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

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Multi-Atlas Labeling Beyond the Cranial Vault

Workshop and Challenge @ MICCAI 2015

Status Quo in Multi-Atlas Segmentation

Most publications based on MRI brain images
(many available public databases)

advances in recent years for
deformable registration and multi-atlas fusion
→ brain parcellation reaches performance ceiling

segmentation of **abdomen and cervix** is a very different challenge
approaches without registration play in important role
(often only evaluated on private datasets)

Are we using the using the right tools?

Multi-Atlas Segmentation of Abdominal Scans

calculate nonlinear transform between atlases & target space

transform manual segmentations towards target scan → label fusion

atlas scan with expert segmentation

target scan (coronal CT)

another atlas scan with expert segmentation

deformations can be extremely large - contrast and noise are challenges

<u>assumption</u>: optimising nonrigid registration is most important concern

Standard Registrations of NiftyReg

NiftyReg[1] has excellent performance on brain MRI,
and also on large lung motion EMPIRE10

→ **yet performance for abdomen before label fusion is underwhelming**
$D \approx 30\%$ (avg. single-atlas)

potential issues: 1) local minima of gradient-based optimisation
and 2) low performance of mutual information metric

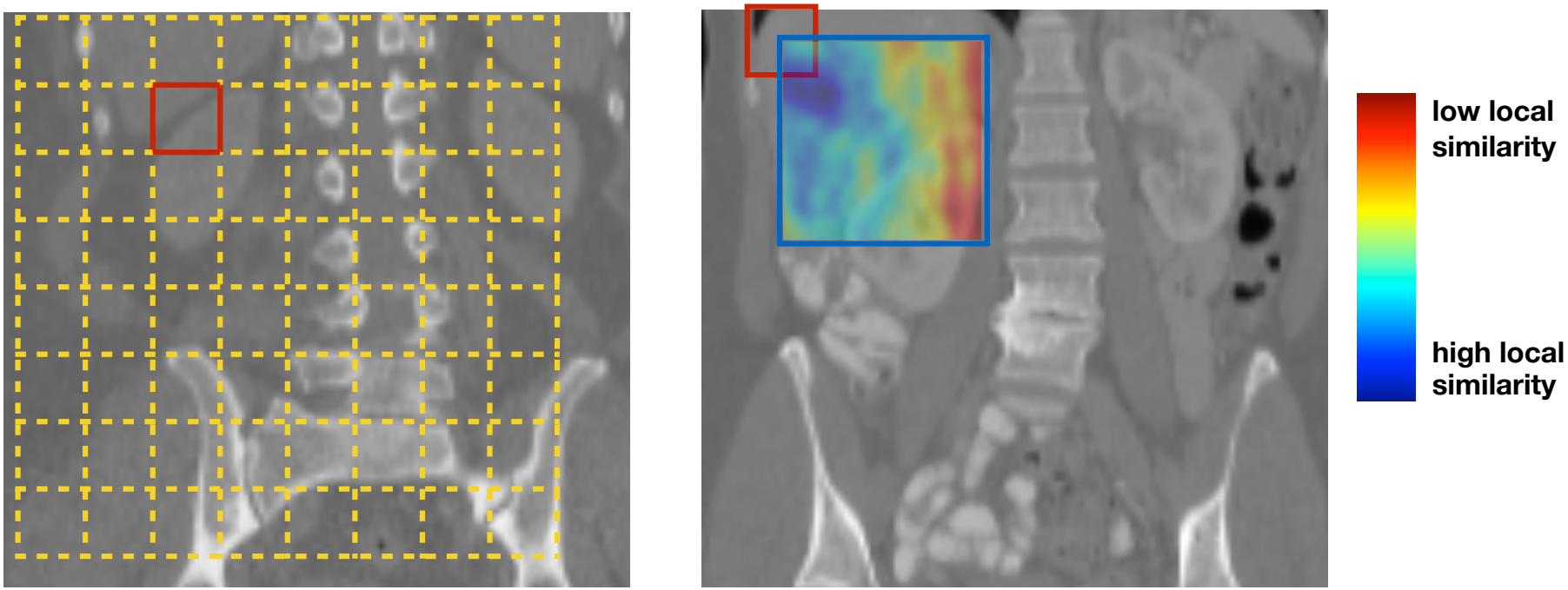
our approach: 1) use discrete optimisation package **deeds**
and 2) **self-similarity context** as similarity metric
3) employ widely used joint label fusion afterwards

