

# Descriptor-based Structural Similarity and Neural ODEs for Multimodal Diffeomorphic Registration

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## MOTIVATION

**Diffeomorphic registration** is a task in medical image analysis whose goal is finding a dense non-rigid transformation that spatially aligns two given images, referred to as moving and fixed. Registration is parametrized by a quasi-time varying flow encoded by a **Neural ODE** [1]

$$\frac{\partial \Phi}{\partial t}(t, x) = v_\theta(\Phi(t, x)), \text{ such that } \Phi(0, \cdot) = \text{Id}_\Omega.$$

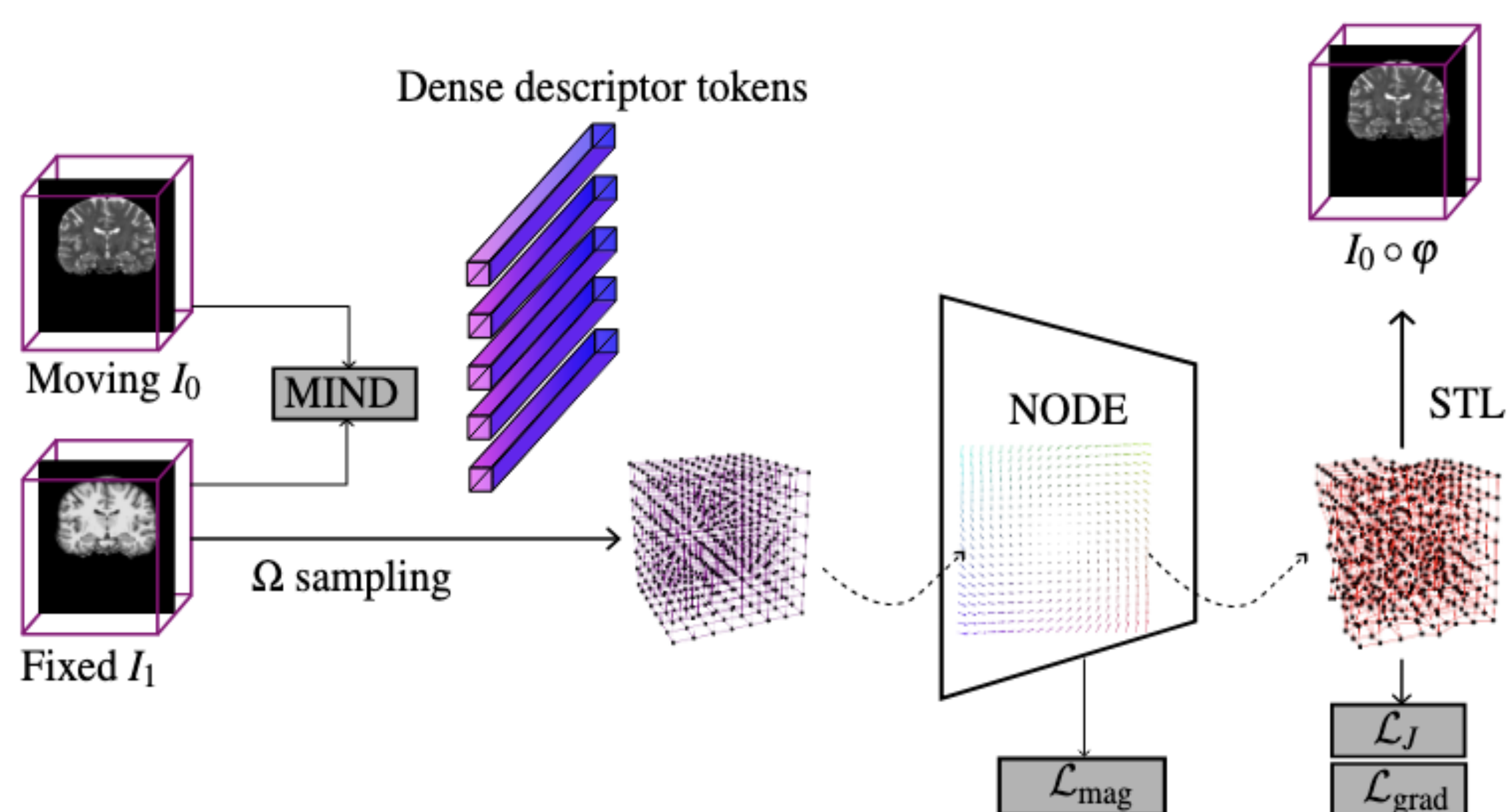
We address diffeomorphic registration on a **multimodal setting**. This setting is challenged by: (1) Poor generalization of gradient descent or second-order methods; (2) Intrinsic miscorrespondence in local features; (3) Matching sparseness due to gradient miscorrespondence. We compute dense descriptors by **spatial self-similarity** [3] in **gradient and texture**, and **robust to noise**.

