HybridMorph: Towards usage of synthetic with real data for medical MR images registration

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Presentation Overview

Introduction

Registration

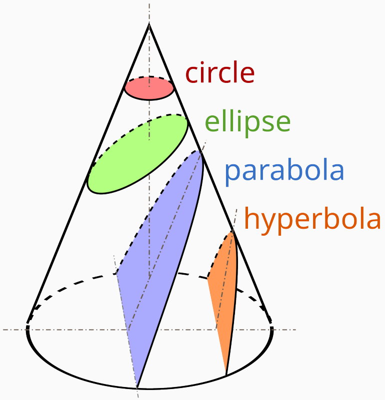


Figure 1: Conic sections on a cone.

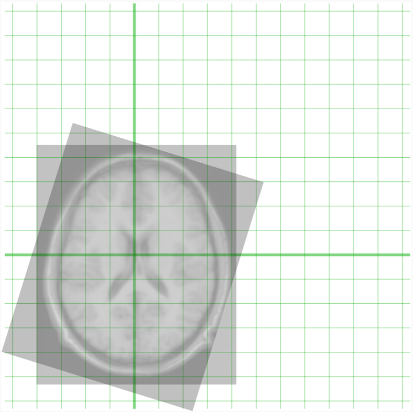


Figure 2: Registration of two MRI images of the brain.

Figure 1. Image credits: Magister Mathematicae, CC BY-SA 3.0 via Wikimedia Commons.
Figure 2. Image credits: Andrew janke, Public domain, via Wikimedia Commons.

Methods

1. **Real Data-based:** VoxelMorph (Proposed by Balakrishnan et al.) - uses supervised and unsupervised training on real image data.
    - Drawbacks: scarcity and high cost of acquisition for the data-sets.
2. **Synthetic Data-based:** SynthMorph (Introduced by Hoffmann et al.) - uses synthetic images generated from a noise distribution for training.
    - Drawbacks: Lower registration accuracy and performance.

Proposed Improvements

- Hybrid Data Models for Enhanced Adaptability by utilizing Real and Synthetic Data for Improved Registration Performance.

We outline the following data-driven models:

1. Few-shot Learning: Trained Voxelmorph on limited MR images.
2. Transfer Learning: Pre-trained models with synthetic images and fine-tuned with few real MR images.
3. Weighted Transfer Learning: Pre-trained models with synthetic images and fine-tuned using hybrid training model with real and synthetic images.

Methodology

Synthetic Data Generation

We generate input label maps $L \sim G(\theta)$ with random geometric shapes, which are then deformed $D = F(L, \phi)$ to create segmentation maps and then the images are generated by sampling intensities from normal distributions $I = S(D, \mu, \sigma, \beta)$

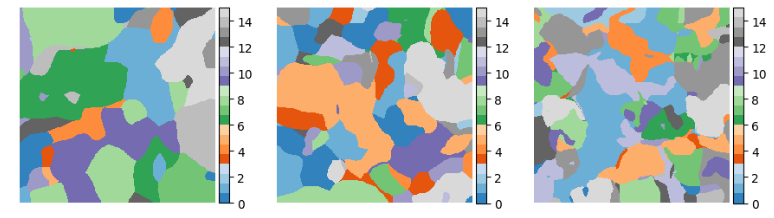


Figure 3: Random geometric shapes in synthetic images generated from noise distributions.

Real Datasets

We utilized weighted T1 Images from:

1. **OASIS 1**: 414 Coronal images
2. **OASIS 2**: 373 Sagittal images
3. **BraTS 2021**: 391 Axial images

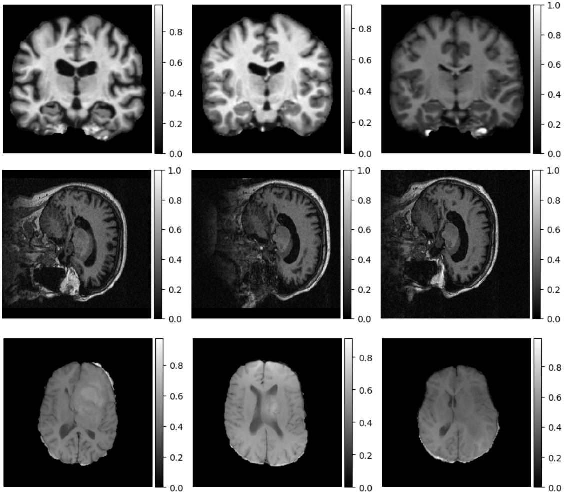


Figure 4: T1 weighted MR brain images normalized. Top: OASIS 1 dataset (Coronal slices). Center: OASIS 2 dataset (Sagittal slices). Bottom: BraTS 2021 dataset (Axial slices).

