Learning contrast synthesis in MRI using a constrained contrastive learning approach

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MOTIVATION

Clinical MR protocols typically acquire multi-contrast/multi-parametric images

Pros: Provide complementary tissue-specific information (e.g., T1, T2, diffusion, etc.) to radiologists for decision making

Cons: Acquisition of multiple sequences lead to longer scan times that may not be conducive to all patient populations

Self-supervised Learning

- ❑ Representational learning techniques like contrastive learning (CL) [1] help deep learning (DL) models understand explanatory factors hidden in the observed data
- ❑ CL learns data representations such that distance between pairs of examples in the representational space approximate the semantic similarity between them

PURPOSE

In this work, we explore if

1) learning tissue-specific MR contrast information with a self-supervised pretraining approach improve DL model performance on downstream MR *contrast synthesis* tasks
2) using DL tools to synthesize new MR contrast with limited examples help *accelerate overall image-acquisition times*

BACKGROUND

- A recent work by **Umapathy et al.** [2,3] extended CL to learn meaningful local representations that embed tissue-specific MR contrast information (Figure 1) in the representational space via a constraint map.
- A constraint map summarizes information from a multi-contrast space to guide local representation during CL (Figure 2)
- Models pretrained with constrained contrastive learning (CCL) performed better on downstream segmentation tasks with limited annotated data [2]

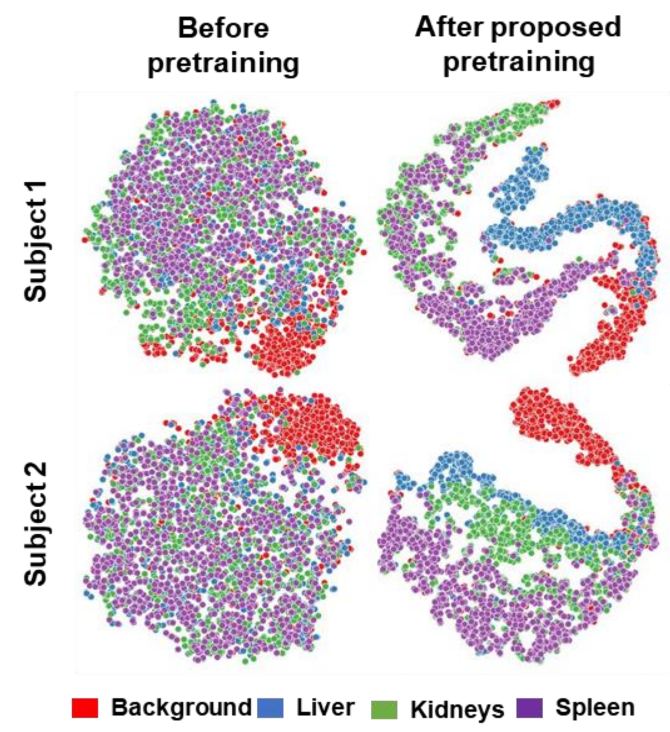

Figure 1: *t-SNE visualization of the representational space of randomly selected tissues from a T2-weighted abdomen MR image before and after pretraining with CCL is shown here. Feature vectors embed T2 information and form local groups based on underlying T2 values. Figure used from Umapathy et al. [2]*

METHODS: DATA

We hypothesize that learning local representations that embed underlying tissue characteristics (e.g., T1 or T2) using CCL approach should help improve the synthesis of corresponding MR contrast images

Data: To test the hypothesis, we use multi-parametric data from the public 2021 Brain tumor segmentation (BraTS) dataset [4] consisting of T1w, T1-Gd enhanced, T2w, and T2-FLAIR MR images (Figure 2)