[1]Modat et al.: "Fast free-form deformation using graphics processing units" Comp Meth Prog Bio '10

dense **d**isplacement **s**ampling (**deeds**[2])

divide fixed image in non-overlapping blocks
→ **calculate block-matching over 'dense' sampling region**

infer regularity over **joint displacement probabilities** (of neighbouring blocks)
using MRF optimisation on minimum-spanning-tree



MRF avoids local minima - has high computational efficiency (<5 secs for inference)

[2]Heinrich et al.: "MRF-based deformable registration of lung CT" IEEE Trans Medical Imaging '13

dense **d**isplacement **s**ampling (**deeds**[2])

pre-processing: resampling to 2.2^3 mm^3 cropping 180x140x190

affine registration with block-matching and trimmed least squares

multi-scale approach with decreasing block-size and sampling region

initial level uses **2197 displacements** and 66 mm capture range

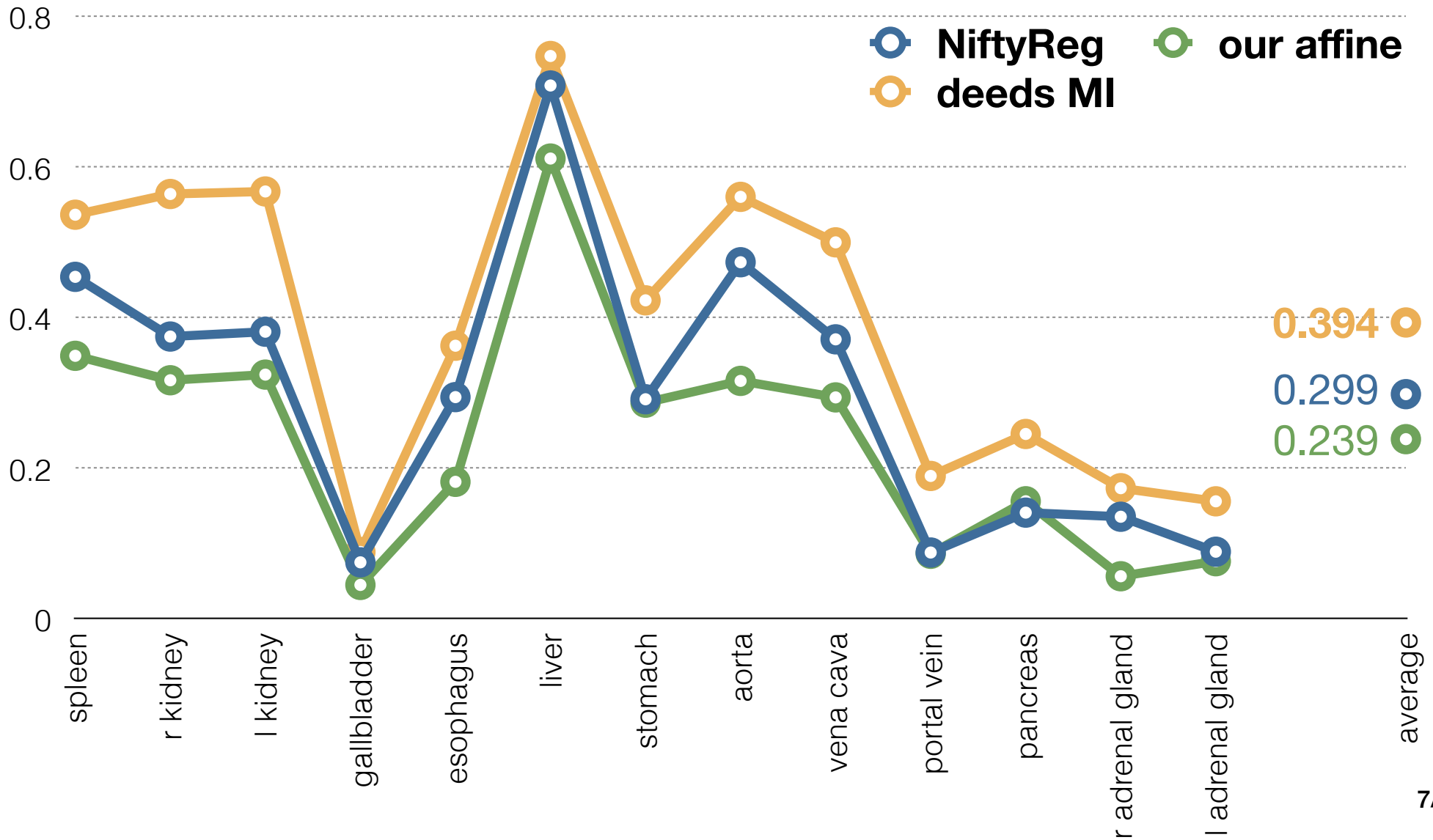
local mutual information (over patch) with 8 bins, Parzen window