Network

- **Input**: Two image volumes,f (fixed) and m (moving) concatenated together.
- **Output**: Displacement field u that aligns m with f
- **Model**: CNN, $g_\theta(f, m) = u$, where θ are network parameters

The CNN architecture is based on a UNet structure, consisting of encoder and decoder sections with skip connections.

- **Encoder** using strided convolutions with a feature map size of [32, 32, 32, 32].
- **Decoder** using upsampling and convolutional with a feature map size of [32, 32, 32, 32, 32, 16].

- **Weighted Training Function**: The input distribution can be thought of as a mixture distribution

$$X \sim \begin{cases} P_{real}(x) & \text{with probability } \alpha \\ P_{synth}(x) & \text{with probability } 1-\alpha \end{cases} \tag{1}$$

The expected output of the VXM model can be written as:

$$\mathbb{E}[Y] = \alpha \cdot \mathbb{E}_{x \sim P_{real}(x)}[f(x)] + (1-\alpha) \cdot \mathbb{E}_{x \sim P_{synth}(x)}[f(x)] \tag{2}$$

where Y is the target output random variable, and $f(x)$ is the transformation learned by the VXM model.
The loss function can be written as:

Training and Loss Function ii

$$L(f(x), y) = \alpha \cdot L(f(x), y) + (1 - \alpha) \cdot L(f(x), y) \tag{3}$$

where L is the MSE loss function.
The optimization objective of the VXM model can be written as:

$$\min_f \mathbb{E}_{x \sim P_{real}(x)}[L(f(x), y)] + \frac{1 - \alpha}{\alpha} \cdot \mathbb{E}_{x \sim P_{synth}(x)}[L(f(x), y)] \tag{4}$$

- A MSE loss metric is used to measure the difference between the predicted and ground-truth registration fields.

Process Flow

Block Diagram

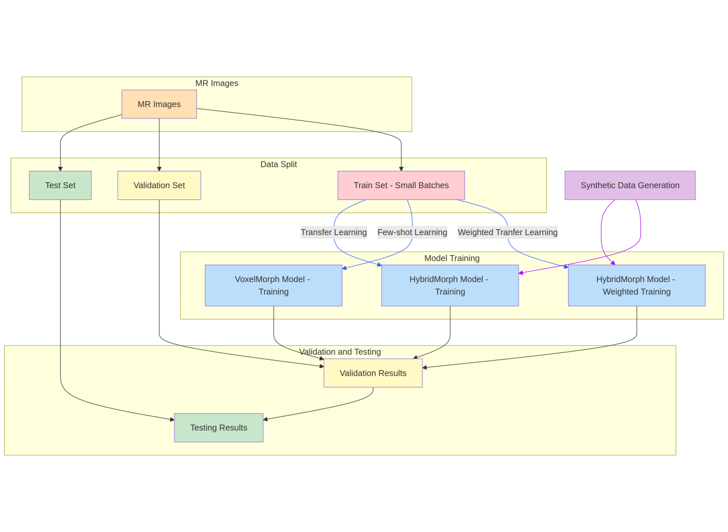


Figure 5: Block diagram explaining the modeling paradigms.

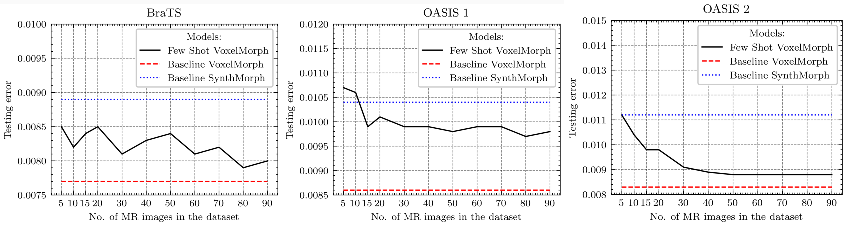
Results

Setup

- All datasets were split into training, validation, and testing sets in a ratio of 60:20:20.
- The training was performed with 100 steps per epoch using the Adam optimizer.
- The model loss was evaluated using batches with 1000 steps.