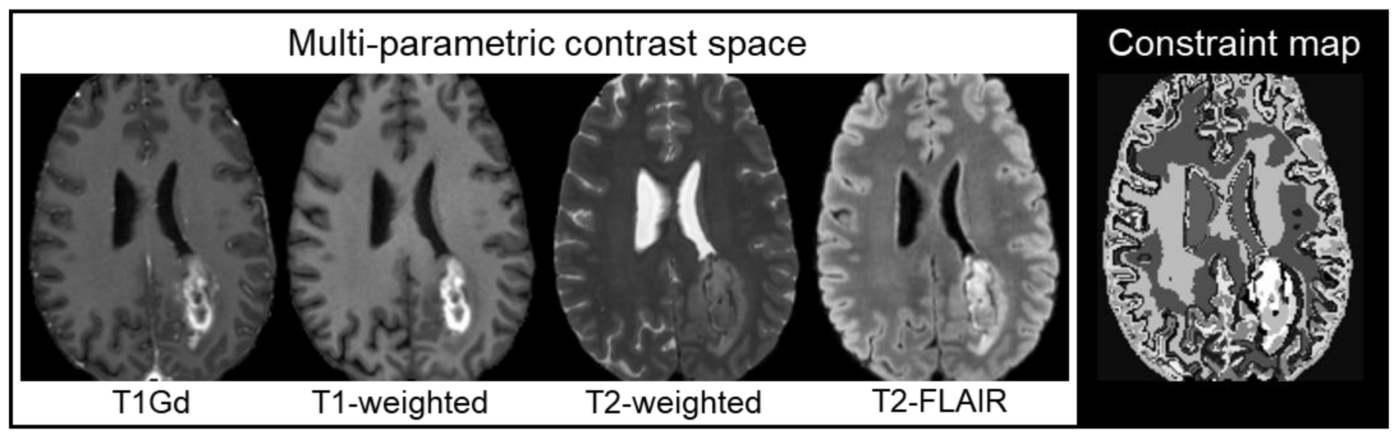

Figure 2: An example of a MR contrast space from the BraTS dataset that contains tissue T1 and T2 information. CCL approach uses the constraint map to generate semantically consistent positive and negative local regions for contrastive learning, and learn representations that better characterize underlying tissues

