Rethinking the **Design of Learning based Inter-Patient Registration** using Deformable Supervoxels

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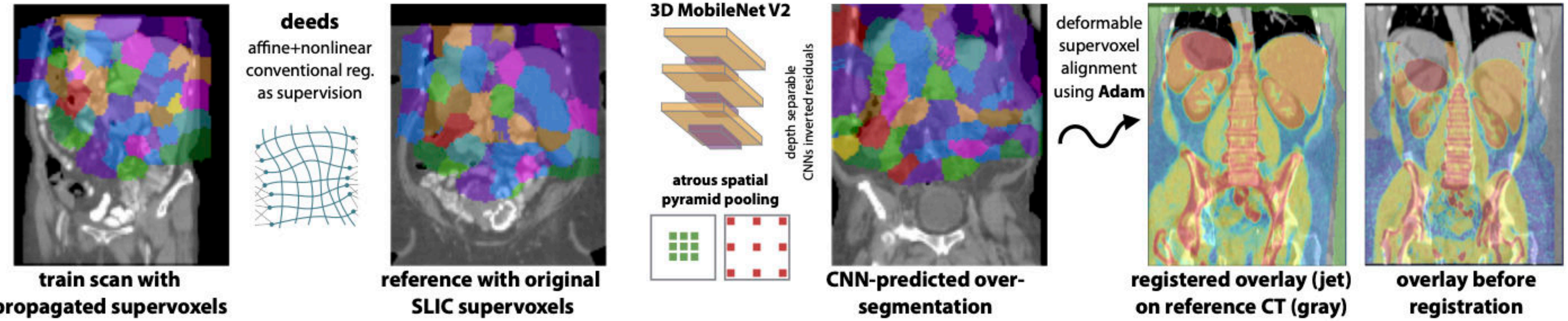
→ **Solve registration by segmentation** (and without anatomical labels)

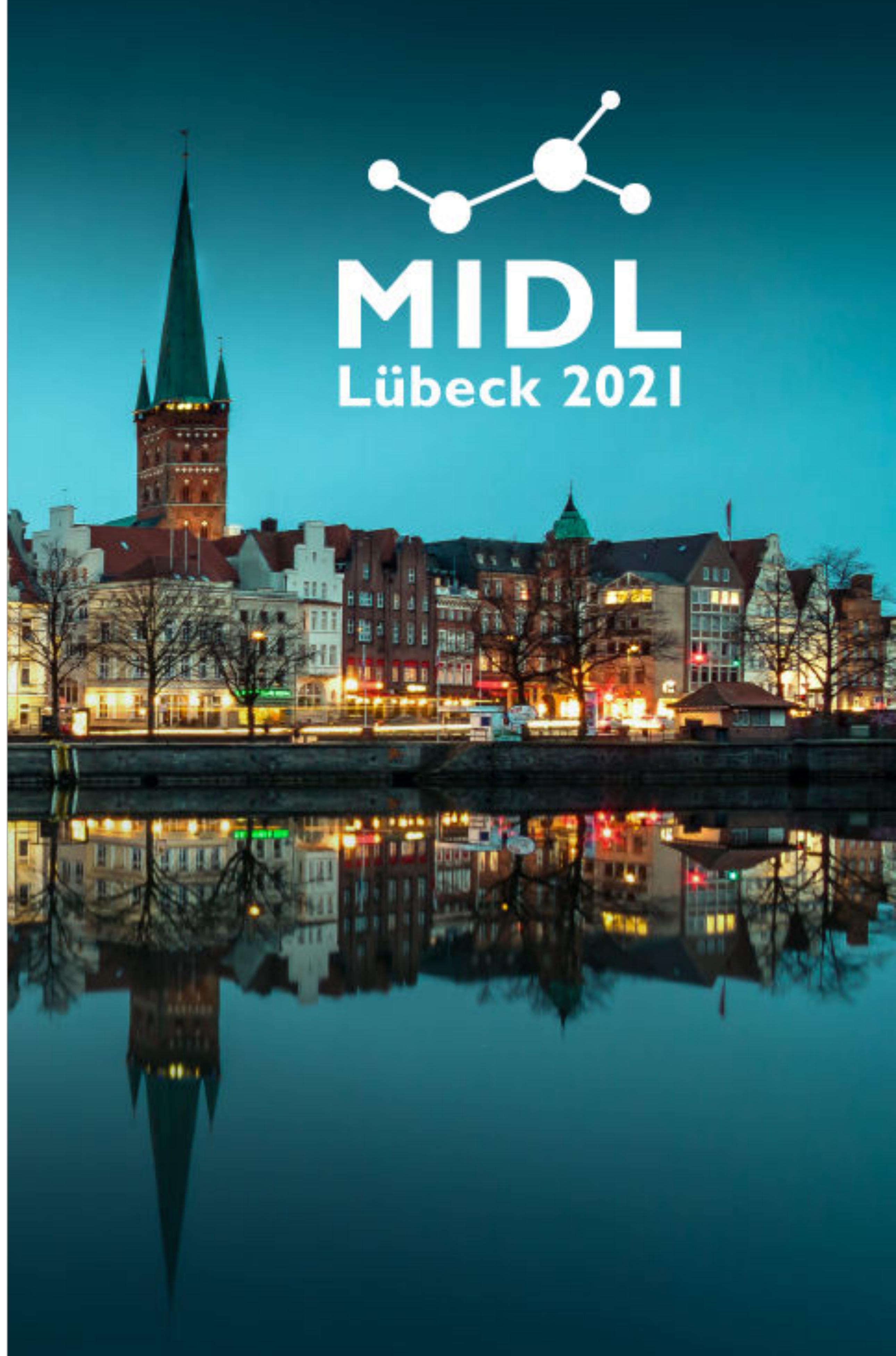
- **modular design** that lets us to **leverage any segmentation pipeline**
- novel **integer encoding of spatial canonical coordinates self-supervised** framework **w/o any expert annotations**
- **superior registration quality** without need for pre-alignment



