AGHSSO - Short Description of the Contribution to the ACROBAT Challenge

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Abstract. This short note describes the contribution of the AGHSSO team to the ACROBAT challenge organized during MICCAI 2022.

Keywords: ACROBAT · Image Registration

1 Introduction

We present a brief description of our contribution to the ACROBAT challenge [4]. The presented contribution is a part of the DeeperHistReg framework (work in progress). The full DeeperHistReg framework will be released openly soon [5].

2 Methods

The proposed method consists of three consecutive steps: (i) a preprocessing, (ii) an initial alignment to robustly calculate the affine transformation, (iii) a nonrigid registration to calculate the dense displacement field and recover the fine-details.

2.1 Preprocessing

The preprocessing starts with resampling the images to a resolution desired during the nonrigid registration step. Then, the images are padded to the same shape, converted to grayscale, and inverted. Finally, we apply the CLAHE algorithm [7].

2.2 Initial Alignment

The initial alignment is based on a feature-based affine registration, followed by an intensity-based affine instance optimization.

The feature-based affine registration starts with calculating the SIFT [2] and SuperPoint [1] keypoints and descriptors. The SuperPoint model is used directly as provided by the authors, without any additional fine-tuning. The keypoints and descriptors are matched using RANSAC and SuperGlue [3] methods. The process is repeated for several angles (by rotating the source image by 60 degrees), resolutions (from 200 to 600 pixels in the smaller dimension), and transformation types (rigid and affine). The best transformation is chosen based on a sparse descriptor error.

The feature-based registration is fine-tuned by iterative affine registration. The method is based on an instance-optimization implemented in PyTorch. The registration is multi-level (4) and the highest resolution is 256 in the smaller dimension. The method optimizes the local normalized cross-correlation (NCC) with the window size equal to 7.

2.3 Nonrigid Registration

The nonrigid registration is a multi-level instance optimization-based iterative procedure implemented in PyTorch. It optimizes the weighted sum of local NCC (window equal to 7) and the diffusive regularization. The algorithm is run for a predefined number of iterations (400) for each pyramid level with a constant learning rate, using the Adam optimizer. The regularization coefficient varies between levels, starts from 1.2 and decreases to 0.6.

3 Results

The proposed method successfully registered all the validation pairs expect the ID 61 (flipped image, extremely blurred). The achieved score in terms of 90th percentile of median TRE and 90th percentile of mean TRE is: 144.50, and 235.43 respectively (not visible in the leaderboard).

The average registration time (GeForce RTX 3090 Ti) is: (i) 27.8, (ii) 38.28, (iii) 59.78, (iv) 156.17 seconds for the 1024, 2048, 4096, 8192 pixels in the smaller dimension respectively (for the nonrigid registration). The number of pyramid levels is 6, 7, 8, 9 respectively. Interestingly, the lowest TRE error was achieved for 2048 pixels in the smaller dimension, even though the visual assessment of the registration at higher resolutions have shown better alignment of the fine-details. However, the differences between subsequent resolutions are not statistically significant.

4 Discussion and Conclusion

The proposed method successfully registered the majority of the H&E/IHC WSI pairs. However, the algorithm has several drawbacks that will be addressed in future work:

- The initial affine transformation search should be greatly simplified. Due to the multi-resolution and multi-descriptor approach the initial affine registration takes around 20 seconds with a GPU acceleration. In future work, we will try different approaches and change the best transformation decision from sparse descriptor error to e.g. robust dense similarity measure within tissue or characteristic of the keypoint matches (number of matches, confidence of a particular match).
- The affine registration is very sensitive to parameter changes. The number and the influence of the parameters should be decreased.
- The nonrigid method is unable to register the images at full resolution. With resolution above 12000 x 12000 the GPU memory saturates. We will use the patch-based approach to nonrigid registration [6] at the highest resolution as a step after the initial nonrigid registration.

Undoubtedly, the most difficult challenge was to perform a robust initial registration. Since the quality of the slices varies strongly, it was problematic to directly use simple feature- or intensity-based methods in a fully automatic procedure.

The quantitative results strongly vary between slices. The more the missing data (target slice further from the source slide), the worse the registration results. It is expected because registering images without correspondences is hardly possible.

Interestingly, our experiments have shown that increasing the resolution does not improve the quantitative results, even though the qualitative assessment favors the higher resolutions.

A detailed description of the experiments, ablation studies and deep nonrigid networks will be released in a publication releasing the DeeperHistReg framework.

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