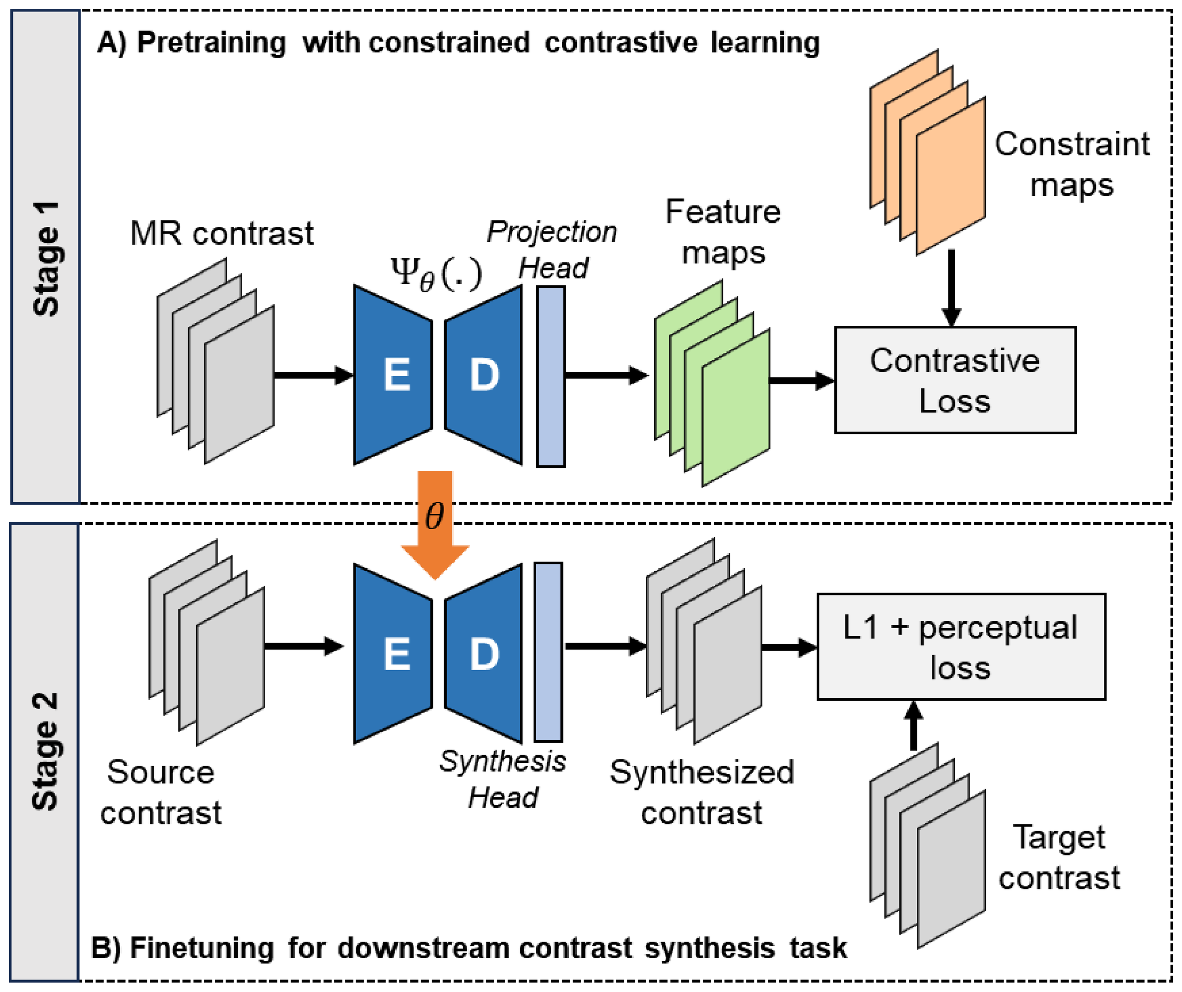

Figure 3: Illustration of the multi-stage training approach for MR contrast synthesis task. The model is first pretrained in Stage 1 to embed T1 and T2 contrast information via constraints on the contrastive loss. In the second stage, the pretrained model is finetuned for a joint T1 and T2 MR contrast synthesis task.

METHODS: TRAINING APPROACH

A 3D encoder decoder architecture is trained using a two-stage approach (Figure 3):

Pretraining: Constraint map from multi-parametric multi-contrast images [T1w, T1Gd, T2-w, T2-FLAIR] (n=80) is used to embed T1 and T2 information in representational space using CCL approach

Finetuning: The learned weighted are finetuned with limited labeled data for joint T1w and T2w contrast synthesis task from input T1-Gd and T2-FLAIR images (n=10).

RESULTS

- DL model was able to jointly synthesize T1w and T2w MR contrast images from T1Gd and T2-FLAIR images (Figure 4)
- Tables below compare the mean squared error (MSE), structural similarity (SSIM), and peak signal to noise ratios (PSNR) between Baseline (training from scratch) and CCL-pretrained DL model
- Results show that pretraining with CCL strategy, on average, yielded lower MSE, higher SSIM and PSNR across the two contrasts

