Learn2Reg Tutorial MICCAI 2019

Discrete Deep Learning Registration

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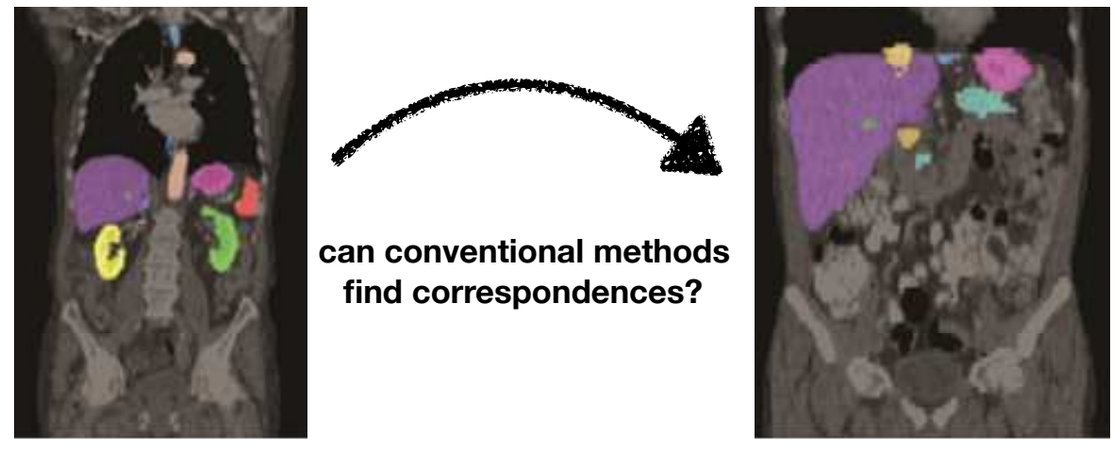
Hands-On: kaggle.com/mattiaspaul/learn2reg-tutorial

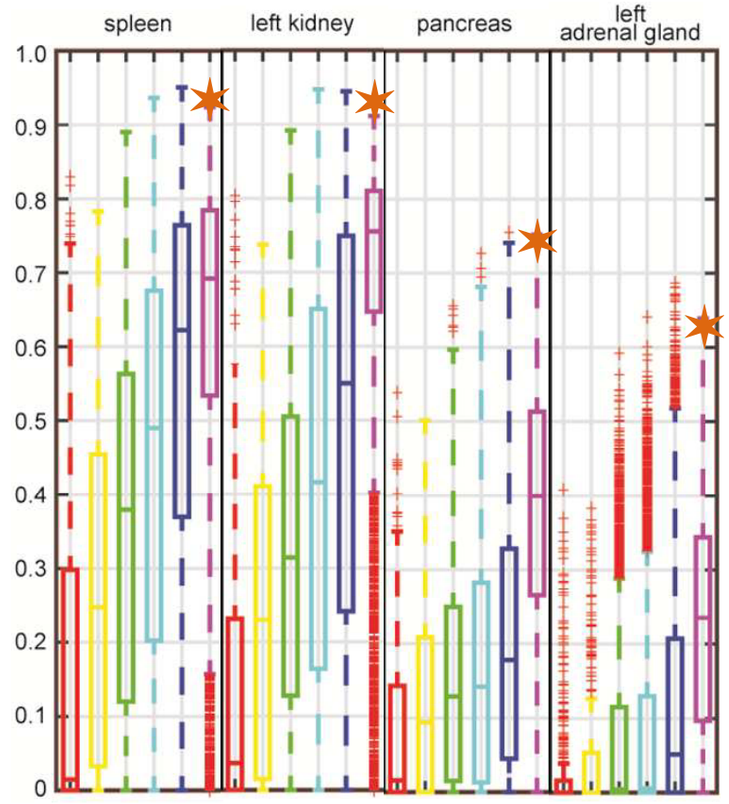
Motivation for Discrete Registration and Overview

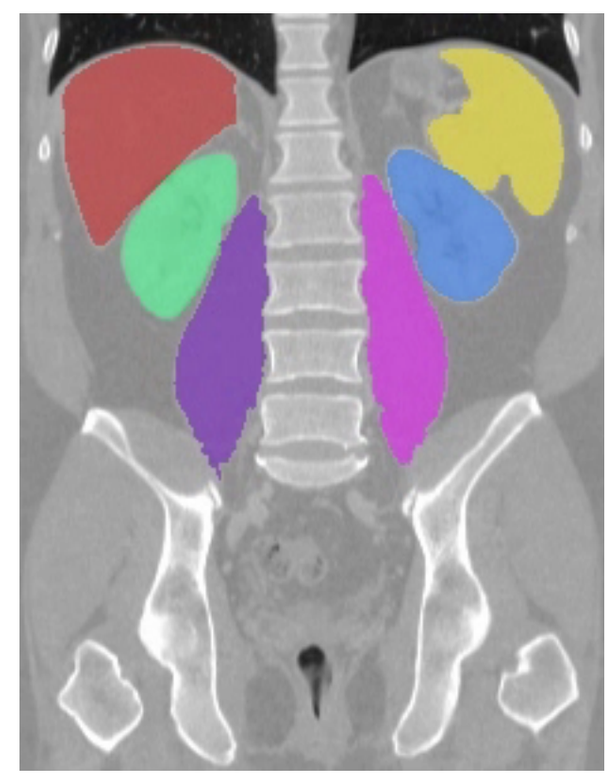
thoracic and abdominal scans have exhibit very large deformations: registration using standard DL architectures cannot directly capture this



data available https://www.synapse.org/#!Synapse:syn3193805/wiki/89480

Z. Hu: "Evaluation of Six Registration Methods for the Human Abdomen on Clinically Acquired CT" **IEEE TBME 2016**



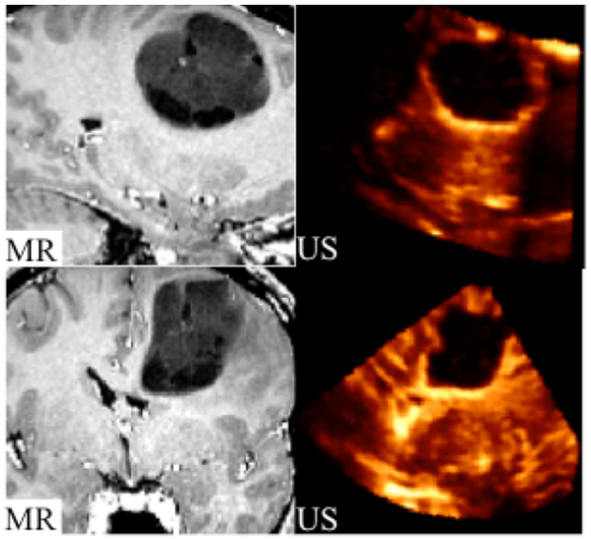


"We see a new direction in fundamental design for the registration method towards the challenging problems in abdomen. deeds (discrete registration) yields the best performance in this study, and it is different from other methods mainly by using discrete optimisation. This type of **discrete design can capture a large range of potential deformations**, and thus coped well with the discontinuous pattern between structures of interest in abdomen."

