Unsupervised Learning of Multi-modal Affine Registration for PET/CT

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Check out the short paper for more

Introduction

Background: Deep learning (DL) has shown promise in image registration, but their use in PET/CT affine registration remains underexplored. PET provides functional information, while CT offers anatomical information, making registration challenging.

Objective: This study makes two key contributions:

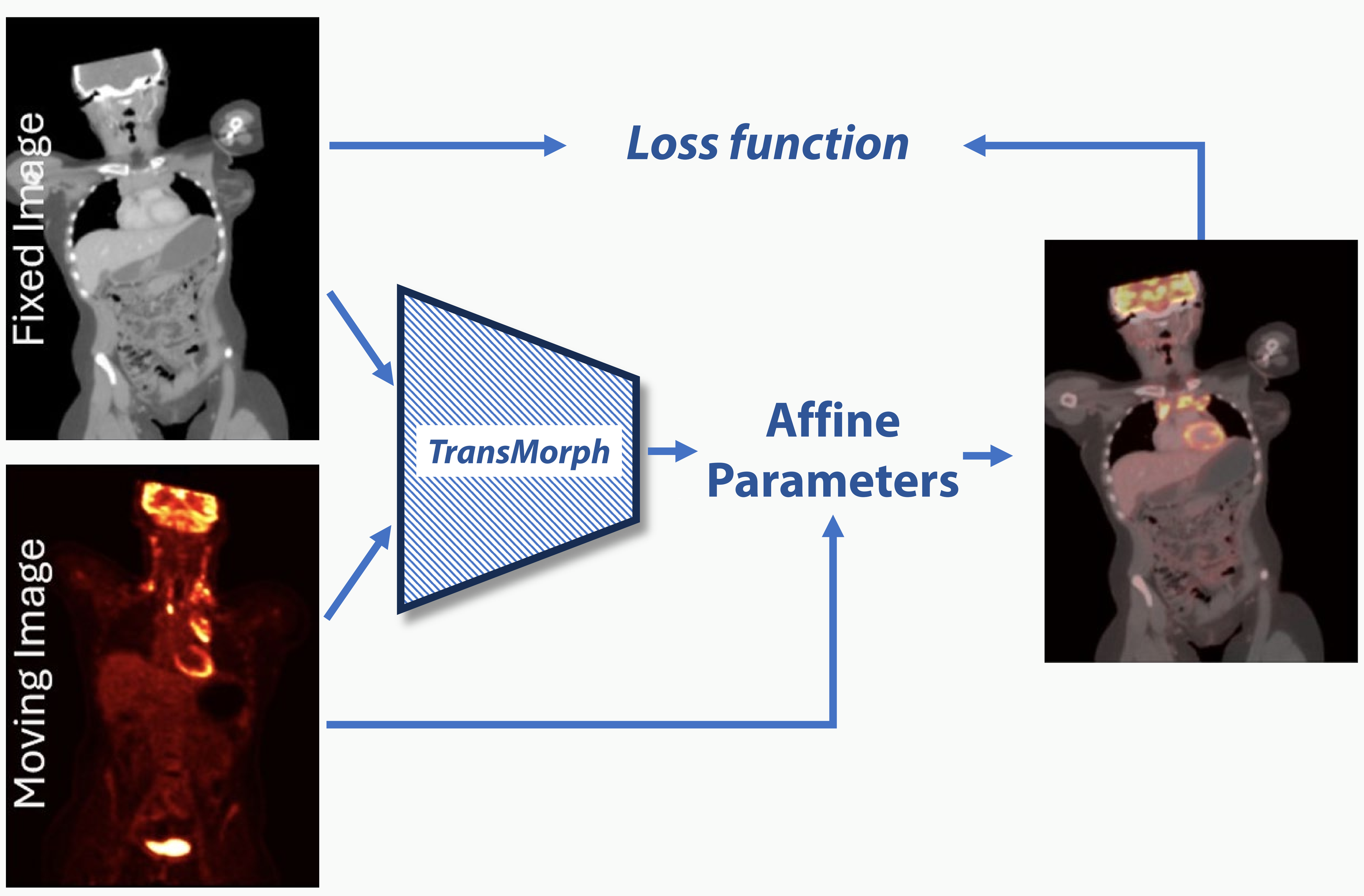
1. Evaluating the effectiveness of DL-based methods for PET/CT affine registration.
2. Investigating the ***correlation ratio*** (CR) as an alternative to ***mutual information*** (MI) for registration.

Source code is available on our GitHub:
github.com/junyuchen245/Correlation_Ratio

Methods

Problem Formulation:

- Let ***m*** and ***f*** represent the moving (PET) and fixed (CT) images, respectively.
- We use TransMorph [1] to predict 12 affine transformation parameters: 3 for translation, 3 for rotation, 3 for scaling, and 3 for shearing, facilitating the registration process between PET and CT images.



New loss function for multi-modal registration:

- ***CR***, introduced in [2], predicts the intensity values in image Y using values from image X, defined as:
- $\eta = \frac{Var[E(Y|X)]}{Var[Y]}$
- CR was originally implemented using a discrete approach, which limits its compatibility with DNN training.
- We use Parzen windowing method with Gaussian kernels to approximate the conditional expectation.

Methods (Cont.)