Code + Data publicly available

https://github.com/multimodallearning/slic_reg

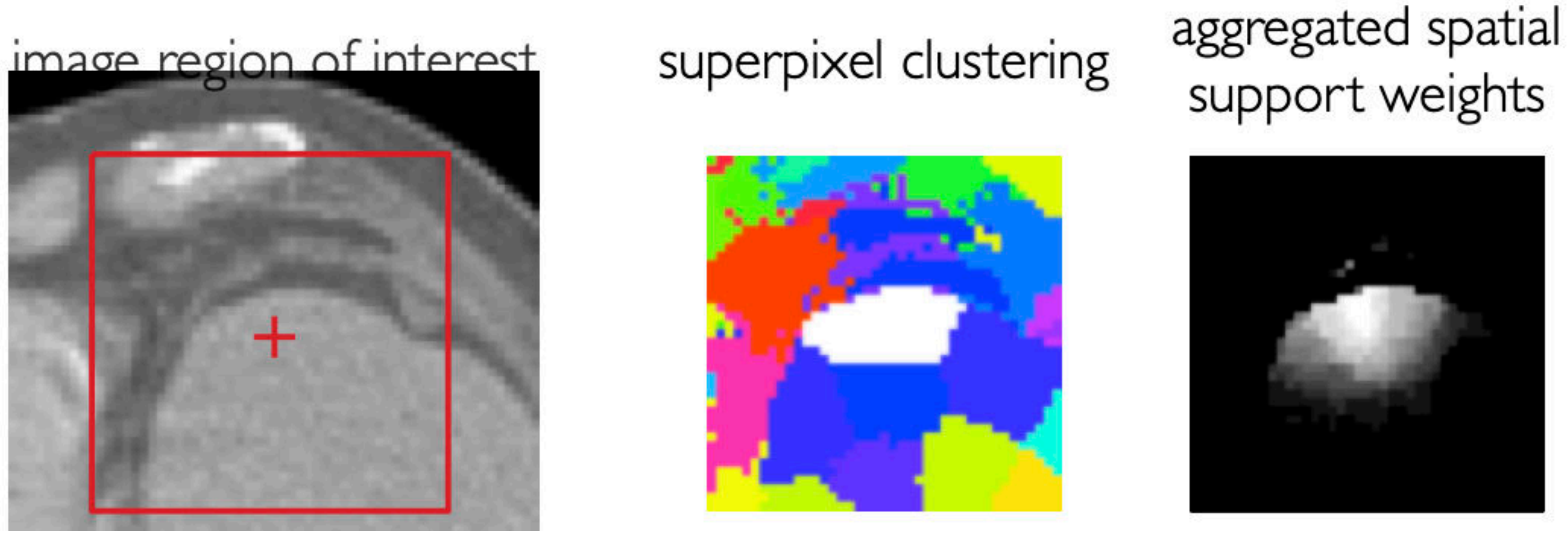
try to beat us at learn2reg.grand-challenge.org (MICCAI 2021 workshop)



→ Idea: Solve registration by segmentation but without using anatomical labels

- to leverage segmentation pipelines we need an **integer encoding of spatial coordinates** (within a canonical space *supervision*)
- finding a **good compromise** between too large number of classes and spatial precision (3D SLIC supervoxel algorithm for template)

