VoxelMorph Smoothness Study

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1 Introduction to VoxelMorph

Image registration is a fundamental task in medical imaging, aiming to align pairs of images through spatial transformations. Deep learning-based registration models, such as **VoxelMorph** (1), have gained popularity for their efficiency and accuracy. VoxelMorph learns to predict displacement fields that warp a moving image to align with a fixed image. It is trained in an unsupervised manner using a combination of image similarity losses (e.g., MSE or NCC) and smoothness regularization on the deformation field.

In this study, we investigate how different smoothness regularization types and their weights influence registration performance and deformation quality in VoxelMorph. We analyze the tradeoff between alignment accuracy and the regularity of the deformation field by examining the validation MSE loss and the percentage of non-positive Jacobian determinants.

For conducting our experiments, we modified the original VoxelMorph repository, available at: `https://github.com/voxelmorph/voxelmorph`.

2 Dataset and Experimental Setup

We conduct our experiments using the Neurite-OASIS dataset[1] (2), which contains 414 preprocessed T1-weighted brain MRI scans. We randomly split the dataset into 248 training and 166 validation scans. Since we do not perform hyperparameter tuning, no separate test set is required.

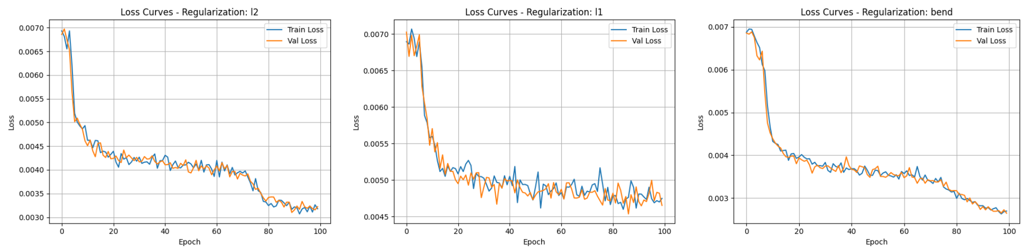
We build upon the official PyTorch implementation of VoxelMorph and extend it to support our experiments. Specifically, we adapted the codebase to work with the Neurite-OASIS dataset, implemented several smoothness regularization strategies (including L_1, L_2, and bending energy), and developed scripts for training, evaluation, and analysis. All training runs use default VoxelMorph parameters, and are executed for 100 epochs with a batch size of 1.

The entire experimental framework, including setup instructions, training scripts, and evaluation tools, is organized and documented in our repository. The README file provides clear guidance for reproducing each experiment. Our repository is publicly available at GitHub: `https://github.com/harel147/voxelmorph-smoothness-study`

3 Smoothness Analysis of Deformation Fields

Our goal is to investigate the role of smoothness regularization in VoxelMorph. To that end, we perform two main experiments: one analyzing the effect of different regularization types, and the other studying the effect of varying the weight of regularization.

[1] `https://github.com/adalca/medical-datasets/blob/master/neurite-oasis.md`



(a) L2 (b) L1 (c) Bending Energy

Figure 1: Training and validation loss vs. epoch for each regularization.

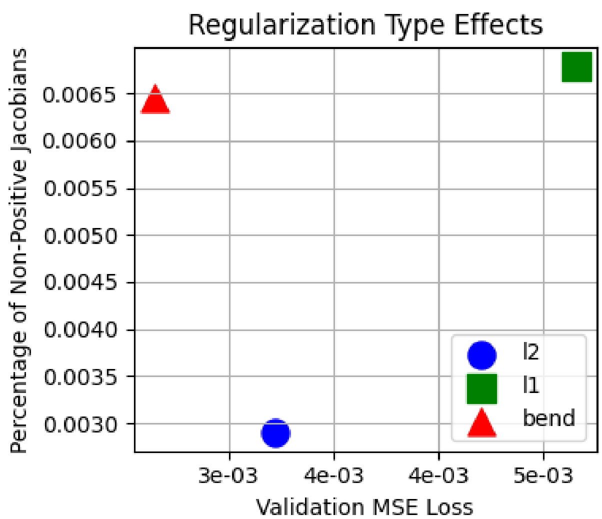


Figure 2: Validation MSE vs. percentage of non-positive Jacobians for each regularization type.

3.1 Regularization Type Comparison

We compare three common regularizations:

- **L2 Regularization**: Penalizes the squared gradient magnitude:

$$\mathcal{L}_{\text{L2}} = \frac{1}{N} \sum \|\nabla \phi\|^2$$

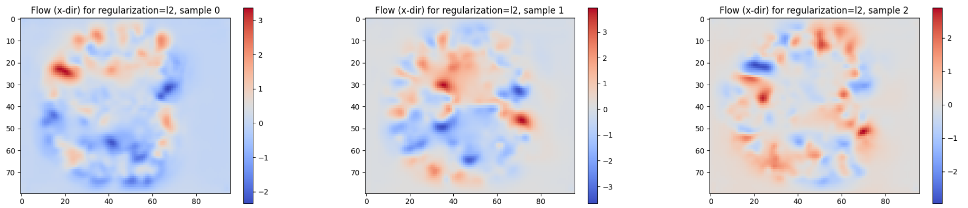
- **L1 Regularization**: Penalizes the absolute gradient:

$$\mathcal{L}_{\text{L1}} = \frac{1}{N} \sum |\nabla \phi|$$

- **Bending Energy**: Penalizes second-order derivatives:

