LDDMM Meets GANs: Generative Adversarial Networks for Diffeomorphic Registration

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1. Image Registration

1. Deformable image registration is a fundamental problem in medical image analysis. The problem consists of computing the deformation that best warps a source image into a target image. Useful for:

- Multi-modality fusion, where information acquired by different imaging devices or protocols is fused to facilitate diagnosis and treatment planning.
- Longitudinal studies, where temporal structural or anatomical changes are investigated.
- Population modeling and statistical atlases used to study normal anatomical variability.

2. Large deformation diffeomorphic metric mapping (LDDMM)

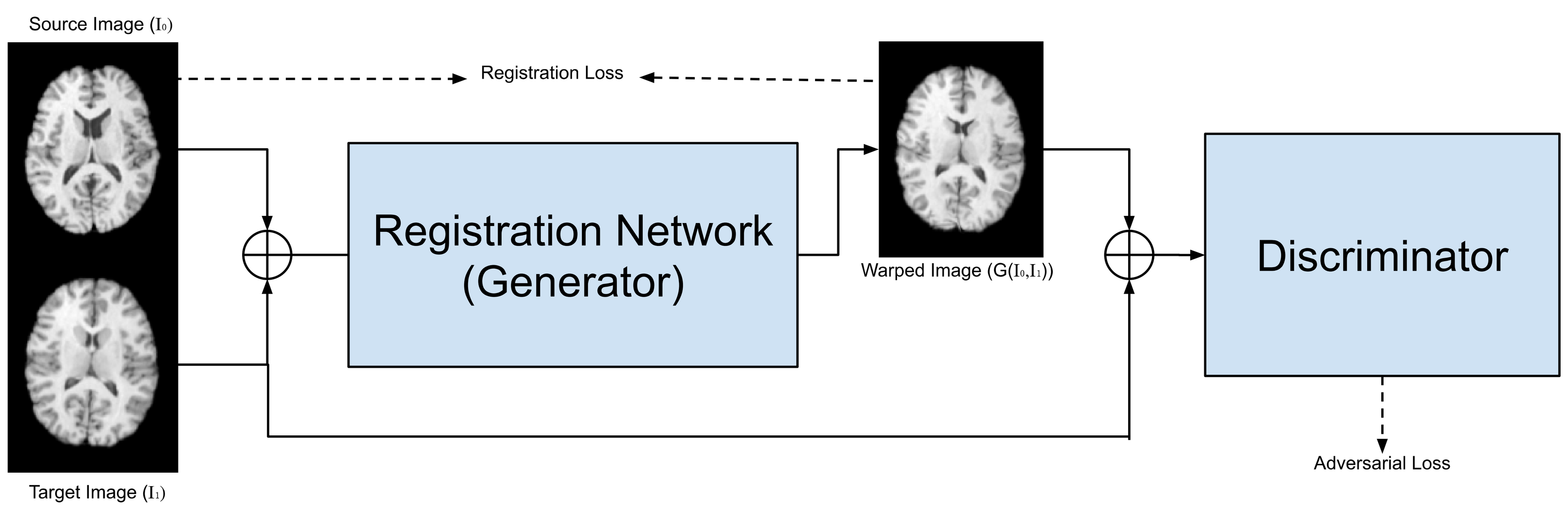
1. Diffeomorphism that minimizes energy E(v) between images I_0 and I_1.

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

2. Large computational complexity.

3. Different parameterizations for *v*: stationary, non-stationary, EPDiff-constrained.

3. Generative Adversarial Registration Framework



1. Registration network predicts deformation of source image to target image.

2. Discriminator identifies correctly warped images.

$$L_D = \begin{cases} -\log(p) & c \in P^+ \\ -\log(1-p) & c \in P^- \end{cases}$$

3. Loss fucntion is sum of LDDMM energy and discriminator cost.

$$L_G = L_{\text{adv}} + \lambda E(v, I_0, I_1)$$

4. Experiments and Results

1. 2D dataset of simulated ellipses.

2. 2D deformations present visual similarity to model-based approaches.