→ **layers of supervoxels°** 16 x 128 (alternative: hierarchical softmax)

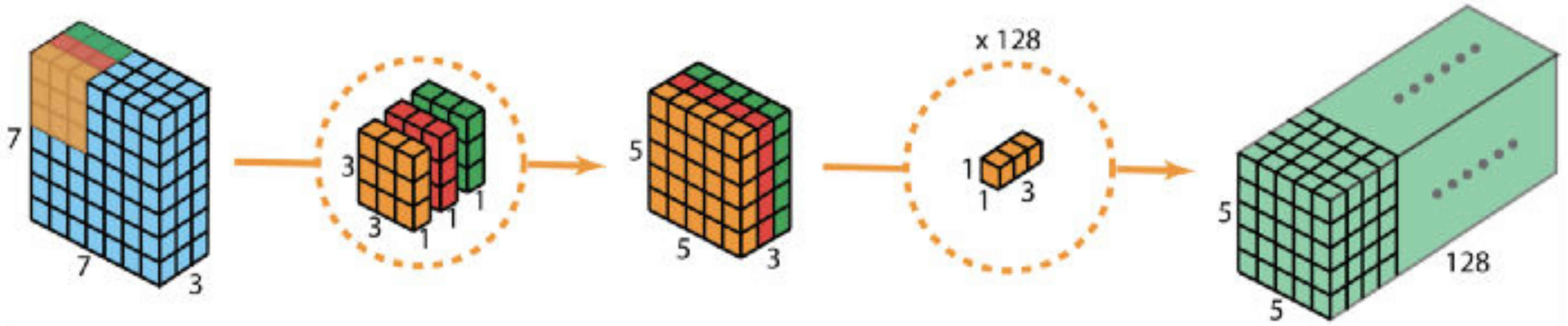


***supervision*:** we select one scan as template for groupwise alignment and run **deeds** (MIND+discrete optimisation) for **self-supervision** github.com/mattiaspaul/deedsBCV

→ deeds displacements are used to warp the template supervoxels

°Edge- and detail-preserving sparse image representations ..
http://www.mpheinrich.de/pub/IPMI2013_mycopy.pdf **IPMI 2013**

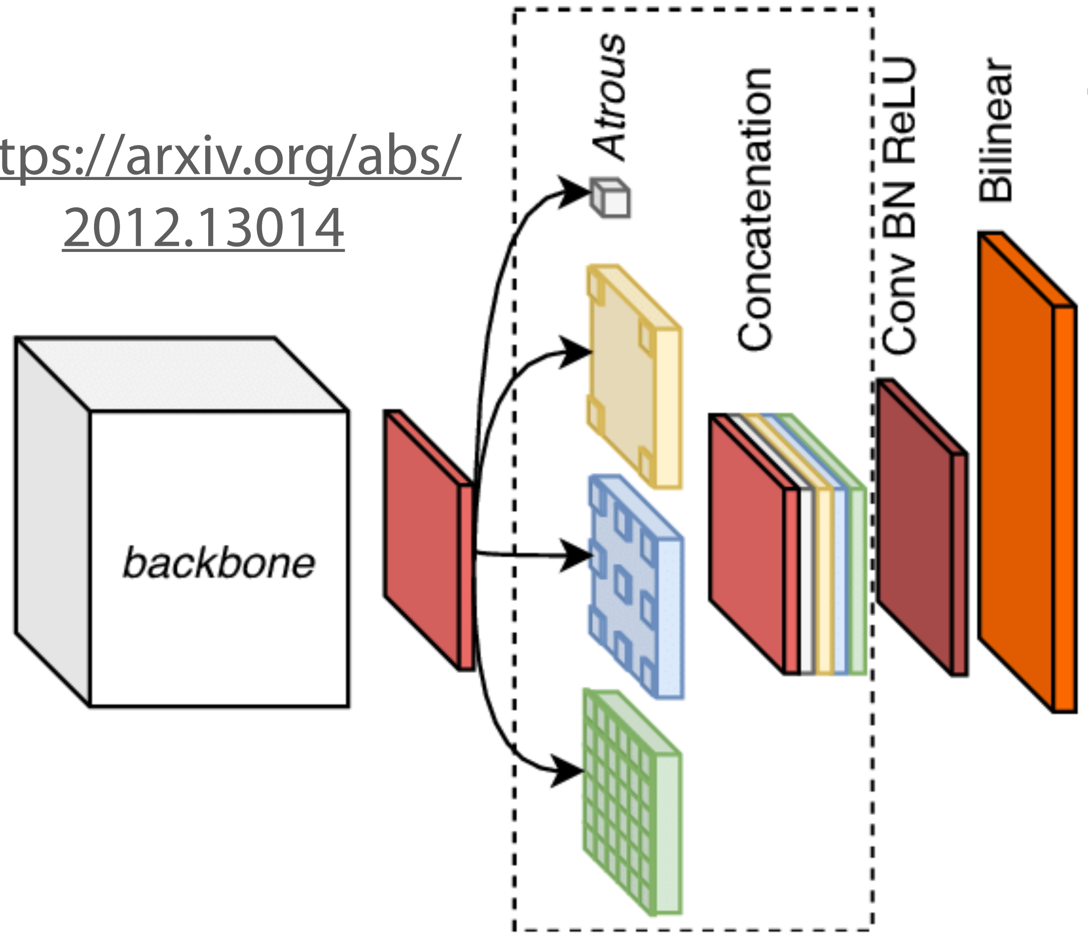
leverage segmentation to predict integer encoding of spatial canonical coordinates



