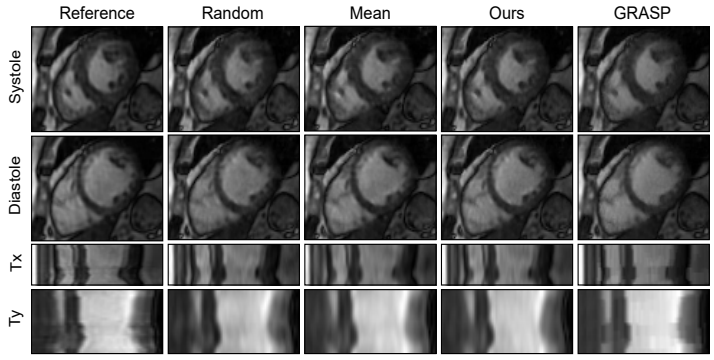

Figure 2: Short axis view at systole and diastole with the horizontal and vertical temporal profiles. Under-sampling for 17x and 26x acceleration. Reference fully sampled.

Results. Table 1. compares the FSIM reached at different training epochs using the same NF-cMRI architecture. The improvement shows that our method effectively shortens the required training time to reach equal levels of performance. Additionally, for longer training sessions our method still reaches comparable FSIM values to GRASP, 0.793 and 0.783 for 17x and 26x factors, respectively. Fig. 2, provides the reconstructions for a representative subject from the testing set. Compared to GRASP, our method reconstructs a more detailed frame to frame image, but some blurring remains in the temporal direction.

	FSIM@5	FSIM@10	FSIM@30
Random (x17)	0.748	0.759	0.767
Mean (x17)	0.752	0.757	0.764
Ours (x17)	**0.772**	**0.782**	**0.790**
Random (x26)	0.732	0.749	0.753
Mean (x26)	0.735	0.752	0.757
Ours (x26)	**0.757**	**0.769**	**0.774**

Table 1: FSIM (Feature Similarity Index Method) value at consecutive training epochs. Initialisation comparison.

Discussion. The proposed approach effectively shortens the training times required to obtain acceptable reconstructions with INR, providing an starting point for real-time reconstructions. The framework is highly flexible and can be extended to different formulations of the problem. Further extensions to different inner methods will be included as future work.

References. **1.** Haft PT et al. *Bildverarbeitung für die Medizin*. 2024;82-87. doi:10.1007/978-3-658-44037-4_26 **2.** Catalán T et al. 2023. doi:10.48550/arXiv.2307.14363 **3.** Nichol A et al. 2018. doi:10.48550/arXiv.1803.02999 **4.** El-Rewaidy H et al. *Magn Reson Med*. 2021;85(3):1195-1208. doi:10.1002/mrm.28485 **5.** Feng L et al. *Magn Reson Med*. 2014;72(3):707-717. doi:10.1002/mrm.24980