recalculate histogram for every search position

→ **90 secs.** per 3D registration (compared to 5 sec. for optimisation)

[2]Heinrich et al.: "MRF-based deformable registration of lung CT" IEEE Trans Medical Imaging '13

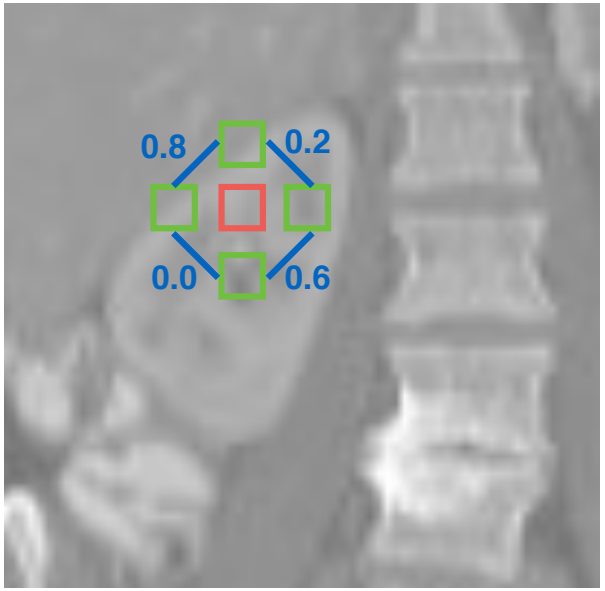
dense **d**isplacement **s**ampling (**deeds**)



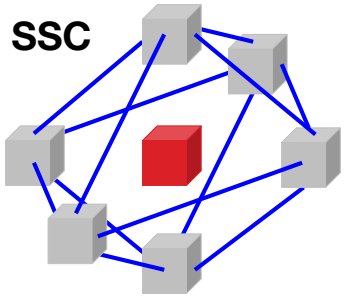
Metric: Self-similarity Context

self-similarity context as similarity metric (extension from MIND)

self-similarity D_p is measured by patch-wise SSD (sum of squared differences)
variance estimate V makes descriptor insensitive to locally varying contrast



$$\mathrm{MIND}(I,\mathbf{x},\mathbf{r}) = \frac{1}{n}\exp\left(-\frac{D_p(I,\mathbf{x},\mathbf{x}+\mathbf{r})}{V(I,\mathbf{x})}\right) \quad \mathbf{r}\in R$$