FSL, ANTS-CC, ANTS-MI, IRTK, NiftyReg, deeds

try out: github.com/mattiaspaul/deedsBCV

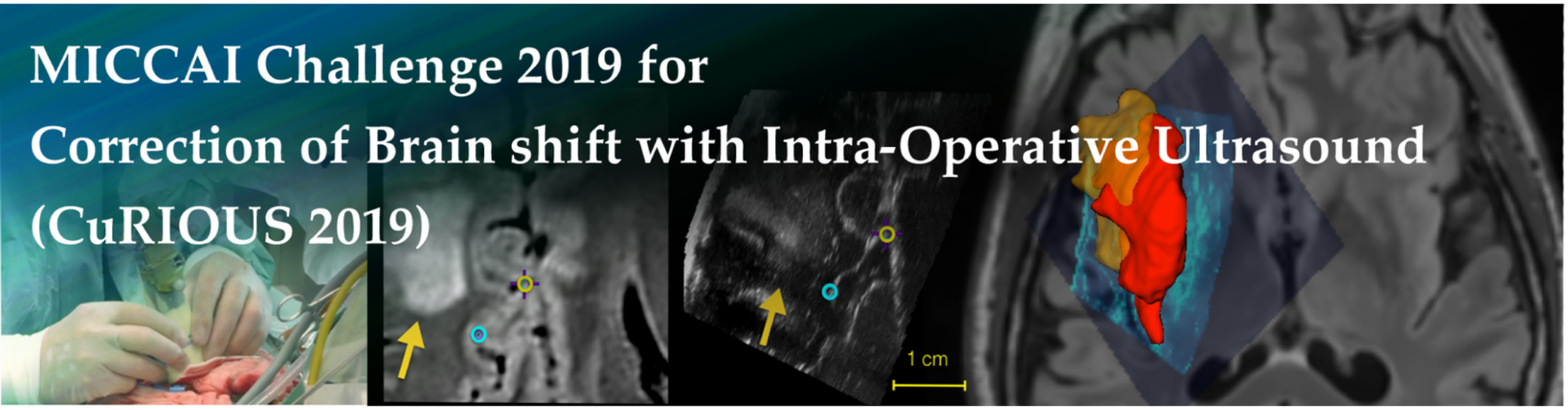
More registration tasks hard to solve with DL



ultrasound guided brain tumour surgery (MNI McGill)

large initial misalignment and different contrast
limited field of view in ultrasound
→ 3/3 DL-approaches failed (last places)

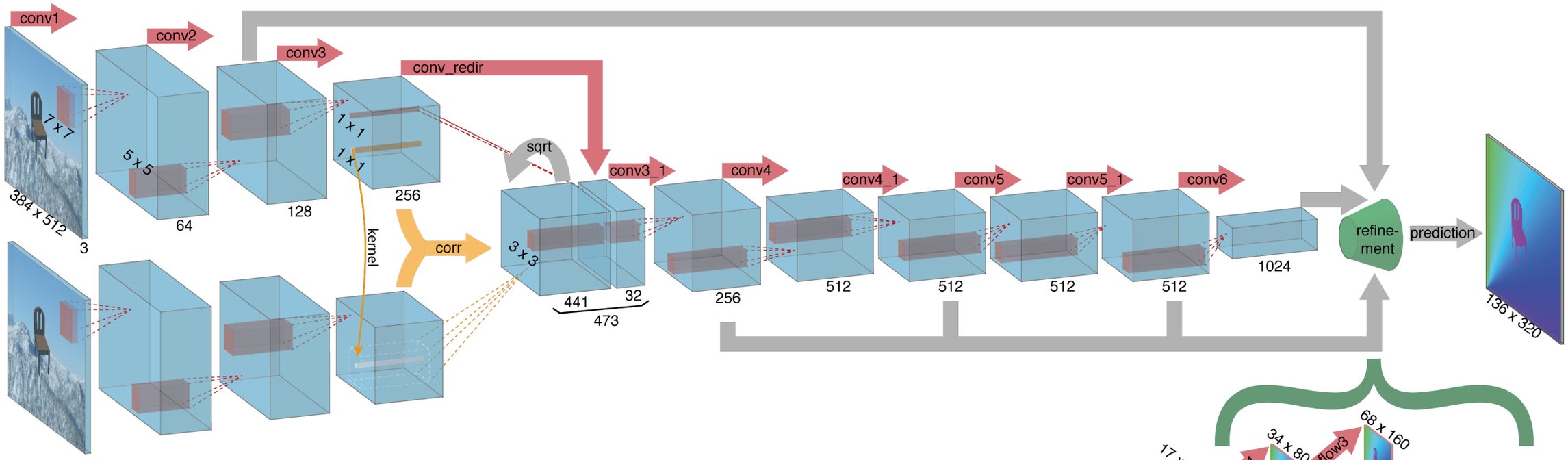
open for participation:
https://curious2019.grand-challenge.org

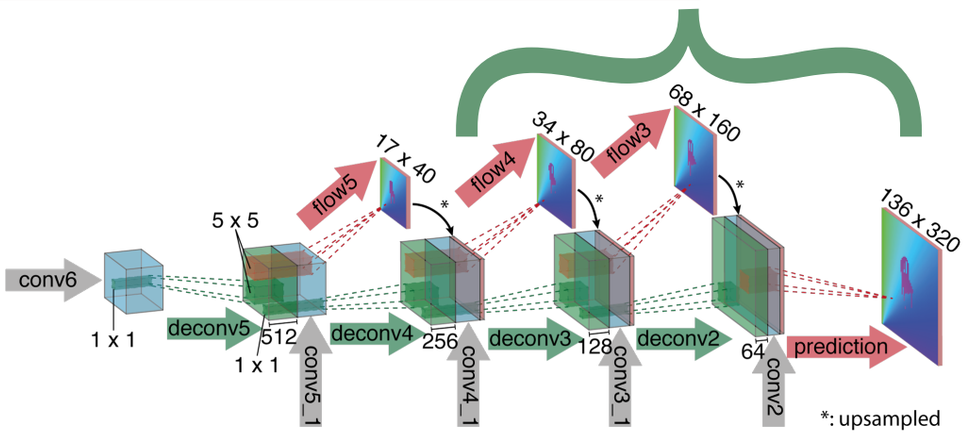


Large deformations with discrete displacements

P Fischer, et al.: "FlowNet: Learning Optical Flow with Convolutional Networks" ***CVPR 2015***