Few-shot Learning

We trained the VoxelMorph model with varying dataset sizes (5-90 images) for 1000 epochs each.

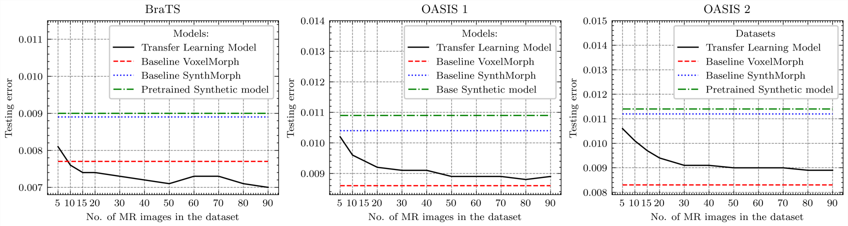


(a) BRaTS dataset **(b)** OASIS 1 dataset **(c)** OASIS 2 dataset

Figure 6: Testing loss on VoxelMorph with few-shot data, demonstrating the model's performance under varying training dataset sizes.

Transfer Learning

We pre-trained a SynthMorph model on a large dataset of synthetic images for 900 epochs, then fine-tuned it on real images (5-90 images) for an additional 100 epochs.

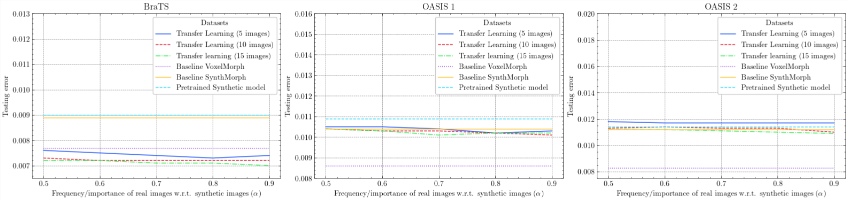


(a) BRaTS dataset **(b)** OASIS 1 dataset **(c)** OASIS 2 dataset

Figure 7: Testing loss on SynthMorph with transfer learning, demonstrating the model's performance under varying numbers of training images.

Weighted Transfer Learning

We fine-tuned a pre-trained SynthMorph model on 5-15 real images, adjusting the weight of real images (α) from 0.5 to 0.9 in increments of 0.1.



(a) BRaTS dataset **(b)** OASIS 1 dataset **(c)** OASIS 2 dataset

Figure 8: Testing loss on HybridMorph model with varying values of α, demonstrating the model's performance under different weighting of real and synthetic images.

Observations

- Real data is essential: VoxelMorph achieves lowest error rates across datasets.
- Synthetic data is a useful supplement: SynthMorph achieves competitive error rates with synthetic images.
- HybridMorph excels: Combines strengths of synthetic and real data to achieve error rates better than SynthMorph.
- Robustness and invariance: HybridMorph exhibits robustness to image type and intensity, generalizing well across different image types.
- Key benefits: More accurate and robust than SynthMorph, reliable and versatile approach for biomedical image registration tasks.
- α sensitivity: HybridMorph model is relatively robust to changes in weighting of synthetic and real data (α).

Future Scope

- Expanding to other biomedical image analysis tasks: Explore application of hybrid models to image segmentation, object detection, and disease diagnosis.
- Improving synthetic data generation techniques: Develop new techniques to further improve performance of hybrid models.
- Multi-task learning and meta-learning: Investigate use of hybrid models in multi-task learning and meta-learning scenarios.
- Rare disease diagnosis and personalized medicine: Leverage HybridMorph model's ability to operate effectively in scenarios with scarce or difficult-to-obtain real data.

Key Contributions

- Hybrid Approach: HybridMorph combines synthetic and real data for MR image registration.
- Improved Performance: Competitive error rates and robustness to image type.
- Reduced Data Requirements: Efficient and cost-effective solution with less annotated data.
- Transfer Learning: Effective adaptation to new datasets and reduced overfitting risk.
- Weighted Transfer Learning: Accurate registration with limited real data.

Thank you for your attention!