EPDIFF-JF-NET: Adjoint Jacobi Fields for Diffeomorphic Registration Networks

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Abstract

This paper presents a deep learning unsupervised approach for diffeomorphic image registration called EPDiff-JF-Net. We propose a novel parallel transport layer to compute the gradients necessary for training with adjoint Jacobi fields. We test our method on two independent brain MRI datasets and obtain state-of-the-art results.

Introduction

Given a source image and a target image, deformable image registration aims to compute a transformation such that the resulting warped image is similar to the target image. Deformable image registration is a fundamental tool in the field of medical imaging and is used in many applications [1]. Large Deformation Diffeomorphic Metric Mapping (LDDMM) stands out among traditional optimization-based methods as a mathematically well-established approach [2]. The only major recognized limitation of optimization-based LDDMM and all its variants is its high computational cost. To circumvent this problem, in recent years a new approach to deformable image registration has emerged in the form of deep learning.

Methods

We base our diffeomorphic parameterization on Jacobi EPDiff PDE-LDDMM [3], where the problem is parameterized on the initial velocity fields, which are then used in the Euler-Poincare differential equation (EPDiff) in a process called geodesic shooting to obtain the time-varying velocity fields and in the transport equation to obtain the final transformation.

Network architecture

We design our network architecture following a 3-level multi-resolution scheme, where each level features a resolution factor of half of the previous level. For each resolution level, a different registration network is used, which takes an 8-channel input composed of the source and target images, and the prediction from the previous level, and computes the initial velocity field and final transformation. Each registration network follows a traditional convolutional neural network (CNN) design. Following the LDDMM paradigm, we define a loss function based on the original formulation with a regularization component and an image similarity component.

Parallel transport layer

To avoid the costly computation of the gradient, we implement a parallel transport layer, which can compute the gradient at the initial time, needed for training, from the gradient at the final time via Adjoint Jacobi fields, which is then backpropagated through the rest of the registration network. This is done in a very similar manner as originally proposed for traditional optimization methods [3,4].

Results

To validate the performance of the proposed model, we compare registration results on two different 3D brain MRI scan datasets with two state-of-the-art LDDMM traditional optimization methods [3,4] and a deep learning method from one of our previous works [5]. The OASIS [6] dataset features 414 brain MRI volumes, of which 20 we used for testing and the rest for training. The NIREP16 [7] dataset features 16 volumes, all of which were used for testing only. We train our model and the baseline deep-learning model on random pairs from the OASIS training subset and test all methods on the same image pairs from the test datasets. In Table 1 you can see the quantitative results for the described experiments. DSC score is a measure of overlap, used to determine the accuracy of the registration. The number of negative determinants of the Jacobian gives us a measure of regularity. Our method obtains the best registration results for both datasets while obtaining regular transformations with no negative values of the Jacobian determinants.

Conclusions

We have presented EPDiff-JF-Net, a novel unsupervised deep-learning method for diffeomorphic registration. We evaluate our method in two independent 3D brain MRI datasets and show competitive results with current traditional and deep-learning diffeomorphic registration methods.

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Table 1. Quantitative evaluation results on the NIREP16 and OASIS datasets. Dice score, percentage of non-positive Jacobian determinants, and mean computation time

	Method	DSC	No. of $\|J_\phi\| \leq 0$	Time(s)
OASIS	FLASH	75.2 ± 2.6	**0**	1200.52
	J. EPDiff PDE-LDDMM, st. eq.	70.8 ± 4.9	**0**	570.60
	GAN-NET	74.4 ± 18.7	58491	1.30
	EPDIFF-JF-NET(ours)	$\mathbf{76.1 \pm 2.1}$	**0**	2.43
NIREP	FLASH	55.1 ± 1.4	7563	1189.21
	J. EPDiff PDE-LDDMM, st. eq.	$\mathbf{56.4 \pm 2.4}$	**0**	485.84
	GAN-NET	55.8 ± 1.8	4857	1.27
	EPDIFF-JF-NET(ours)	$\mathbf{56.4 \pm 1.6}$	**0**	2.40