FlowNetCorr



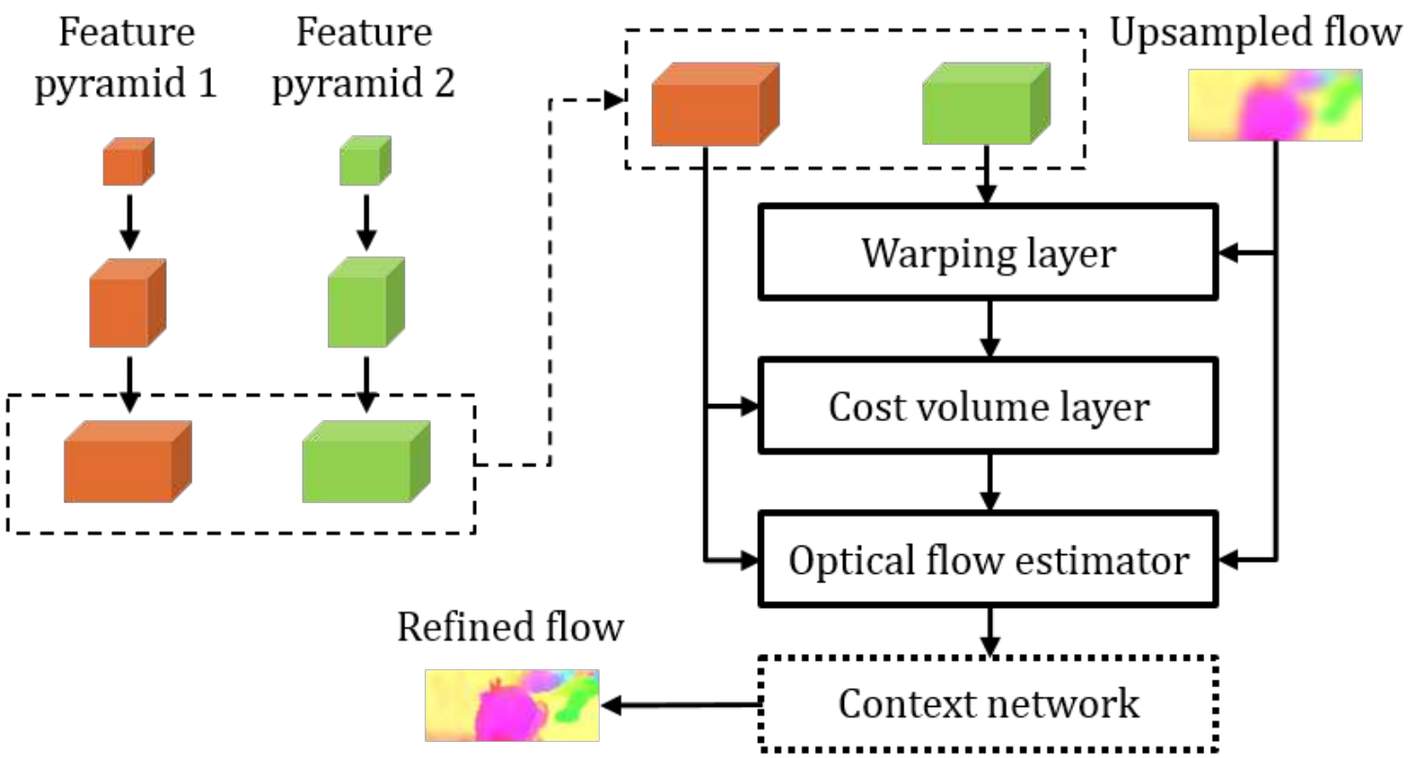


(large motion) correlation layer

- previous approaches are **limited in capture range**, by receptive field and limited number of conv. layers
- **FlowNetC** uses correlation layer without trainable weights but computation of (CC)-**metric over 441 discrete displacements** at once
- in addition FlowNet uses **deep supervision**, i.e. a loss at multi-resolution levels

trained on millions of synthetic image pairs (ask for details if interested)

Multi-stage / multi-resolution architecture

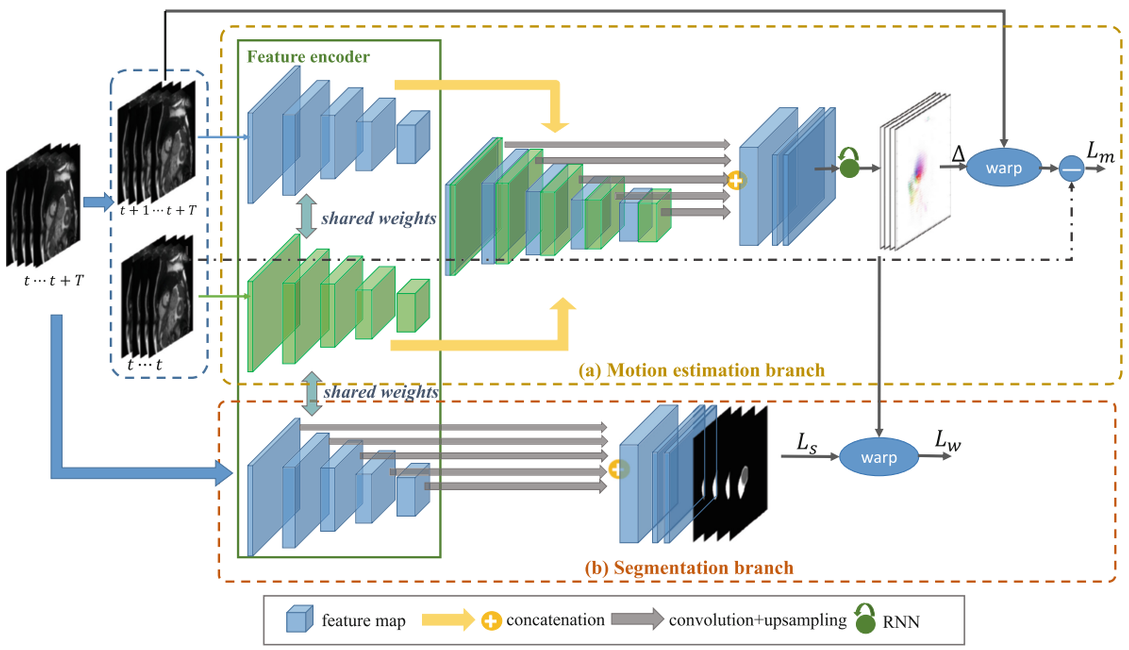


D Sun et al.: "PWC-Net: CNNs for Optical Flow Using Pyramid, Warping, and Cost Volume"
CVPR 2018