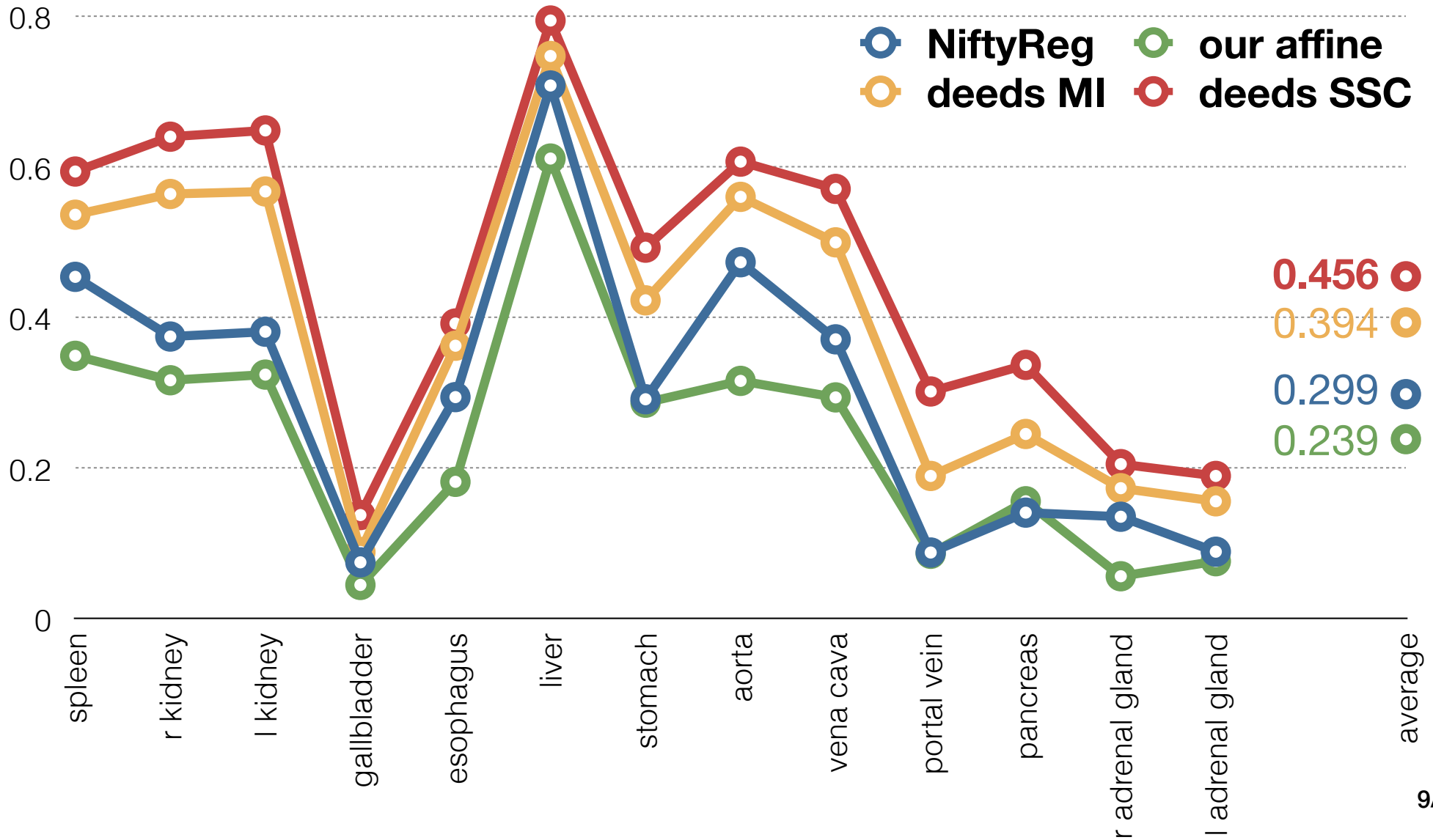
Pairwise self-similarities in neighbourhood[3]
Context → robust to noise, sensitive to curvature

Quantise descriptor into binary string
(0.8,0.2,0.6,0.0) → 0111,0001,0011,0000

Distance between descriptors is **Hamming weight**
reduces computation time for similarity metric to **15 secs.**

[3]Heinrich et al.: “Towards realtime multimodal fusion using self-similarity context” MICCAI ‘13