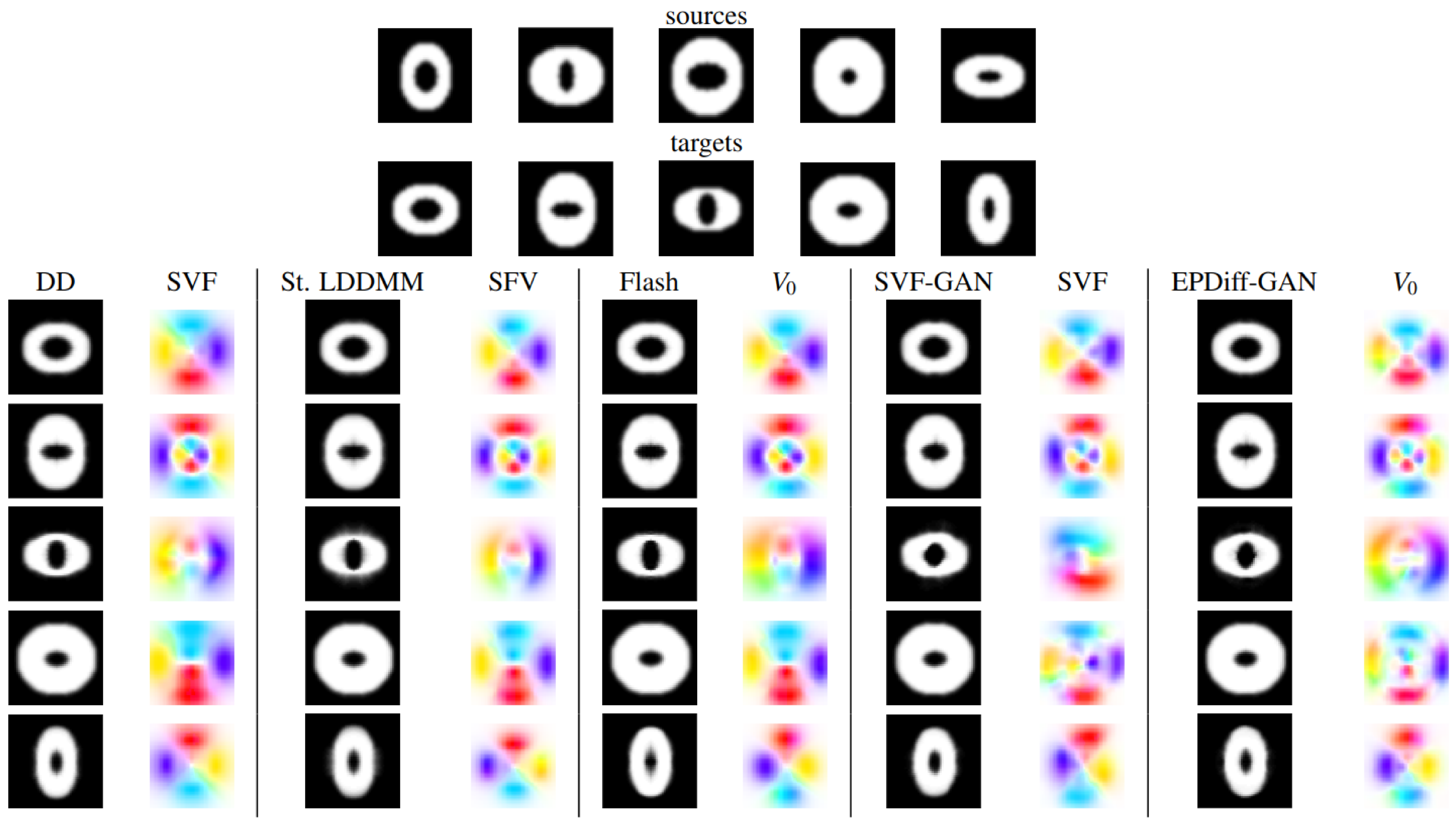


Figure: Example of simulated 2D registration results. Up: source and target images of five selected experiments. Down, left to right: deformed images and velocity fields computed from diffeomorphic Demons (DD), stationary LDDMM (St. LDDMM), Flash, and our proposed SVF-GAN and EPDiffGAN. SVF stands for a stationary velocity field and v_0 for the initial velocity field of a geodesic shooting approach, respectively.

3. 3D training uses 2113 T1-weighted brain MRI images from the ADNI dataset.

4. 3D results show comparable accuracy with state of the art model-based and previous deep-learning models commonly used as benchmarks.