PWC-Net (outperformed FlowNet2 by large margin)
- at each pyramid level **features are warped with upsampled (previous) flow**
- a discretised **cost volume** (similar to correlation layer) is computed and processed using CNNs
- context network refines the (continuous valued) flow using large **receptive field dilated convs.**

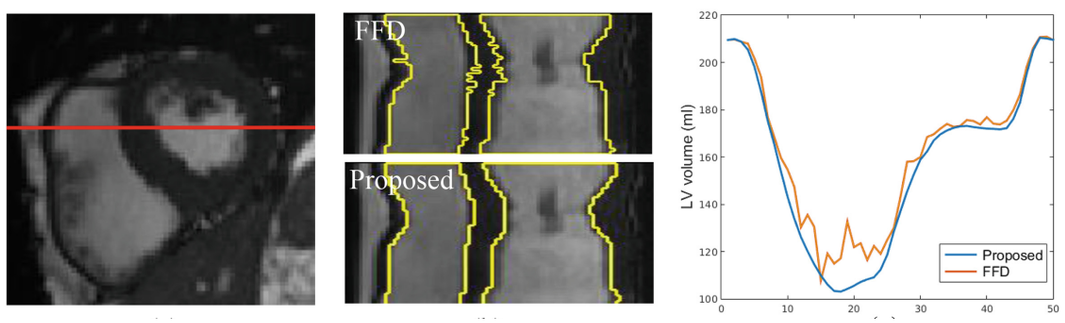
combines correlation layer and multi-resolution
(state-of-the-art in computer vision)

Multi-stage / multi-resolution architectures



multi-stage with recurrent network

C. Qin et al.: "Joint Learning of Motion Estimation and Segmentation for Cardiac MR Image Sequences" ***MICCAI 2018***



joint segmentation & cardiac motion estimation

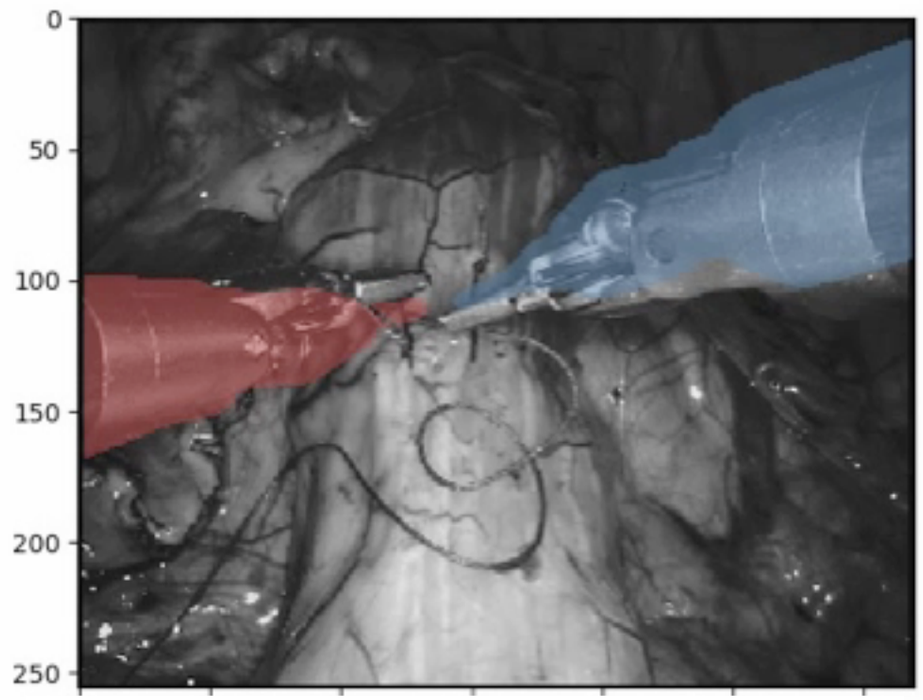
- **shared conv. weights** are used to extract **joint features** for both registration and segmentation
- a r**ecurrent network** is used to **iteratively refine** the estimated motion fields

some recent work on CT lung registration using multi-resolution networks

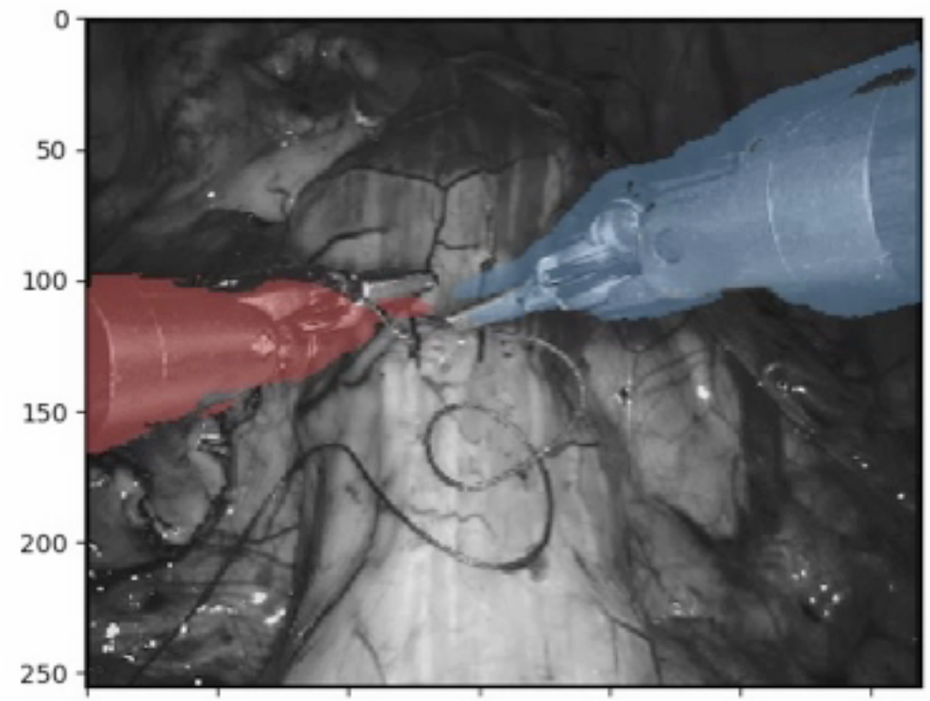
B de Vos, et al.: A deep learning framework for unsupervised affine and deformable image registration. ***Medical image analysis 2019***