Self-similarity context



Multi-Atlas Label Fusion

majority vote: same weight for every atlas

locally weighted fusion: with non-local search

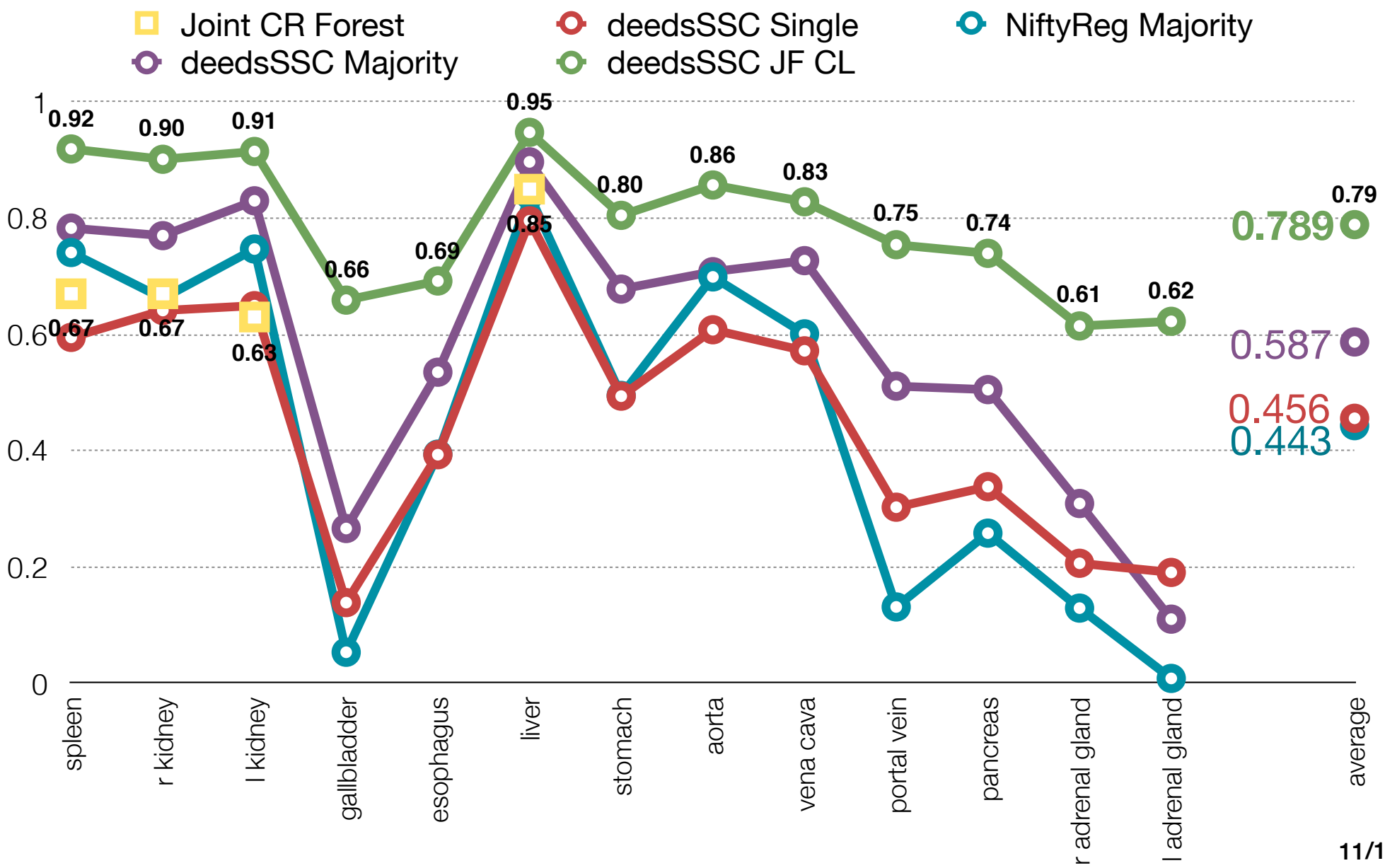
joint fusion[4]: estimation of dependencies for local atlas weights

corrective learning[5]: fixes segmentation errors

as comparison: joint classification and regression forests[6]

[4]Wang et al.: “Multi-atlas segmentation with joint label fusion” IEEE PAMI ’13
[5]Wang & Yushkevich: "Multi-Atlas Segmentation with Joint Label Fusion and Corrective Learning" Frontiers in Neuroinformatics ’13
[6]Glocker et al.: "Joint classification-regression forests for spatially structured multi-object .." ECCV ‘12

Multi-Atlas Label Fusion



Conclusion and Outlook

Discrete optimisation helps overcome local minima

Self-similarity context is slightly more accurate and **faster than MI**

Very fast (45 secs. per atlas) and **accurate**
www.mpheinrich.de/software.html

Majority Voting alone is not sufficient
→ **Joint label fusion** (D=0.79, d=2.26mm) but very slow

Patch-MI workshop 2015 (faster joint label fusion)[7]

Cervix segmentation even more challenging (D=0.63)

[7]**Heinrich et al.**: "Multi-Atlas Segmentation using Patch-Based Joint Label Fusion with Non-Negative Least Squares Regression" **MICCAI Patch-MI '15**