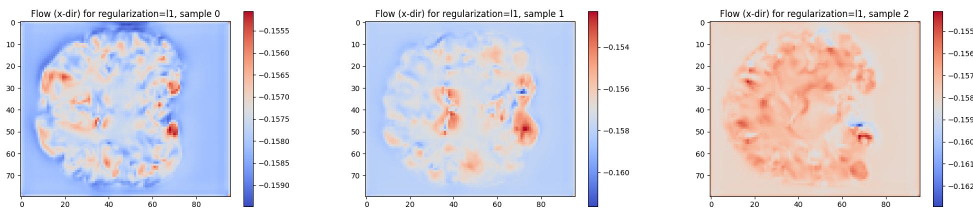
$$\mathcal{L}_{\text{Bend}} = \frac{1}{N} \sum \left(\nabla^2 \phi\right)^2$$

The training and validation losses for each regularization type are shown in Figure 1. To evaluate the tradeoff between accuracy and deformation smoothness, we plot the final validation MSE against the percentage of non-positive Jacobians in Figure 2. It can be seen that L2 regularization offers the best tradeoff, achieving both low validation error and relatively smooth deformations. Representative examples of deformation fields for each regularization are visualized in Figures 3, 4, 5.



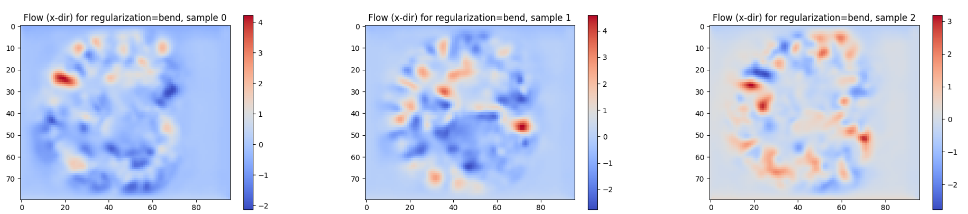
(a) Flow 1 (b) Flow 2 (c) Flow 3

Figure 3: Examples of flow fields for L2 regularization.



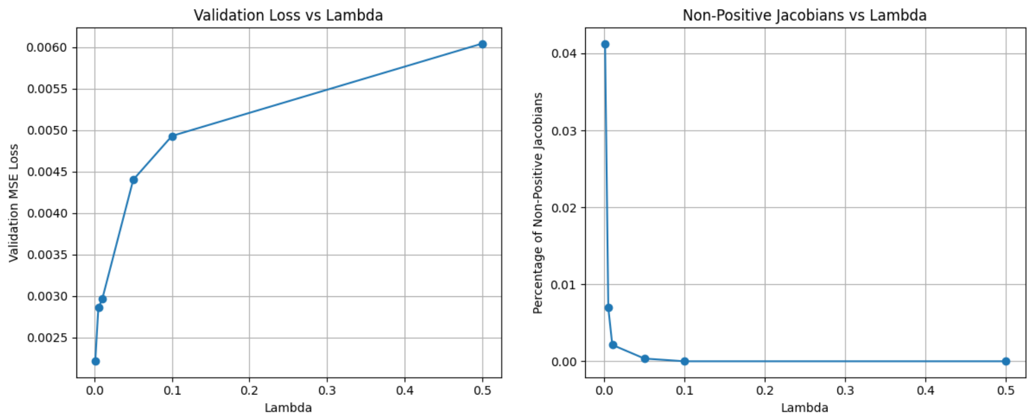
(a) Flow 1 (b) Flow 2 (c) Flow 3

Figure 4: Examples of flow fields for L1 regularization.



(a) Flow 1 (b) Flow 2 (c) Flow 3

Figure 5: Examples of flow fields for Bending Energy regularization.



(a) MSE vs. λ

(b) Jacobians vs. λ

Figure 6: Validation MSE vs. λ and percentage of non-positive Jacobians vs. λ.

3.2 Regularization Weight Sensitivity

In this experiment, we fix the regularization to L2 and vary its weight λ to observe the tradeoff between accuracy and deformation smoothness.

Figure 6 shows the validation MSE as a function of the regularization weight λ, and the percentage of non-positive Jacobians as a function of the regularization weight λ. As λ increases, the deformation becomes smoother (fewer non-positive Jacobians), but registration accuracy degrades.

References

[1] 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*, vol. 38, no. 8, pp. 1788–1800, 2019.

[2] D. S. Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C. Morris, and R. L. Buckner, "Open access series of imaging studies (oasis): cross-sectional mri data in young, middle aged, nondemented, and demented older adults," *Journal of cognitive neuroscience*, vol. 19, no. 9, pp. 1498–1507, 2007.