A Hering et al.: "mlVIRNET: Multilevel Variational Image Registration Network" ***MICCAI 2019***

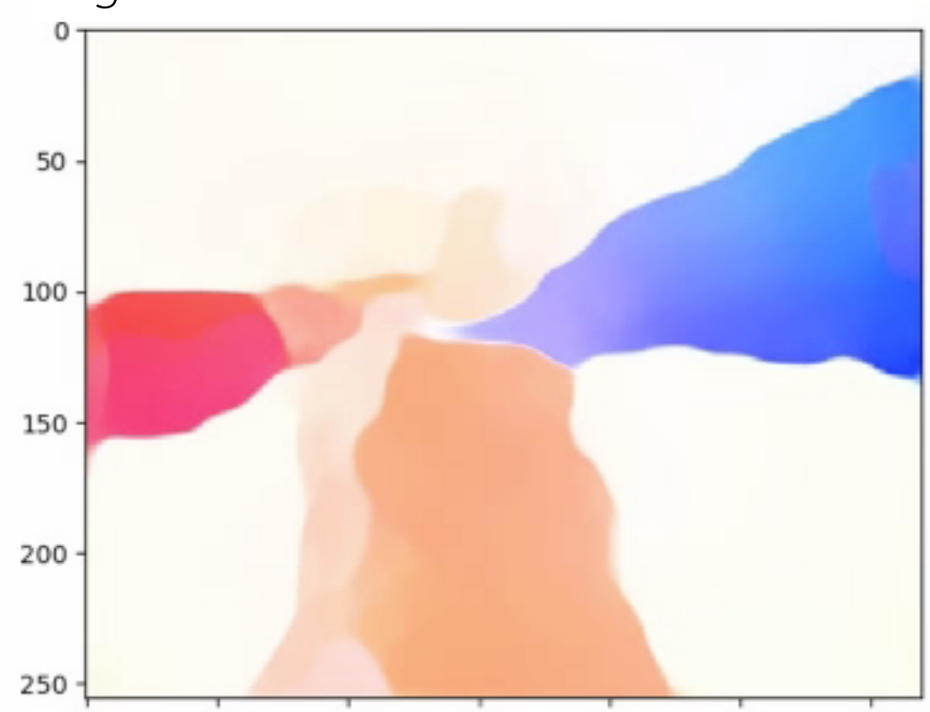
How well does the discrete FlowNet work for surgical tools?



no registration: copy segmentation from previous frame



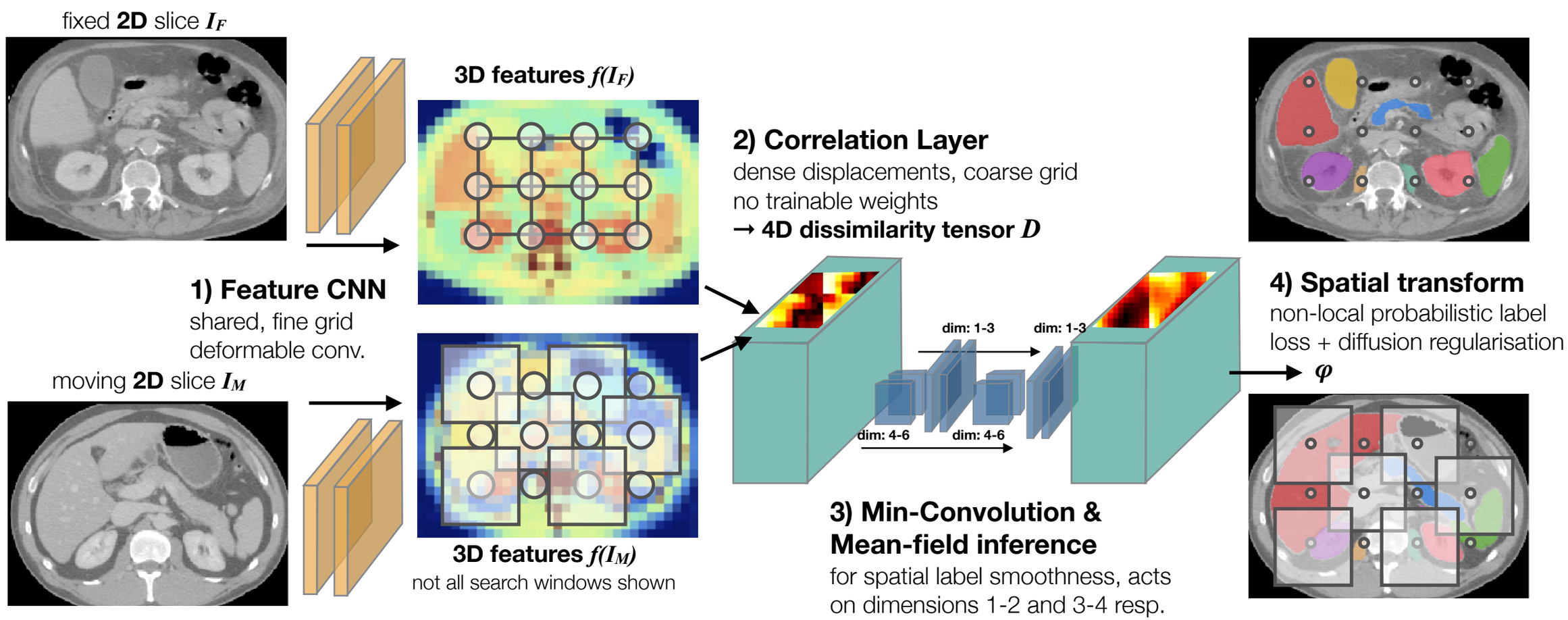
FlowNet registration: transformed segmentation + estimated flow field



- in general **reasonable performance for 2D+t surgical videos** (despite large motion due to low sampling frequency)
- but **fine-tuning is expected to yield more accurate motion** tracking

How does the discrete correlation layer work?