Non-negative Least Squares Regression

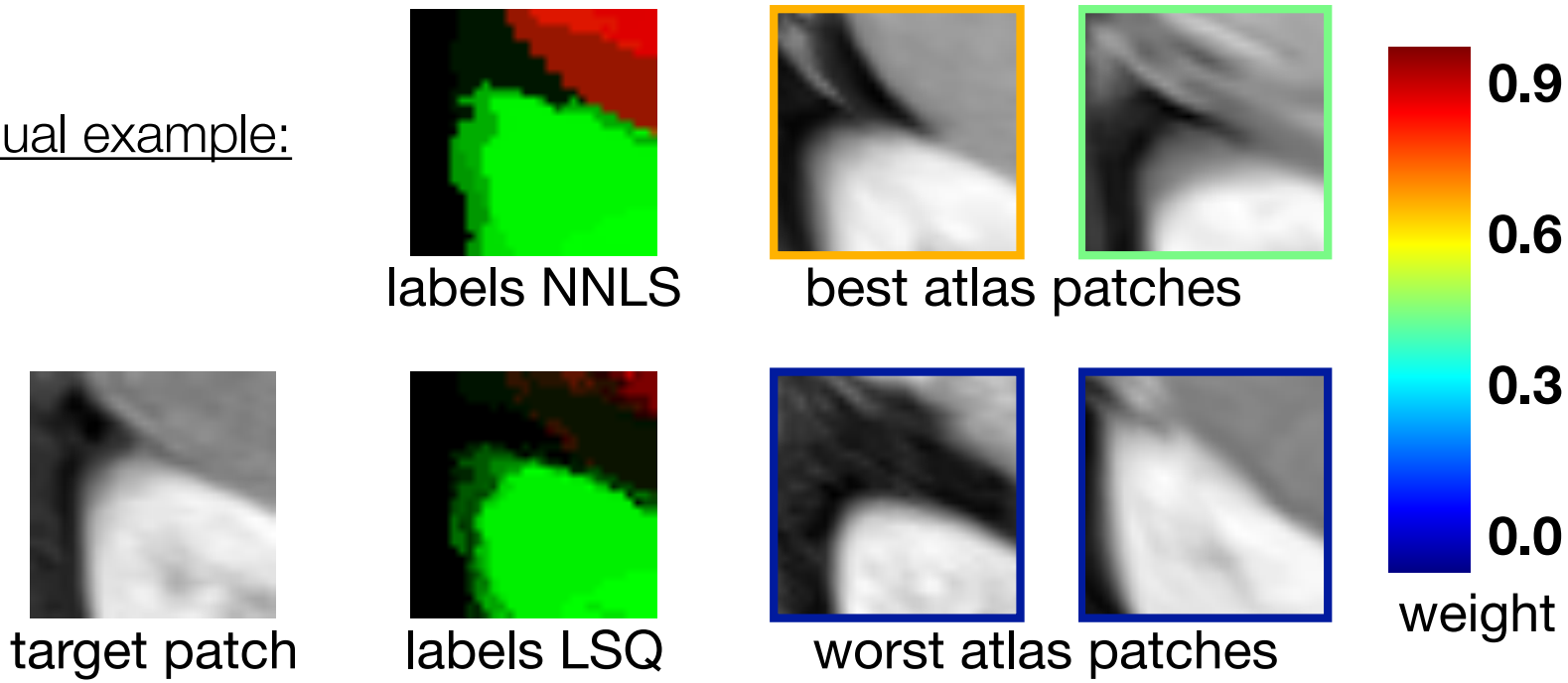
additional non-negativity constraint

$$\underset{\boldsymbol{c}}{\operatorname{argmin}} ||\mathbf{A}\boldsymbol{c} - \boldsymbol{b}||_2^2 \quad \boxed{\text{subject to } c_i \geq 0 \; \forall \; i = \{1, 2, \ldots, n\}}$$

implicitly this formulation **promotes sparsity**[3] (c.f. LASSO L_1 regularisation)

<u>advantages</u>: fast solvers are available, no weighting parameter required

<u>visual example:</u>



[3]Slawski and Hein: “Sparse recovery by thresholded non-negative least squares" NIPS ‘11