## METHOD

**Neural ODE** [1] encodes the flow field and is trained on **Euler solver on instance-specific optimization**

$$\mathcal{L}_{\text{NODEO}} = \mathcal{S}(I_0 \circ \varphi^*, I_1) + \lambda_J \mathcal{L}_J + \lambda_{\text{grad}} \mathcal{L}_{\text{grad}} + \lambda_{\text{mag}} \mathcal{L}_{\text{mag}}$$

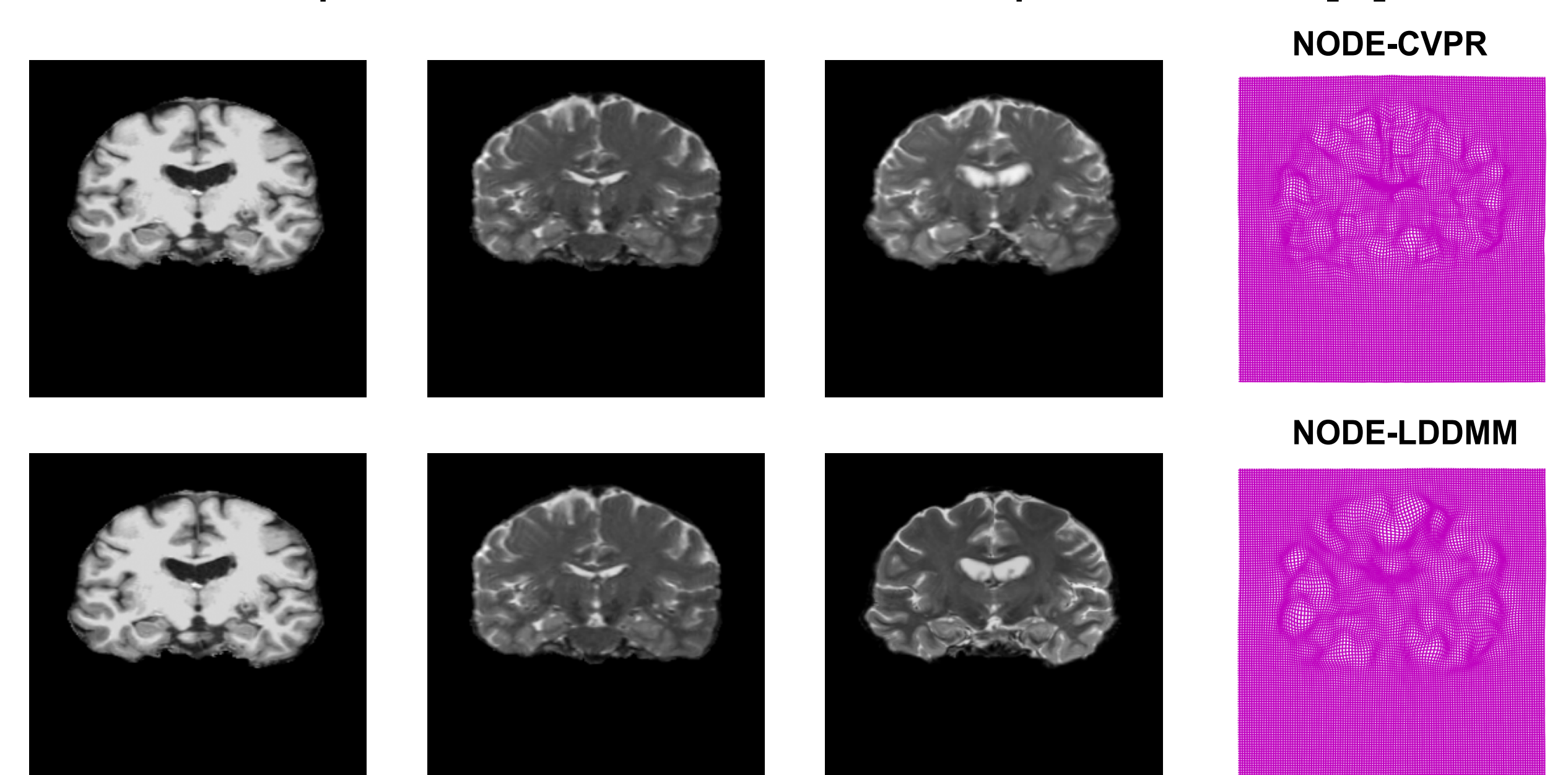
This parametrization exploits the benefits of numerical optimization methods with **fast function evaluations** of deep learning networks on GPUs.



**Figure 1. Multimodal registration by Neural ODEs.** The pairwise method uses a differentiable sampler (Spatial Transformer, STL) to interpolate on the image domain.

## RESULTS

We optimize the registration result by computing distances on the sum of square differences on descriptor tokens [3].



**Figure 2. Qualitative registration results.** Comparison on the same scan.

T1-T2 OASIS-3 Test Set			
Baseline	DSC (%) ↑	Sum $ J_\phi  \leq 0$ ↓	% of $ J_\phi  \leq 0$ ↓
ANTs-SyN	68.75 ± 2.55	0	0
NiftyReg [44]	70.93 ± 1.50	0	0
NODE + Similarity $\mathcal{S}(\cdot, \cdot)$	DSC (%) ↑	Sum $ J_\phi  \leq 0$ ↓	% of $ J_\phi  \leq 0$ ↓
NODE + MIND [21]	75.64 ± 1.70	0	0
NODE-LDDMM + MIND [23]	75.10 ± 2.11	0	0
NODE + Local MI [46]	70.49 ± 3.80	0	0
NODE + Global MI [46]	44.90 ± 14.40	2.94 · 10 <sup>-3</sup>	1.01 · 10 <sup>-6</sup>
NODE + NGF [19]	72.40 ± 4.12	0	0

**Figure 3. Quantitative evaluation results.** Comparison on the same scan with the NODE and PDE-constrained framework.

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