https://towardsdatascience.com/a-comprehensive-introduction-to-different-types-of-convolutions-in-deep-learning-669281e58215

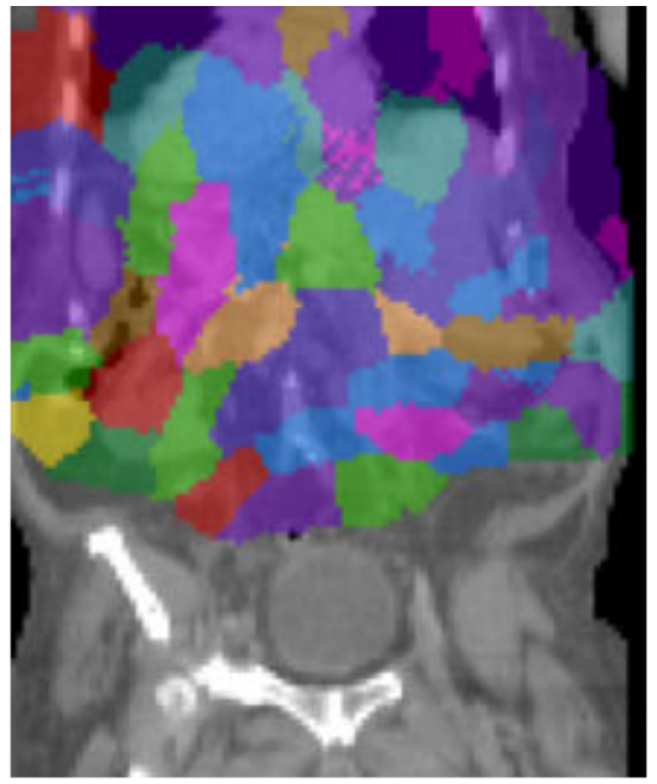
3D MobileNet v2 backbone with 220k trainable parameters