Multi-scale instance-specific optimization:

- After the DNN predicts the affine parameters, they are used as an initialization for the optimal transformation.
- We then apply instance-specific optimization (ISO), which iteratively refines these parameters for each image pair using gradient descent, further improving the registration accuracy.

Algorithm 1 Multi-scale instance-specific optimization

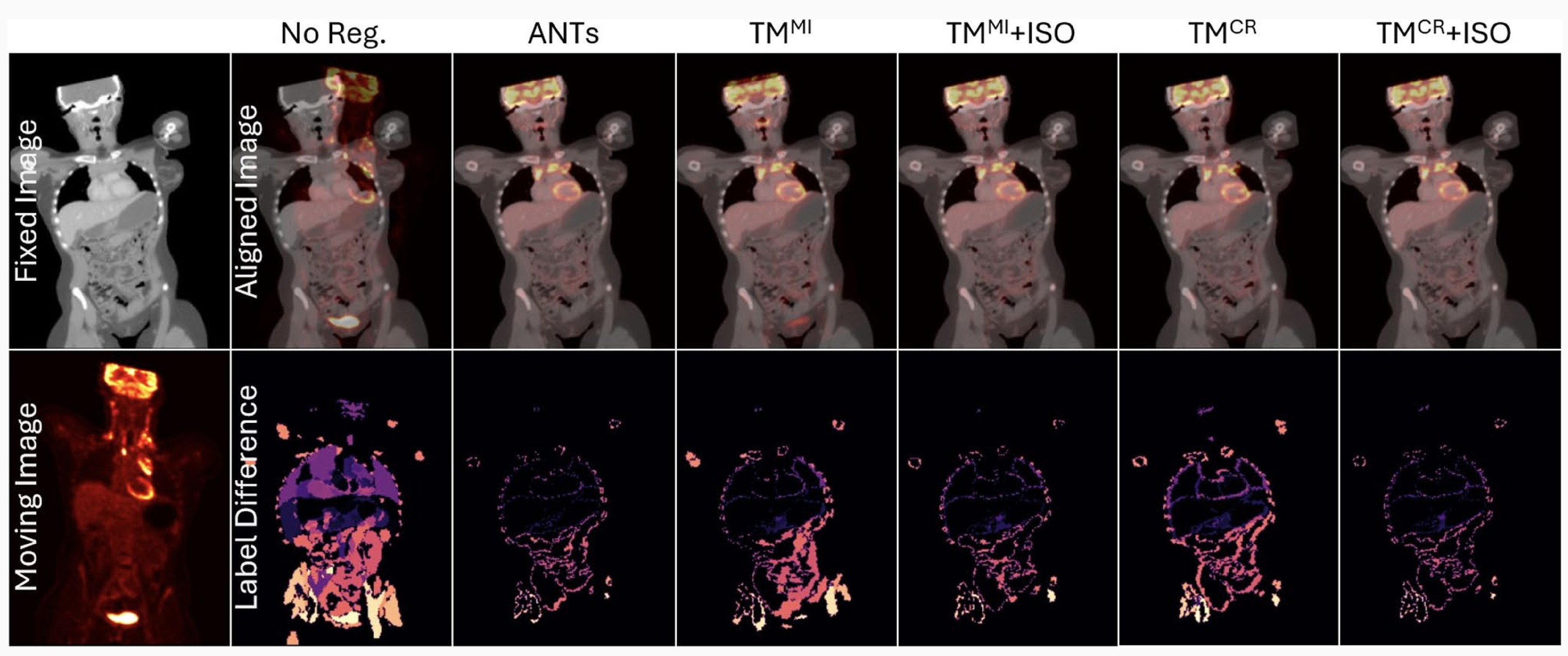
Data: m and f; **Result:** α
$\alpha = \mathrm{DNN}(m, f)$ ▷ DNN estimates affine parameters
$scales = [16, 8, 4, 2, 1]$ ▷ Downsampling factors
$iters = [100, 100, 120, 140, 160]$ ▷ Num. of iterations
for idx **in** $\texttt{enumerate}(scales)$ **do**
  $\hat{m} = \texttt{downsample}(m, scales[idx])$
  $\hat{f} = \texttt{downsample}(f, scales[idx])$
  for $iter$ **in** $\texttt{enumerate}(iters[idx])$ **do**
    $\ell = \texttt{ImgSim}(\hat{m} \circ \alpha, \hat{f})$
    $\alpha \leftarrow \ell$ ▷ Gradient descent to update α
  end for
end for

Results

Dataset:

- autoPET [3] - 628, 90, and 178 images for training, validation, and testing, respectively.
- Random affine perturbation for paired PET/CT.
- All images were resampled to the same voxel dimension of 2.8×2.8×3.8 mm^3.

Results:



	No Reg.	ANTs	TM^{MI}
DSC	0.202±0.054	0.867±0.037	0.629±0.111
	TM^{MI}+ISO	TM^{CR}	TM^{CR}+ISO
DSC	0.843±0.087	0.684±0.119	0.870±0.059

Reference

1. Chen, Junyu, et al. "Transmorph: Transformer for unsupervised medical image registration." *Medical image analysis* 82 (2022): 102615.
2. A. Roche et al., "The correlation ratio as a new similarity measure for multimodal image registration," in *MICCAI*, 1998, pp. 1115–1124.
3. S. Gatidis et al., "A whole-body fdg-pet/ct dataset with manually annotated tumor lesions," Scientific Data, vol. 9, no. 1, p. 601, 2022.