LDDMM Meets GANs: Generative Adversarial Networks for Diffeomorphic Registration

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Abstract

In this work, we propose an unsupervised adversarial learning LDDMM method for 3D mono-modal images based on Generative Adversarial Networks. We have successfully implemented two models with stationary and EPDiff constrained non-stationary parameterizations of diffeomorphisms. Our approach has shown a competitive performance with respect to benchmark supervised and model-based methods.

Introduction

Since the 80s, deformable image registration has become a fundamental problem in medical image analysis [1]. A vast literature on deformable image registration methods exists, providing solutions to important clinical problems and applications. Traditionally, the great majority of deformable image registration methods were based on energy minimization models, involving different ingredients such as the deformation parameterization, the regularization and image similarity metrics, and the optimization method used in the minimization of the energy. This traditional approach is model-based, in contrast with recent deep-learning approaches that are known as data-based. Since the advances that made it possible to learn optical flow using CNNs (FlowNet [2]), dozens of deep-learning methods have been proposed to approach the problem of deformable image registration in different clinical applications [3]. The trend is augmenting considerably in the last three years. From them, some interesting proposals have been performed for diffeomorphic registration [4, 5].

The purpose of this work is to contribute to the state of the art of data-based methods for diffeomorphic registration and propose an adversarial learning LDDMM method for pairs of 3D mono-modal images.

Background on LDDMM

The LDDMM variational problem was originally posed in the space of time-varying smooth flows of velocity fields, v. The transformation $(\phi_0^v)^{-1}$, computed from minimizing an energy E(v), is the diffeomorphism that solves the LDDMM registration problem between images I_0 and I_1 [6].

$$E(v) = \frac{1}{2}\int_0^1 \langle Lv_t, v_t\rangle_{L^2} dt + \frac{1}{\sigma^2}\|I_0 \circ (\phi_1^v)^{-1} - I_1\|_{L^2}^2.$$

In order to reduce its large computational complexity, the original LDDMM variational problem is parameterized on the space of initial velocity fields or of velocity fields restricted to be stationary.

Methods

Similarly to model-driven approaches for estimating LDDMM diffeomorphic registration, data-driven approaches aim at the inference of a diffeomorphism such that the LDDMM energy is minimized for a given (I_0, I_1) image pair. The functional approximation is obtained via a neural network representation with parameters learned from a representative sample of image pairs. GAN-based approaches depart from unsupervised approaches by the definition of two different networks: the generative network (G) and the discrimination network (D). These networks are trained in an alternating way in an adversarial fashion. In contrast to other unsupervised approaches, the loss function in G is determined from the combination of the LDDMM and the adversarial costs.

In this work, the diffeomorphic registration network G is intended to learn LDDMM diffeomorphic registration parameterized on the space of steady velocity fields or the space of initial velocity fields, which are then used to obtain the diffeomorphic transformation $(\phi_0^v)^{-1}$. Both networks are trained in an unsupervised learning manner and the generator's loss function also incorporates a regularization term based on the LDDMM formulation.

Results

We have tested our method for 2D simulated datasets as well as with the 3D MRI dataset Nirep. Our results so far show 2D deformations present visual similarity to model-based approaches. 3D results show comparable performance with model-based and previous deep-learning models. Figures 1 and 2 show some qualitative results for both 2D and 3D datasets.

Conclusions

We have proposed an adversarial learning LDDMM method for the registration of 3D monomodal images. Our method is inspired by the recent literature on deformable image registration with adversarial learning and combines the best performing generative, discriminative, and adversarial ingredients from these works within the LDDMM paradigm. Our experiments have shown that the inferred velocity fields are comparable to the solutions of model-based approaches. In addition, the evaluation study has shown the competitiveness of our approach with state-of-the-art model- and data-based methods.

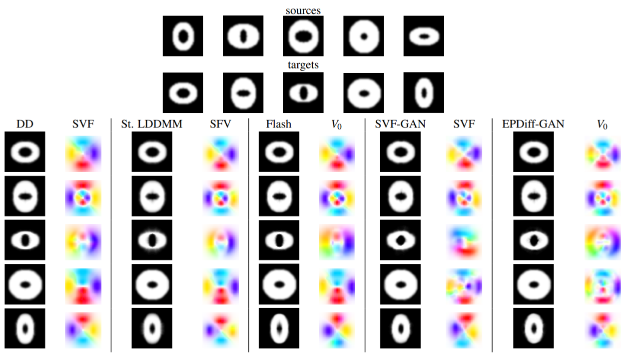

Figure 1: Example of simulated 2D registration results. Up: source and target images of five selected experiments. Down, left to right: deformed images and velocity fields computed from diffeomorphic Demons (DD), stationary LDDMM (St. LDDMM), Flash, and our proposed SVF-GAN and EPDiffGAN. SVF stands for a stationary velocity field and V0 for the initial velocity field of a geodesic shooting approach, respectively.

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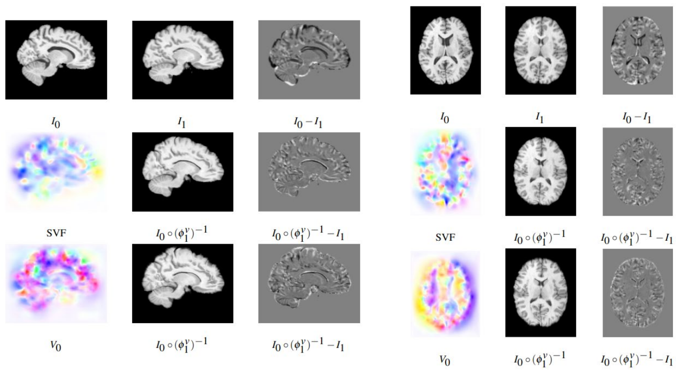

Figure 2: Example of 3D registration results. First row, sagittal and axial views of the source and the target images and the differences before registration. Second row, inferred stationary velocity field, warped image, and differences after registration for SVF-GAN. Third row, inferred initial velocity field, warped image, and differences after registration for EPDiff-GAN.