Image Registration for ACROBAT Challenge: Team MEDAL

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Abstract. We present a methodology of our submission for ACROBAT - a image registration challenge for histopathology whole slide images.

Keywords: Image registration · Whole Slide Images · Histopathology.

1 Methods

We can divide our image registration pipeline in two stages, ie. local registration stage and local correction stage. We briefly describe working of both the stages in following subsections.

1.1 Global Registration

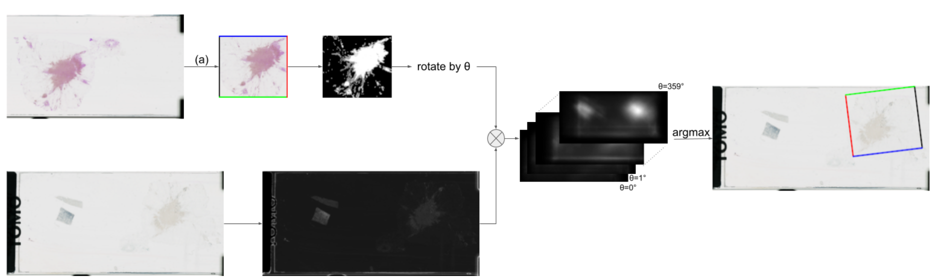

Fig. 1. Global registration estimates shift and rotation between HE and IHC using convolution between pre-processes IHC and rotated pre-processed HE crop. (a) Tissue detection for HE images is done using patch based classification model. Boundaries for HE tissue bounding box and IHC tissue bounding box are colored to highlight orientation.

We detect tissue in HE image using a ResNet-18 based patch classification model trained primarily on patches BRIGHT dataset. We re-train it with patches from ACROBAT dataset. We consider epithelial and stromal region as foreground. After tissue detection we detect tissue dense region in HE images as shown in Figure 2. Specifically, we create a density map of foreground in X and

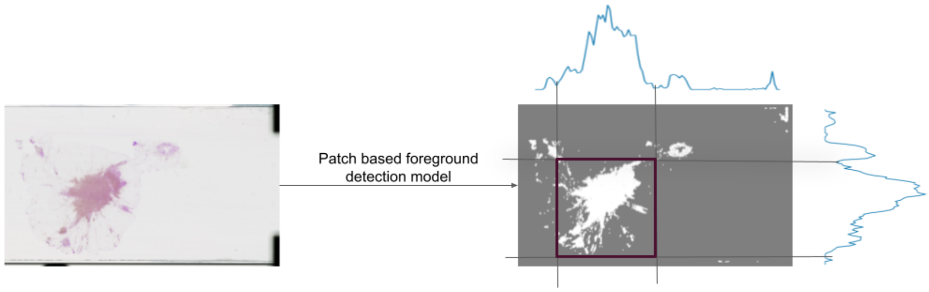

Fig. 2. Tissue detection and bounding box for tissue dense region

Y direction. We cut the HE whole slide image where density map crosses value lesser than 5% of maximum value for a density map.

Next, we estimate shift and rotation of tissue in IHC image with respect to tissue in HE image by template matching using convolution operation. We invert HE bounding box image to get H_i. Similary we invert IHC image to get I_i. We replace black-like pixels in IHC with white pixels to avoid getting maxima at edges. We rotate H_i from $0°$ to $360°$ to get output tensor T of size $360 \times I_{ih} \times I_{iw}$, where I_{ih} and I_{iw} are height and width of I_i respectively. Finally we get global registration of HE and IHC images by taking argmax of T. All the operations at this stage are carried out using images down-sampled by 32 from level 0. PyTorch is used for performing convolution operation.

$$\theta^*, x^*, y^* = argmax(T) \tag{1}$$

1.2 Local Corrections

After obtaining parameters for global registration, we try to estimate local correction to be applied across HE image. We estimate corrections to be applied in X-axis and Y-axis independently. First, we sample the points, $H_p = h_{p1}, h_{p2}, ...$ on HE tissue edges using foreground mask obtained using foreground detection model. We then use global registration parameters θ^*, x^*, y^* to get corresponding point i_p in IHC image.

$$i_p = f(h_p, \theta^*, x^*, y^*) \tag{2}$$

We employ similar strategy as used in global registration to get local corrections. We take 256×256 sized patch from HE image and 640×640 sized patch from IHC image around h_p and i_p respectively. These patches are down-sampled to factor of 16 from level 0. We invert both of these patches and perform convolution operation to get output tensor of size 384×384. *argmax* operation on this tensor gives local correction to be applied for point h_p. For around 50% of points we do not get desired output from this operation. *argmax* of convolution outputs coordinates on the edges if tissue dense region present in IHC patch. We remove those points from further analysis. Specifically, if local correction in any axis crosses 150 pixels of correction, we discard those points. Further, we remove points with sharp maximas.

