

Unsupervised multimodal image registration using generative networks between imbalanced domains

1. General Info

Project Title: Unsupervised multimodal image registration using generative networks between imbalanced domains

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2. Project Abstract

Registration of transrectal ultrasound to magnetic resonance images is a crucial step for doing prostate biopsies. In recent years, researchers proposed different methods to exploit deep learning for this problem. Since the ground-truth data for this task is not available, Hu *et al.* [1] proposed a weakly-supervised method to deformably register TRUS to MR images. They used the segmentation mask from both modalities for training. Manual segmentation of TRUS images by an expert is especially crucial since the noise and quality of the ultrasound image make it impossible for an untrained eye to segment images correctly. The proposed weakly-supervised method made the training procedure feasible but still costly because of the manual segmentation.

On the other hand, in papers focused on multimodal image registration, researchers proposed to use deep generative models to solve this problem in an unsupervised manner [2, 3]. However, these methods rely on the fact both modalities share the same field of view (FoV) and visible organs and textures, such as T1-T2 MR images. The goal of this study is to adjust these methods for registration problems where two modalities are extremely different, namely ultrasound and MR.

3. Background and Motivation

Multimodal image registration is an inevitable step in medical procedures where images from different modalities are acquired. For image-guided biopsies, doctors use ultrasound to get samples from a uniformly spaced grid on the prostate. In targeted biopsies, information from pre-operative MR and PET images is exploited to pinpoint the exact location of suspicious regions. Registration of live US image to the pre-operative MR would allow for accurate sampling of these selected regions by accounting for the deformation in the soft tissue caused by tool insertion.

Generative networks have been used in the context of unsupervised image registration where no pre-registered image pairs or segmentation mask is available. Qin *et al.* [2] proposed to use disentangled representations to decompose an image into content and attribute. They used the extracted content of images from different modalities to calculate the deformation field. Liu *et al.* [3] proposed a multi-tasking framework of image-translation, registration, and segmentation between two modalities. In all of these works, experiments were done on either T1-T2 MR images or CT-MR images where both modalities share the same field of view and mostly show the same structures. In this study, we will focus on modalities where the FoV and the information disclosed is different, namely ultrasound and MR images. The goal of this study is to elaborate on new methods proposed for a more robust image translation between imbalanced domains based on recent works of [4] and [5]. The next step would be to compare the performance of the new method to the state-of-the-art in the registration of TRUS and MR images.

[2] Qin C, Shi B, Liao R, Mansi T, Rueckert D, Kamen A. Unsupervised deformable registration for multi-modal images via disentangled representations. InInternational Conference on Information Processing in Medical Imaging 2019 Jun 2 (pp. 249-261). Springer, Cham.
[3] Liu F, Cai J, Huo Y, Lu L, Harrison AP. JSSR: A Joint Synthesis, Segmentation, and Registration System for 3D Multi-Modal Image Alignment of Large-scale Pathological CT Scans. arXiv preprint arXiv:2005.12209. 2020 May 25.

[5] Patashnik O, Danon D, Zhang H, Cohen-Or D. BalaGAN: Image Translation Between Imbalanced Domains via Cross-Modal Transfer. arXiv preprint arXiv:2010.02036. 2020 Oct 5.

^[1] Hu Y, Modat M, Gibson E, Li W, Ghavami N, Bonmati E, Wang G, Bandula S, Moore CM, Emberton M, Ourselin S. Weakly-supervised convolutional neural networks for multimodal image registration. Medical image analysis. 2018 Oct 1;49:1-3.

^[4] Zhao Y, Wu R, Dong H. Unpaired Image-to-Image Translation using Adversarial Consistency Loss. arXiv preprint arXiv:2003.04858. 2020 Mar 10.



4. Technical Prerequisites

- Good background in deep generative models
- Good background in medical image processing and registration
- Good skills in Python
- Good skills in PyTorch
- Knowledge on statistics and information theory is beneficial

5. Benefits:

- Possible novelty of the research
- Possible publication

6. Students' Tasks Description

Students' tasks would be the following:

Group 1: Imbalanced domain compensation

- Understanding the underlying methods
- Re-implementing the existing method (UMDIR via disentangled representation)
- Adjusting the method for 3D
- Training and evaluating on TRUS-MR volumes
- Changing the underlying architecture to account for imbalanced domains
- Implementing the evolved methodology.
- Training & evaluating the new method on the TRUS-MR dataset
- Testing and documentation.

Group 2: Modified cycle GAN

- Understanding the underlying methods
- Re-implementing the existing method (UMDIR via disentangled representation)
- Adjusting the method for 3D
- Training and evaluating on TRUS-MR volumes
- Modifying losses and architecture based on new cycle consistency loss and DRIT++
- Training and evaluating on TRUS-MR dataset
- Comparing results and documentation

7. Work-packages and Time-plan:

		Description	#Students	From	То
	WP1	Familiar with the literature.	4	01.11	
	WP2	Familiar with PyTorch, PyTorch lightning, MONAI and TensorBoard. Come up with a detailed time-plan (gantt)	4		
	WP3	Imbalanced domain compensation: Implement	2		
	WP4	Modified cycle GAN: Implement	2		
	M1	Intermediate Presentation II	4	17.12.2020	



Technische Universität München – Faculty of Informatics Chair for Computer Aided Medical Procedures (Prof. Nassir Navab) **Practical Course: Machine Learning in Medical Imaging** (2020WiSe)

WP5	Familiar with clinical data (TRUS-MR dataset) and data augmentation	4		
WP6	Implement and Evaluate WP3 on medical data	2		
WP7	Implement and Evaluate WP4 on medical data	2		
WP8	Testing and Documentation	4		
M2	Final Presentation	4	26.02.2021	