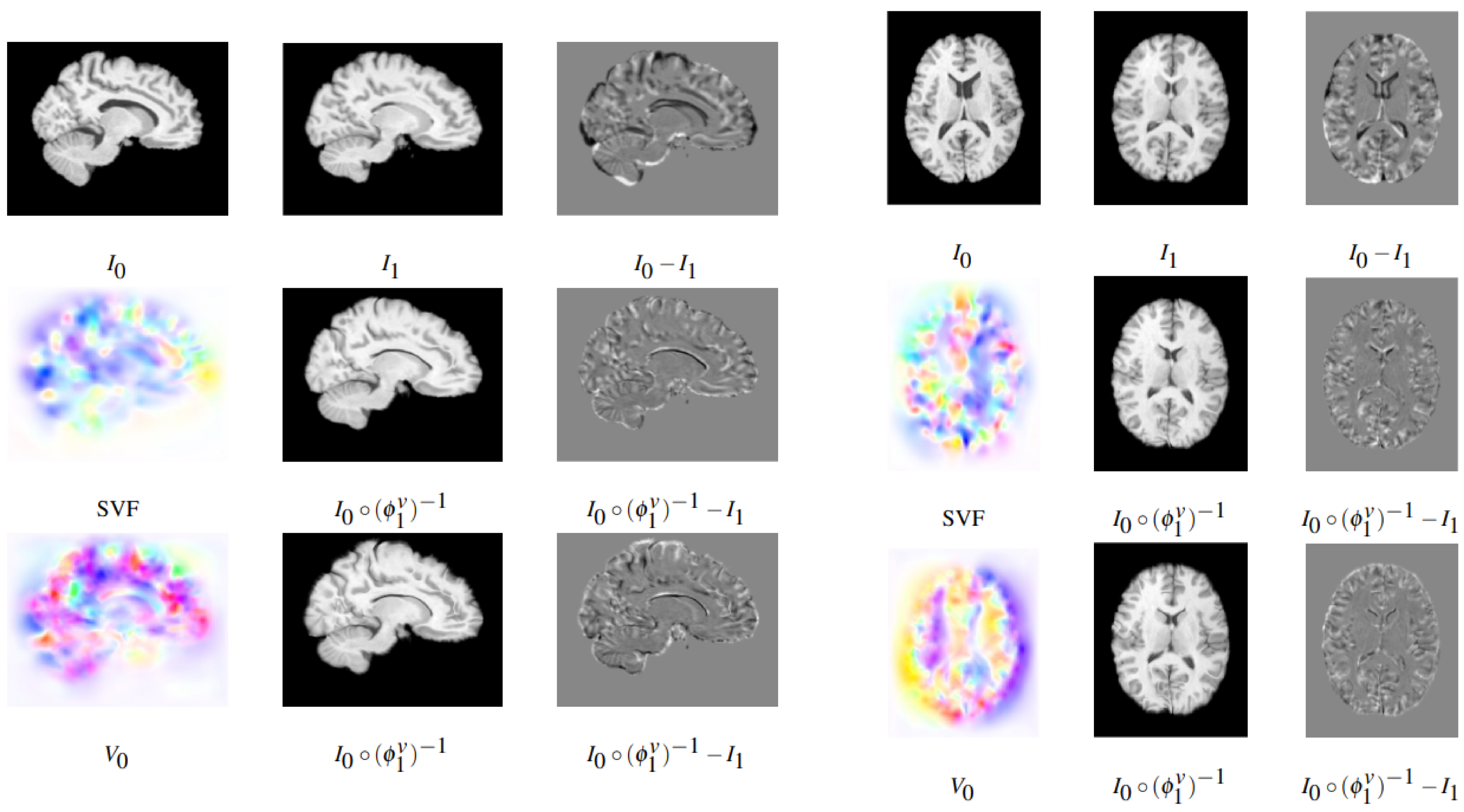


Figure: Example of 3D registration results. First row, sagittal and axial views of the source and the target images and the differences before registration. Second row, inferred stationary velocity field, warped image, and differences after registration for SVF-GAN. Third row, inferred initial velocity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

5. References

[1] A. Sotiras, C. Davatzikos, and N. Paragios, Deformable medical image registration: a survey. IEEE transactions on medical imaging. 2013, 32, pp. 1153–1190.

[2] A. Dosovitskiy, P. Fischere, E. Ilg, P. Hausser, C. Hazirbas, and V. Golkov, Flownet: Learning optical flow with convolutional networks, CoRR, abs/1504.06852. 2015.

[3] H.R. Boveiri, R. Khayami, R. Javidan, and A. Mehdizadeh, Medical image registration using deep neural networks: A comprehensive review. Computers Electrical Engineering. 2020, 87, p. 106767.

[4] G. Balakrishnan, A. Zhao, M. R. Sabuncu, J. Guttag, and A. V. Dalca, Voxelmorph: A learning framework for deformable medical image registration, IEEE transactions on medical imaging. 2019, 38, pp. 1788–1800.

[5] X. Yang, R. Kwitt, M. Styner, and M. Niethammer, Quicksilver: Fast predictive image registration - a deep learning approach, NeuroImage. 2017, 158, pp. 378–396.

[6] M. F. Beg, M. I. Miller, A. Trouve, and L. Younes, Computing large deformation metric mappings via geodesic flows of diffeomorphisms. International Journal of Computer Vision. 2005, 61, pp. 139–15.