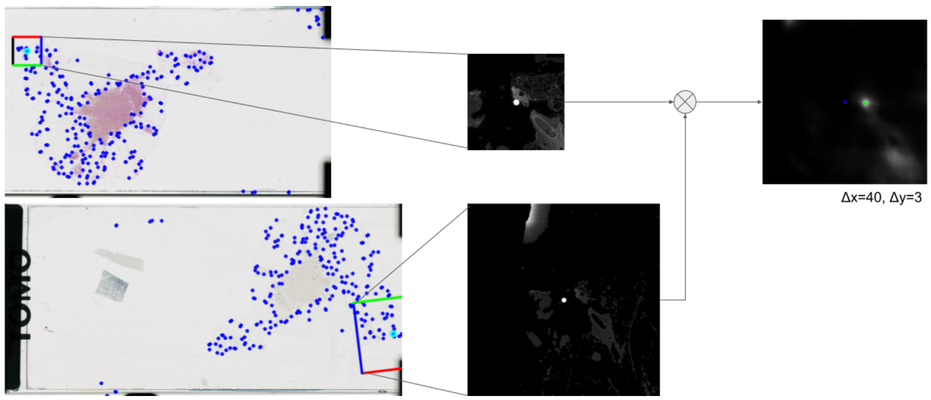

Fig. 3. Points on HE tissue edge are sampled using binary mask obtained from tissue detection model. Corresponding IHC point is obtained using global registration parameters. Square patch around sampled point in HE is inverted. Similarly, a bigger patch around a point from IHC is inverted. *argmax* of convolution gives local correction Δx and Δy

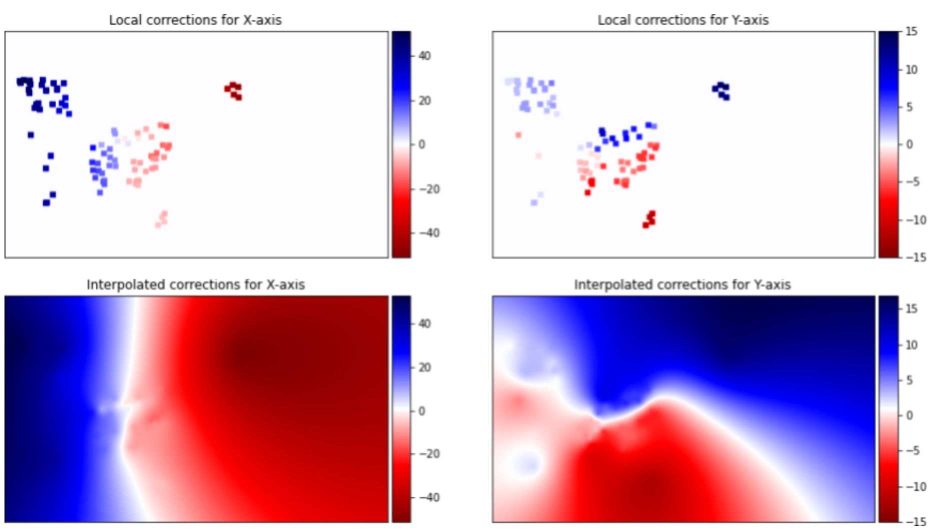

Fig. 4. Interpolation of local corrections in X-axis and Y-axis. Number in color-map correspond to down-sampled numbers by factor 16.

Interpolation: We use radial basis function based interpolation for local corrections in X-axis and Y-axis independently to obtain local correction maps X_c and Y_c across HE image as shown in Figure 4. Finally, we use global registration parameters θ^*, x^*, y^* along-with X_c and Y_c to output the registration map. Interpolation is performed using scipy library.

References

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