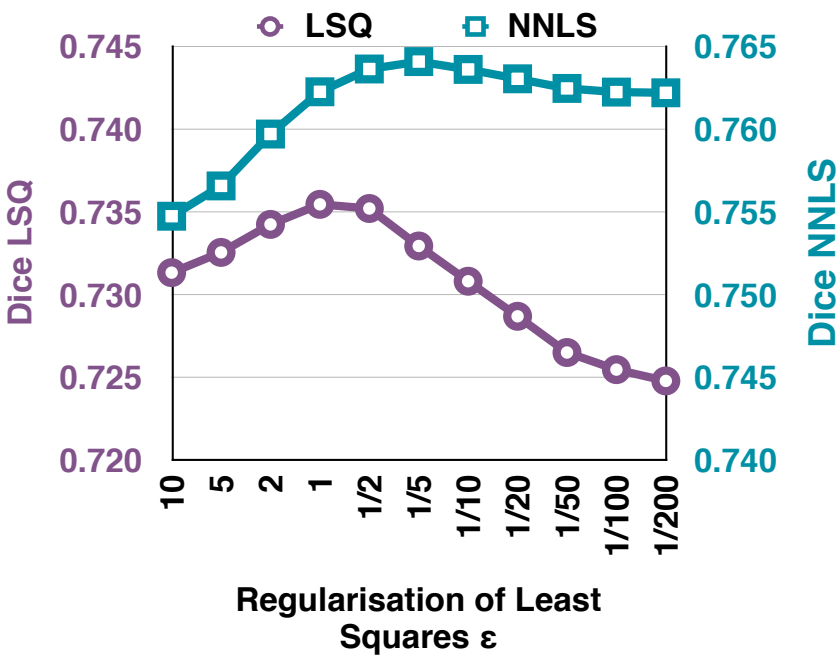
Comparison to state-of-the-art

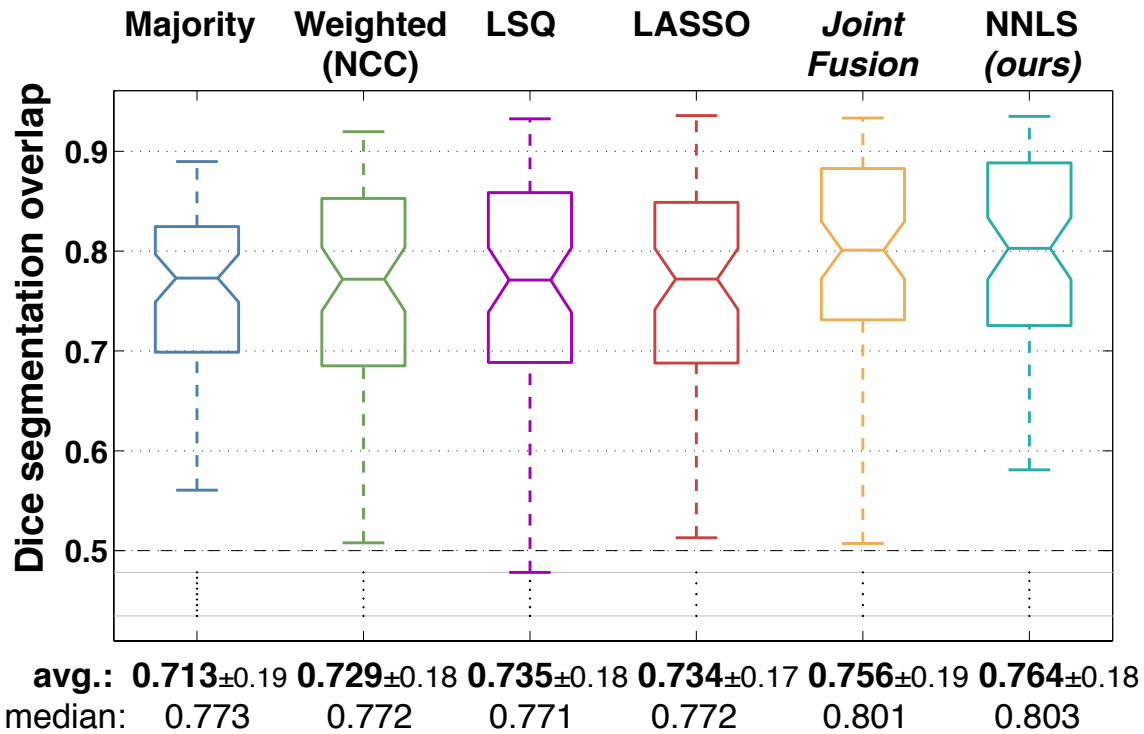
Optimisation of regularisation parameter $\boldsymbol{\varepsilon}$ of least-squares

Weights are applied to the label patch (not only centre-voxel)

Significant improvements (~3% Dice) over NCC, LSQ, LASSO[7]

Small improvements over *Joint Fusion* **and 15-fold speed-up**





[7]Zhang et al.: "Sparse patch-based label fusion for multi-atlas segmentation" MBIA '12