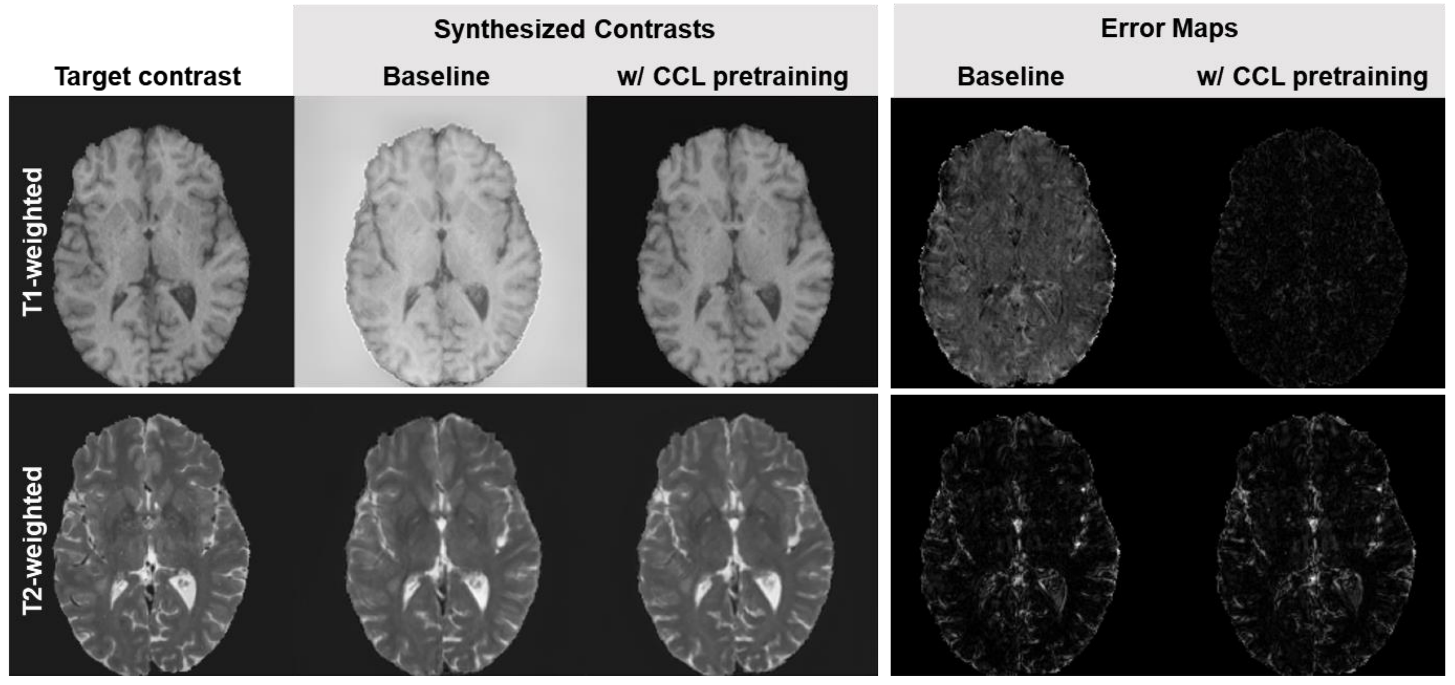

Figure 4: T1w and T2w contrast synthesis from T1Gd and T2-FLAIR images. The DL model pretrained with constrained contrastive learning is compared to a 3D model trained from scratch (Baseline). The error maps show that the Baseline model makes larger errors in T1w contrast synthesis while performing comparable to CCL model on the T2w synthesis task

T1wimage synthesis

	SSIM	MSE	PSNR
Baseline	0.52	1.12	17.22
CCL	**0.78**	**0.11**	**25.30**

T2wimage synthesis

	SSIM	MSE	PSNR
Baseline	**0.729**	0.18	**25.07**
CCL	0.715	0.18	24.47

Tables: Comparison of evaluation metrics for contrast synthesis task

DISCUSSION & CONCLUSION

Although we demonstrate the potential of embedding T1 and T2 information in the representational space in improving contrast synthesis, results are preliminary and require further analysis

Learning to embed tissue-specific MR contrast information

- Could reduce overall image acquisition times by synthesizing complementary MR contrast images
- Potentially provide a priori tissue-specific information for MR reconstruction frameworks using undersampled data

References. [1] Hadsell et al. Dimensionality reduction by learning an invariant mapping *IEEE CVPR 06,* 2006 [2] Umapathy et al. Reducing annotation burden in MR: A novel MR-contrast guided contrastive learning approach for image segmentation. *To appear in Medical Physics,* 2023 [3] Umapathy et al. Reducing annotation burden in MR segmentation: A novel contrastive learning loss with multi-contrast constraints on local representations, *Proc. ISMRM,* 2023 [4] Menze et al. The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS), *IEEE transactions on medical imaging,* 2015.