https://arxiv.org/abs/2012.13014



3D Atrous Spatial Pyramid Pooling

+ **multi-head supervoxel prediction** 16 x 128 classes

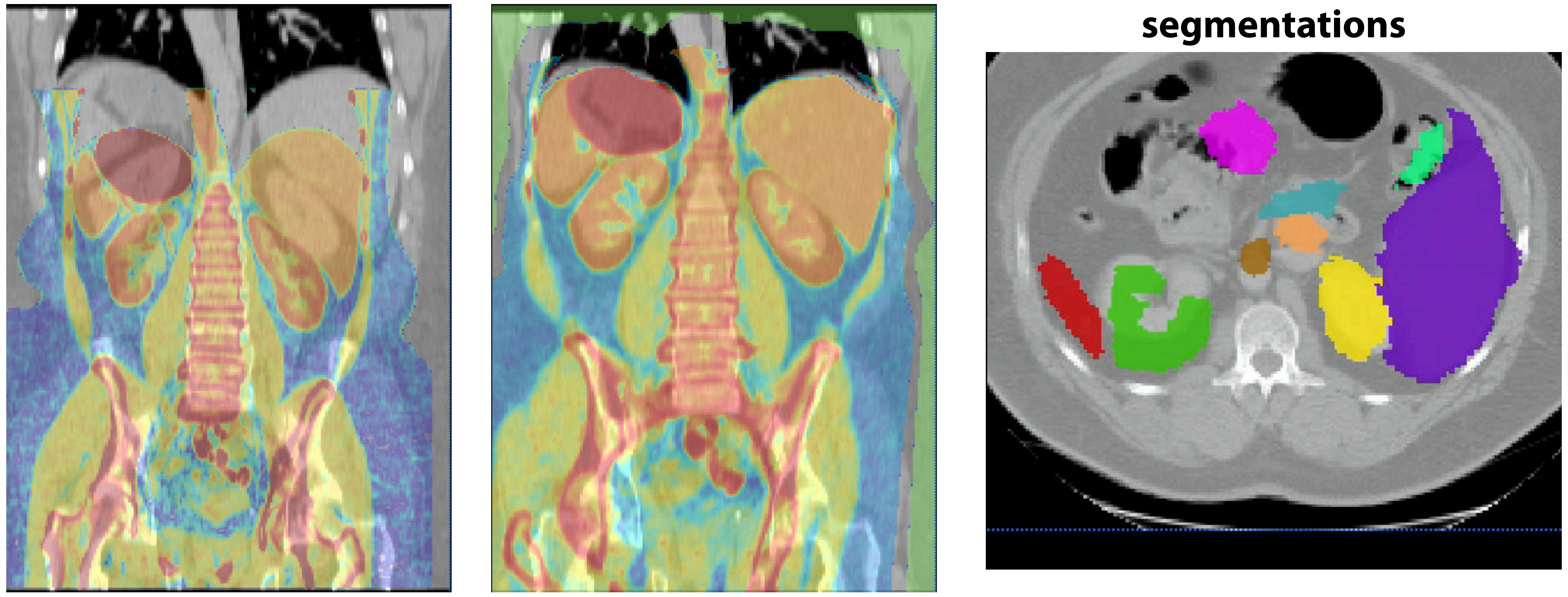


→ pixelwise coordinate classification for each individual scan

from pixelwise supervoxel classification to dense registration

- N=2048 **supervoxel centres form 3D keypoint graph**
- **maximise alignment** of segmentation (**one-hot+STN loss)** and deformation smoothness
- using **iterative Adam optimisation (<1 sec. on GPU)** extrapolate field with thin-plate-spline

```
lr = 0.05; alpha = 0.015; k = 8; num_iter = 100; N = 2048
def adam_optim(kpts_fixed, feat_kpts_fixed, feat_moving,alpha):
    class Flow(nn.Module):
        def __init__(self):
            super(Flow, self).__init__()
            self.flow = nn.Parameter(torch.zeros(kpts_fixed.shape))
        def forward(self):
            return self.flow
    net = Flow().to(device)
    optimizer = optim.Adam(net.parameters(), lr=lr)
    weight = knn_graph(kpts_fixed, k)[2]
    for iter in range(num_iter):
        optimizer.zero_grad()
        flow = net()
        kpts_moving = kpts_fixed + flow
        feat_kpts_moving = F.grid_sample(feat_moving,\
            kpts_moving.view(1, 1, 1, -1, 3),\
            mode='bilinear').view(1, -1, N).permute(0, 2, 1)
        data_loss = F.mse_loss(feat_kpts_moving, feat_kpts_fixed)
        reg_loss = (pdist(flow)*weight).sum()/(kpts_fixed.shape[1])
        loss = data_loss + alpha*reg_loss
        loss.backward()
        optimizer.step()
    return flow.detach()
```



Method	spleen	r.kidney	l.kidney	liver	avg(4)	avg(13)
initial not registered	18.0±17.7	12.5±14.9	9.0±12.5	26.2±18.1	16.4±16.6	8.8±13.4
PDD-Net two warps (s.o.t.a.)	48.8±26.5	49.0±23.3	42.3±23.0	60.2±23.6	50.1±24.0	29.1±25.3
3D UNet + Regression + RW	30.2±16.8	41.9±17.8	35.3±8.8	57.4±8.5	41.2±16.7	23.2±18.2
3D UNet + Slic + Adam	57.1±9.4	38.4±12.1	41.8±12.1	71.8±9.0	52.3±17.0	30.0±22.1
3D DeepLab + Regression + RW	31.1±16.6	45.6±15.6	43.2±10.6	57.7±8.4	44.4±15.9	25.1±19.3
Slic-Reg 3D DeepLab + Slic + Adam	62.4±9.2	50.8±11.8	49.1±13.5	74.1±8.6	**59.1±14.6**	31.8±23.6

when considering the Dice for four major abdominal organs
- **DeepLab** performs **6.8%pt better than U-Net**
- Over-**segmentation is 14.7%pt better than regression**
- **Slic-Reg outperforms PDD-Net** (sota w/ 2 warps) **by 9%pt**

PDD-Net: Closing the Gap between Deep and Conventional Image Registration .. https://arxiv.org/pdf/1907.10931.pdf **MICCAI 2019**