Whole Slide Image Registration Using Deep Features for the ACROBAT Challenge

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This document briefly describes the method used in the AutomatiC Registration Of Breast cAncer Tissue (ACROBAT 2023) challenge[1]. The method is largely based on Awan et al.'s Deep Feature-Based cross-slide Registration method [1] and TIAToolbox WSI processing tools [2]. This document focuses on major differences between [1] and this work. The code is available on GitHub[2,3].

Introduction

The process of spatially transforming a set of images into a unified coordinate system is known as registration [3]. Registering Whole Slide Images (WSIs) is required for cross-slide analysis, multi-modal fusion of images, and 3D construction of tissues [1].

In this year's ACROBAT challenge, a moving image, either an immunohistochemistry (IHC) WSI should be registering with a fixed image, usually a Hematoxylin and Eosin (H&E) stained WSI. The challenge dataset includes a 750-case training set that includes one H&E WSI and up to four IHC (ER, PGR, HER2, KI67) WSIs, a validation set that includes 100 H&E-IHC pairs, and a hidden test set that comprises 200 pairs that can be either IHC-HE and IHC-IHC WSIs.

Method

The registration process involves several steps to pre-process images, perform tissue segmentation, carry out DFBR, and generate output image and landmarks.

Step 1: Pre-Processing

This step involves greyscaling the input image pair and performing adaptive thresholding, which prepare the image for tissue segmentation.

Step 2: Tissue Segmentation

A segmentation model based on U-Net is trained on 179 annotated WSI images from the training set. The images are annotated to distinguish between background, foreground tissue, and control tissue. The model has been trained over 100 epochs. During inference, pre-processed images are segmented using the trained model, producing two tissue masks. The training code is available on GitHub[3].

Step 3: DFBR and Landmark Registration

Following Awan et el.'s method [1] and TIAToolbox registration tools [2], segmented tissues are registered using DFBR, which includes pre-alignment and rigid registration. DFBR employs a pre-trained VGG-16 model that is used extract useful features from input images that aid in producing the DFBR transformation matrix.

Following, landmark registration is carried out by applying the producing transforming to the provided moving image landmarks while considering factors such as processing resolution and output resolution. Figure 1 shows an example output of DFBR using a sample taken from ACROBAT 2023 validation set. A full example Jupyter notebook is available on GitHub[3].

[1] https://acrobat.grand-challenge.org
[2] https://github.com/adamshephard/TIA-Acrobats
[3] https://github.com/TIA-ACROBATS

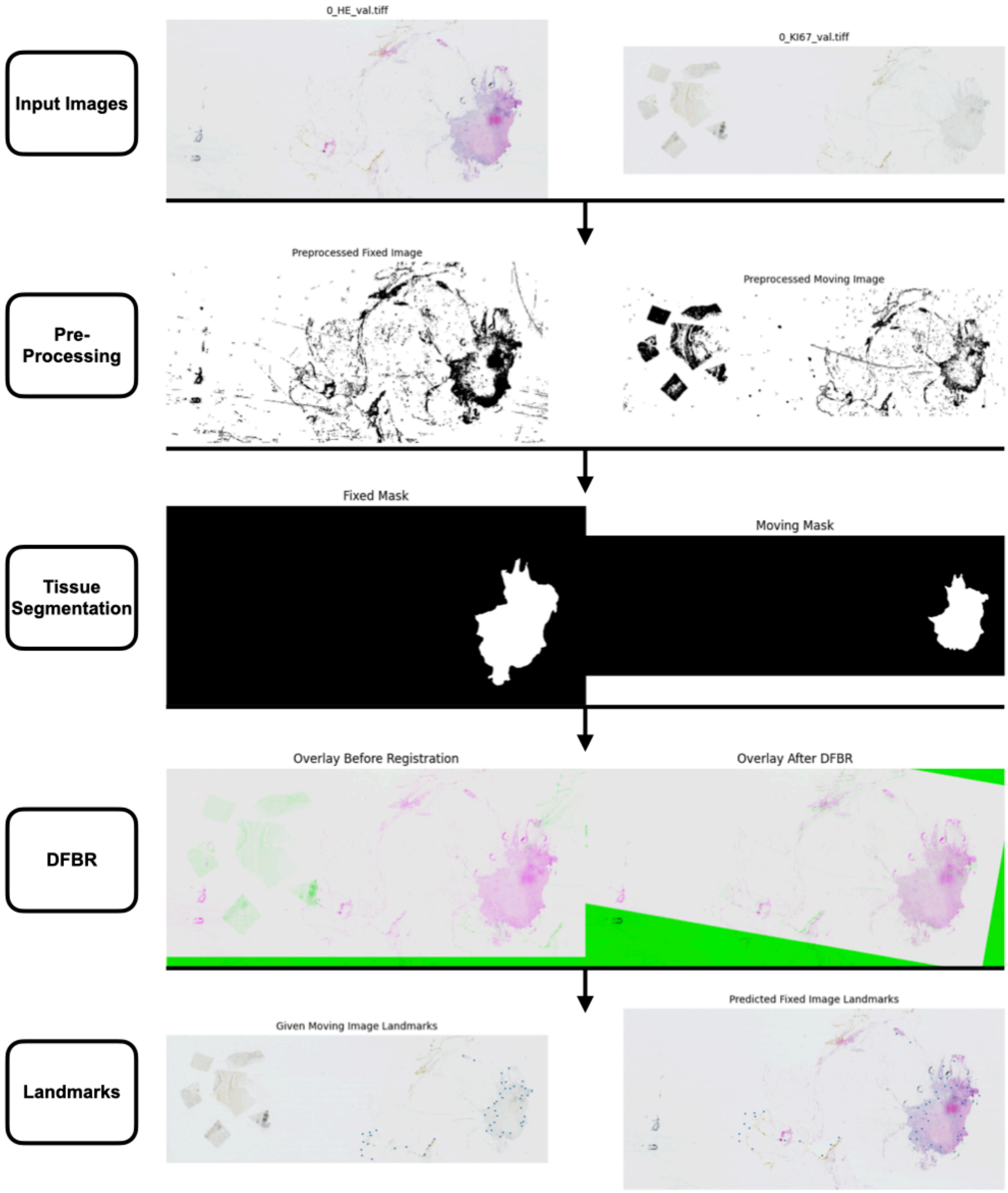

Figure 1. The DFBR pipeline from pre-processing, tissue segmentation, to rigid registration, and transforming landmarks.

Non-Rigid Registration

As a work in progress, TIAToolbox's b-spline-based non-rigid registration method [4] is being extended to incorporate WSIs, and not only selected patches as well as performing landmark transformation based on the output of the b-spline method.

References

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