Three building blocks of DL discrete registration



learn to compute good features
→ only this part is trained

correlation layer: sliding window in moving image, compute SSD → 4D tensor

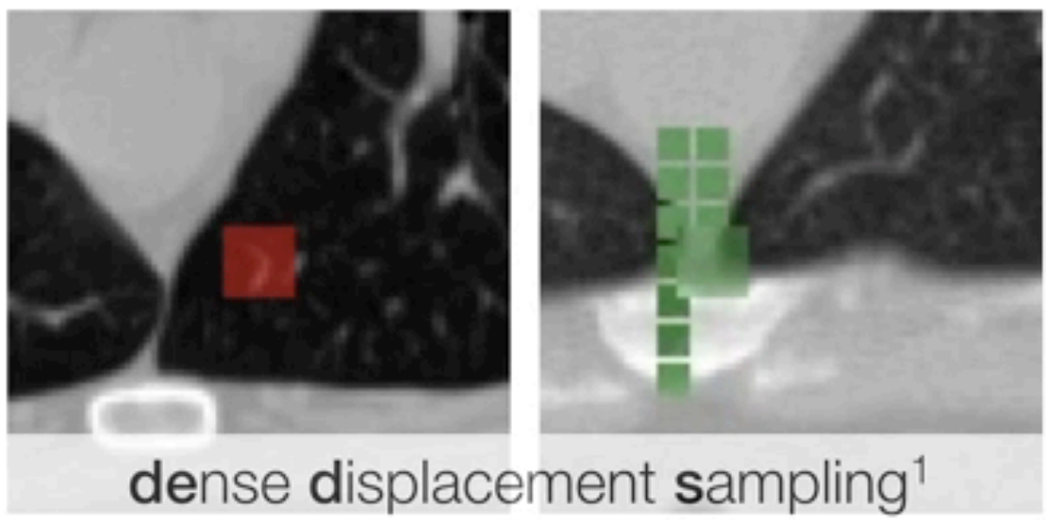
regularisation (not trained)
→ probabilistic map / transform

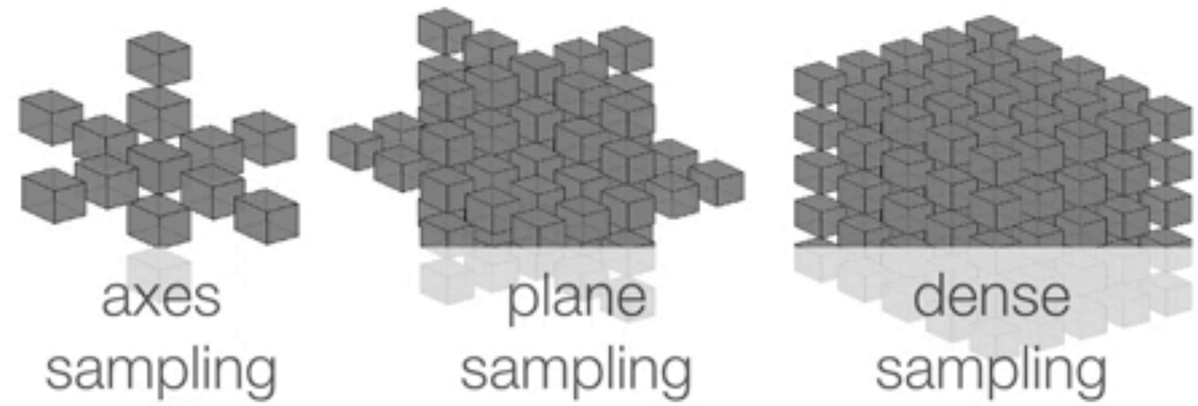
→ decouple feature/metric learning from regularisation, robust to small training dataset
weakly supervised loss (not correspondences but segmentation labels)

Heinrich: Closing the Gap between Deep and Conventional Image Registration using Probabilistic Dense Displacement Networks MICCAI 2019

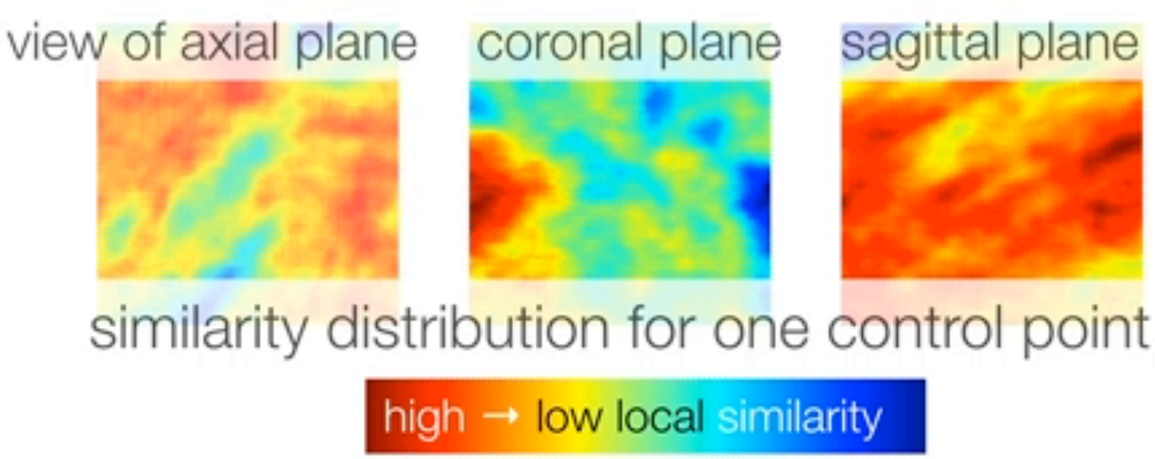
Dense Sampling of Displacement Space

similarity independent for each voxel / control point





exact control over label space
e.g. $\mathcal{L} = \{0, \pm 1, \pm 2, \ldots \pm 15\}^3$
(3D displacement)



point- or patchwise measures:
e.g. SAD, NCC, SSC, ...

