

Zero Shot Image Registration through Feature Extraction (ZSIR -FE)

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Introduction

We introduce a novel image registration framework, termed Zero-Shot Image Registration through Feature Extraction (ZSIR-FE), employing a pre-trained deep neural network for feature extraction. This framework is termed a zero-shot learning approach due to the non-overlapping nature of the training and testing datasets, coupled with the fact that the network modules within the overall network architecture are not trained for image registration. This approach eliminates the need for any training data specific to image registration, as it autonomously estimates the locations of significant features, which we herein termed as key points. Although the model provides the provision to fine-tune the key points as a hyperparameter, in our implementation, it remains fixed. This novel pipeline has been tested on the BraTS dataset, showcasing an enhancement in performance metrics, notably the Dice score, particularly for affine transformations. Moreover, this method yields instantaneous results for registration, irrespective of the input image size. The innovative framework of ZSIR-FE fosters a unified registration model, adept at addressing diverse medical imaging tasks and scenarios across varying domains..

Methods

In our approach, we leveraged a two-part deep learning model. The first component, a feature extractor, was based on the UNET architecture (CNN architecture) and was trained on Brain MRI images for the classification task. While various architectures were experimented with, UNET stood out in its performance. The second component, a transformation network, was a simple neural network trained on synthetically generated data to affine spatial transformations. Our final image registration pipeline is depicted in Figure. The model is not computationally expensive; thus, it can be trained on a local laptop. The components of the architecture is given below.

- Feature Extraction using Pre-trained Architecture
- Keypoint Extraction from the Features with High Activation
- Neural Network Training with Simulated Data
- Transformation Parameter Estimation

Results and Discussion

Table 1: Results of BraTs dataset T1-T2 registration (3D)

Techniques	Dice Score (after - before)	Time Taken per Image
SimpleElastix	+0.263	1.6
SIFT based	+0.248	0.3
VGG19 (pretrained: imagenet) [4]	+ 0.294	0.2
UNET (pretrained: Brain MRI)	+0.352	0.2

- Comparative analysis of the proposed registration method with two standard techniques: SIFT (Scale-Invariant Feature Transform) and SimpleElastix, using the BRATS dataset.
- Before registration, the Dice Score range for the BRATS dataset was measured to be 0.36 ± 0.22 , indicating a wide variability in alignment quality across the dataset.
- After applying our proposed model, the Dice Score range improved significantly to 0.86 ± 0.16 . This performance improvement demonstrates the effectiveness of the registration method in enhancing the alignment of T1 and T2 images from the BRATS dataset.
- These results are detailed in Table and it indicates superior alignment quality compared to both SIFT and SimpleElastix-based techniques.
- Furthermore, our model exhibited efficiency in terms of processing speed, requiring only 0.2 seconds per image.
- The primary limitation of the suggested framework lies in its robustness solely within the realm of affine registration.

References

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