Multi-Organ Segmentation using deeds, Self-Similarity Context and Joint Fusion

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Abstract. A very fast and highly accurate pipeline for automatic multi-organ segmentation of challenging abdominal and cervical CT scans is presented. Pivotal to the approach is the publically available **deeds** deformable registration framework, which is based on discrete optimisation and enables the estimation of very large deformations from atlas scans to patient images in few seconds. The robustness and accuracy are improved by using the local self-similarity context (SSC) as metric and by replacing a standard majority voting with a joint fusion and corrective learning approach.

1 Method

We resampled the scans to an isotropic resolution of 2.2 mm^3 and padded or cropped them to have same dimensions. An affine pre-registration is performed using block-matching on four scale levels. The freely available deformable registration tool **deeds** [1] is then used with the following parameters: number of displacement steps $l_{\max} = [6, 5, 4, 3, 2]$, quantisation steps $q = [5, 4, 3, 2, 1]$, and B-spline grid spacings of $[8, 7, 6, 5, 4]$ voxels. Self-similarity context [2] was used as a similarity metric with a weighting of $\alpha = 0.4$. Computation times are 45 sec. per scan-pair (approx 15 sec. for affine alignment and 30 sec. for deformable registration using an efficient CPU-only OpenCL implementation).

2 Results

Dice overlaps for the abdominal dataset are substantially improved over the provided NiftyReg registrations [3] from 46.3% to 59.2% for a majority vote. These gains stem most likely from the dense displacement sampling and our discrete optimisation. The accuracy can be further improved to 70.2% by non-local means fusion [4], to 77.0% by joint label fusion [5] and to 79.0 % by corrective learning [6]. Table 1 shows an overview of our results for the abdominal data. Our pipeline performance on average best among all challenge participants for both datasets (we have not yet included joint label fusion for the cervix, the score for there **deeds** and non-local means is 62.7 %, entity ID: syn3972060).

Table 1: Numerical results of the label fusion variants (majority voting, non local means, joint fusion and corrective learning) applied to the **deeds** registration results for the abdominal challenge dataset (Dice overlap averaged across 13 organs, mean surface distance reported in mm).

method	niftyMajor	deedsMajor	deedsNLM	deedsJoint	deedsJointCL
average Dice	0.463	0.592	0.702	0.770	0.790
standard dev	0.296	0.240	0.182	0.139	0.117
mean-surface-dist	8.635	4.548	3.623	2.454	2.262
entity ID syn	3498727	3917799	3917814	4635822	4650176

3 Discussion

The bottleneck with over 2 hours processing time (per test scan) is currently the joint label fusion (compared to 22 minutes in total for registrations). We plan to increase the efficiency of this step by exploiting box-filters as presented in our recent work [7]. A further speed-up for the deformable registrations could be obtained when focussing the discrete displacement search on fewer salient keypoints as presented in [8].

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