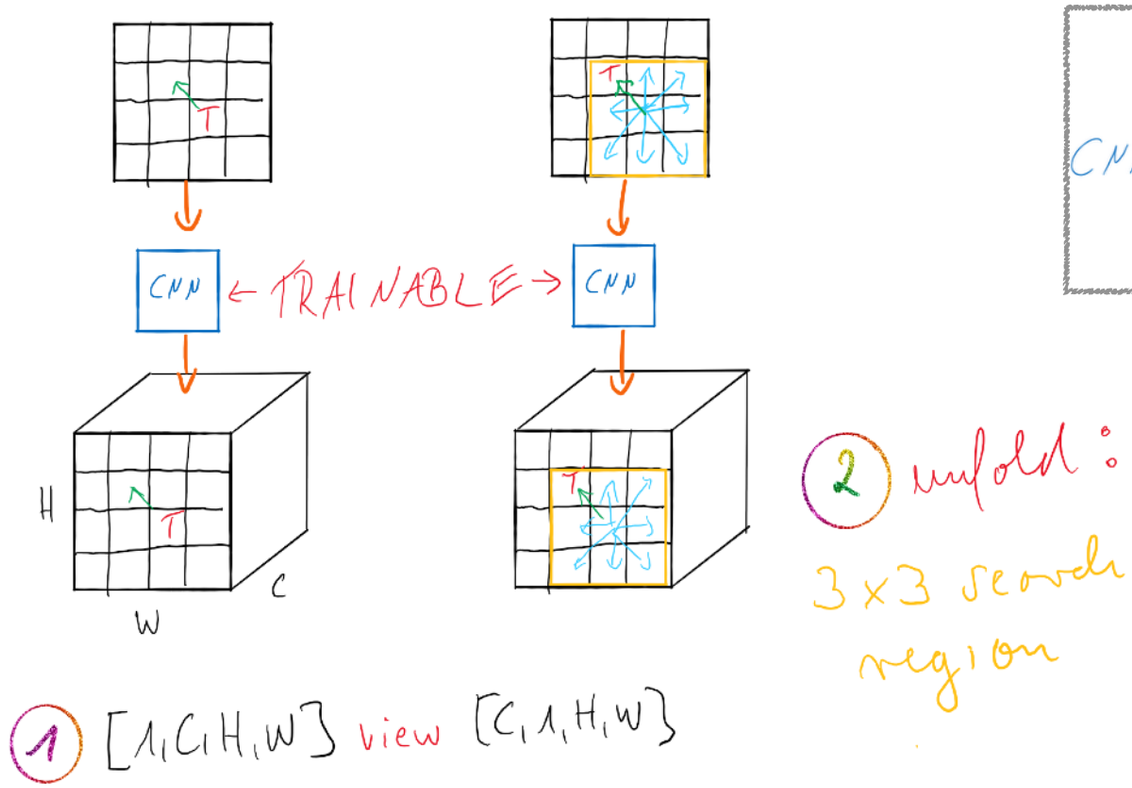
→ so far: no regularisation!

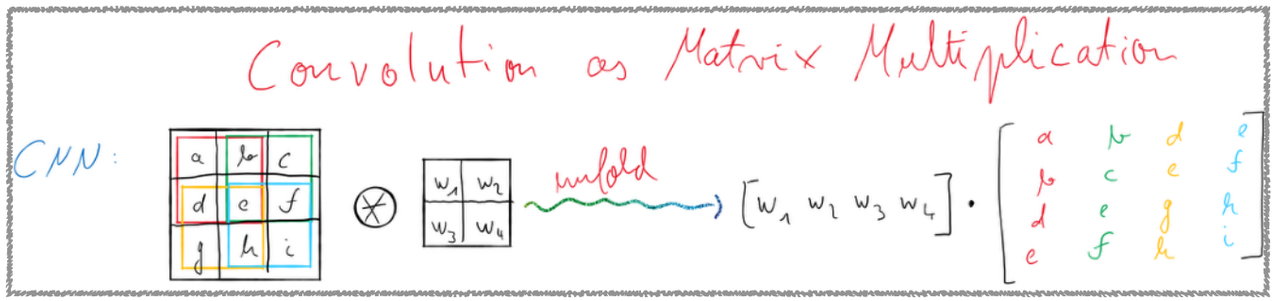
[1]Heinrich et al.: "Globally Optimal Deformable Registration … using Dense Displacement Sampling" MICCAI'12

Implementation details

pytorch correlation layer implementation (here for 2D)

```
scale_factor = 4; disp_range = 11; disp_hw = (disp_range-1)//2; B,C,H,W = feat_fixed.size()
feat_mov_unfold = F.unfold(feat_mov.transpose(1,0),(disp_range, disp_range),padding=disp_hw)
ssd_distance = ((feat_fixed.view(C,1,-1) - feat_mov_unfold)**2).sum(0).view(1, disp_range**2,H,W)
```

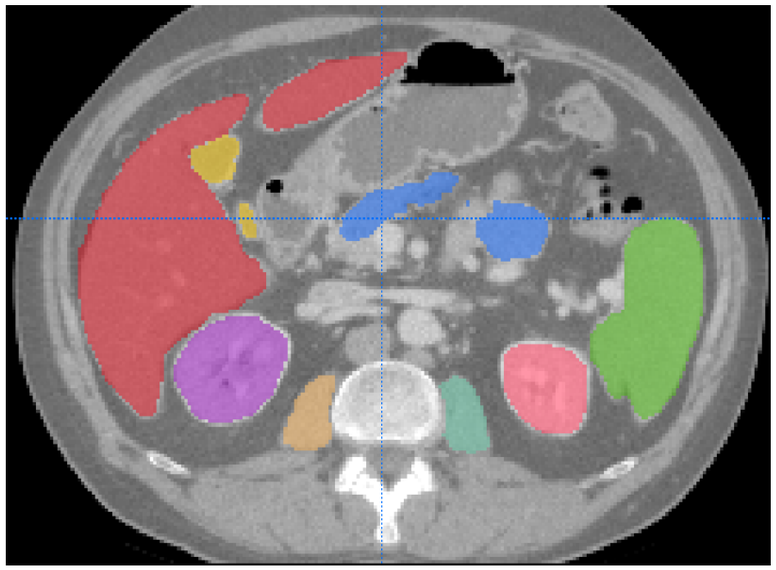




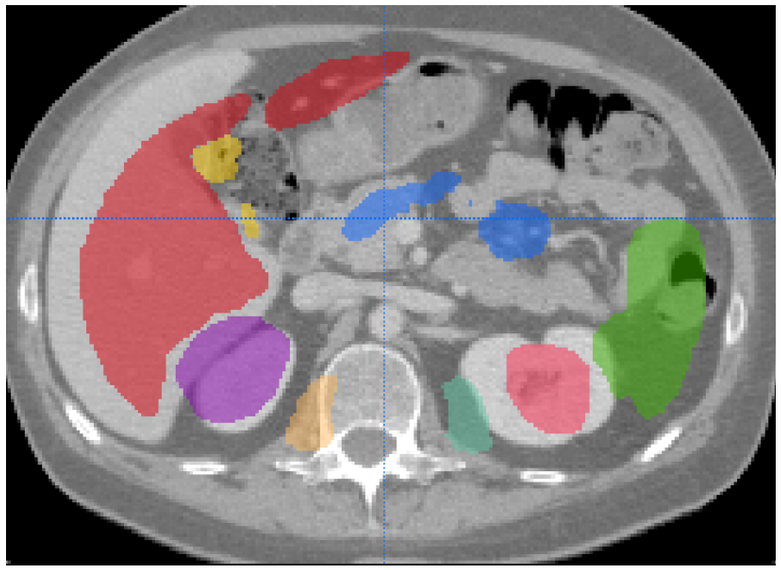
regularisation (approx. min-conv and mean field) no trainable weights

```
pad1 = nn.ReplicationPad2d(5); pad2 = nn.ReplicationPad2d(6)
avg1 = nn.AvgPool2d(5,stride=1); max1 = nn.MaxPool2d(3,stride=1)
minconv = nn.Sequential(pad1,avg1,avg1,max1); meanfield =  nn.Sequential(pad2,avg1,avg1,avg1);
ssd_minconv = -minconv(-ssd_distance.permute(0,2,3,1).reshape(1,-1,disp_range,disp_range))
cost = meanfield(ssd_minconv.permute(0,2,3,1).view(1,-1,H,W))
```

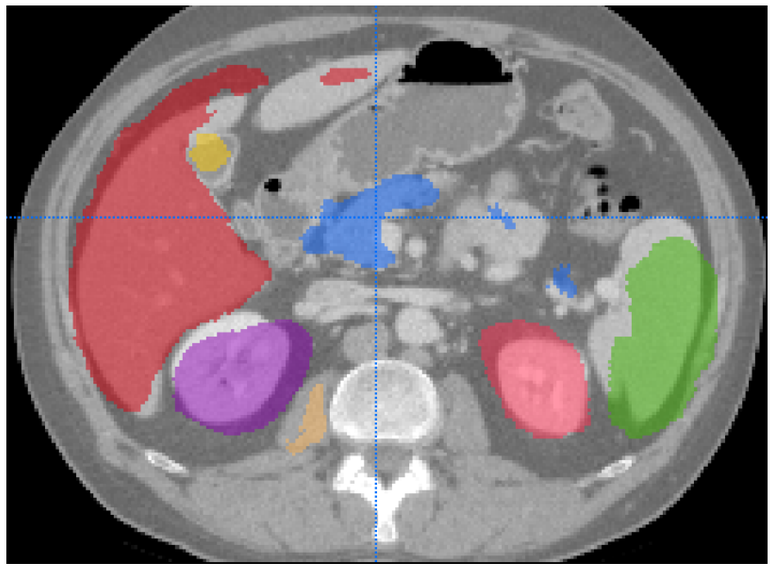
Some visual examples for abdominal CT



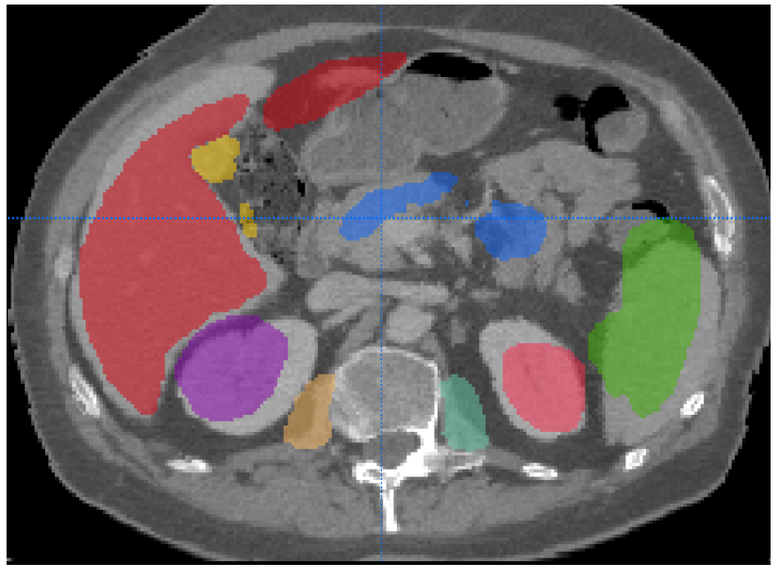
fixed scan + GT fixed seg.



moving scan + GT fixed seg.



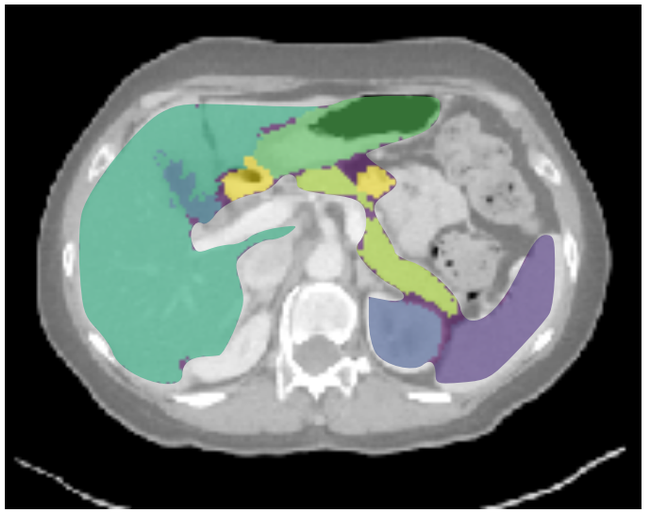
fixed scan + warped mov. seg.

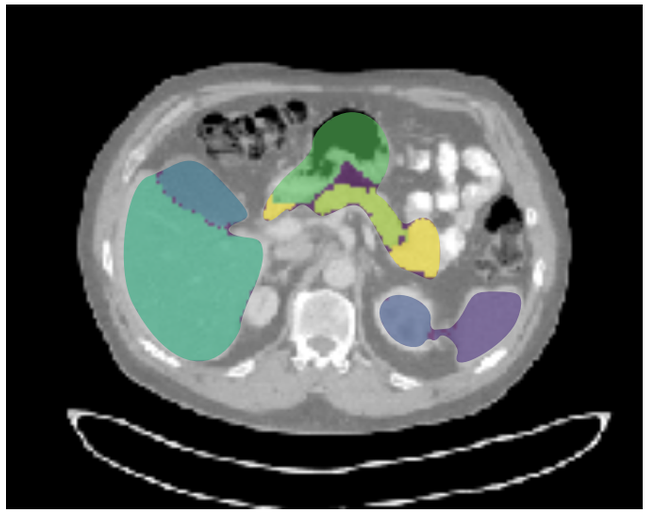


warped mov. scan + GT fix. seg.

hands-on: kaggle.com/mattiaspaul/learn2reg-tutorial

we **created a 2D dataset based on the TCIA** pancreas (Roth/Summers) abdominal CT
→ compensated through-plane deformations using deeds **keep in-plane differences**





corresponding segmentations are available to evaluate / train with supervision (Eli Gibson)

→ Switch to Kaggle Notebook

Outlook 3D: github.com/multimodallearning/pdd_net