Semi-automatic liver tumor segmentation in DCE-CT scans using random forests and supervoxels

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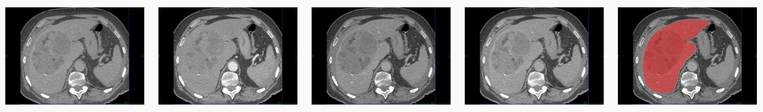
Context

Evaluation of pre-operative locoregional treatments (PLT) response for *hepato-cellular carcinoma* (HCC):

- PLT downstage HCC tumors by necrosis
- standard scores (RECIST, EASL or WHO) do not provide satisfactory results
- **tumor necrosis** (TN) **rate** provides more significant correlation with survival rates

To overcome inter-expert variability induced by visual assessment, we propose a semi-automatic method to estimate **TN rate** from dynamic contrast-enhanced (DCE) CT scans:

- requires the segmentation of healthy liver, tumoral active and necrotic areas
- DCE images provide discriminative information: HCC is characterized by arterial enhancement followed by venous washout in response to contrast agent injection



State-of-the-art

Unsupervised multi-phase methods

- liver tumor segmentation through level sets, k-means or graph cut
- multi-phase voxel-wise features: capture the dynamic in response to agent injection

User interaction appears necessary since arterial enhancement and venous washout depend on contrast agent kinetic and injection protocol.

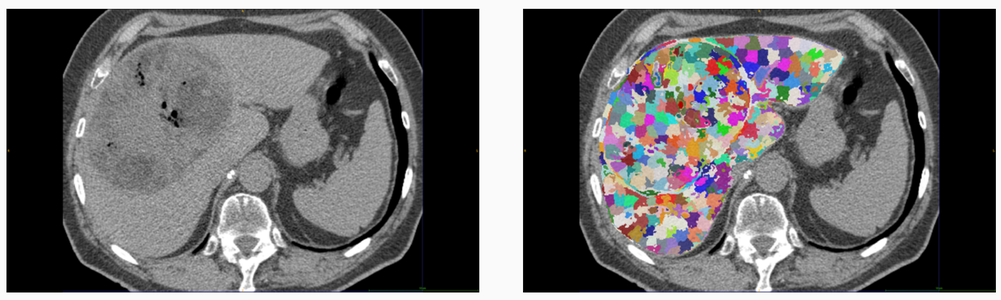
Supervised single-phase methods

- tumor extraction relying on supervised ensemble learning
- spatial features with limited context
- voxel-wise: requires a significant amount of user interaction

Contributions

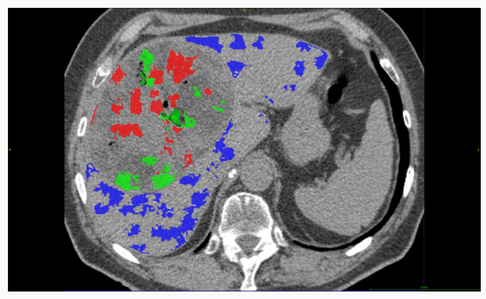
Proposed framework: multi-phase cluster-wise random forest

① Over-segmentation



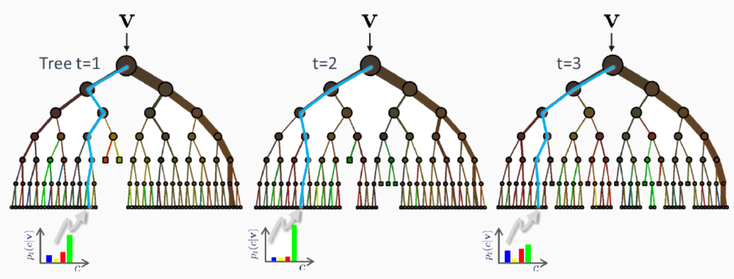
Liver volume decomposed into a set of K_R 3D SLIC supervoxels $\boldsymbol{R} = \{\boldsymbol{r}_i\}_{i \in \{1,\dots,K_R\}}$

② Interaction



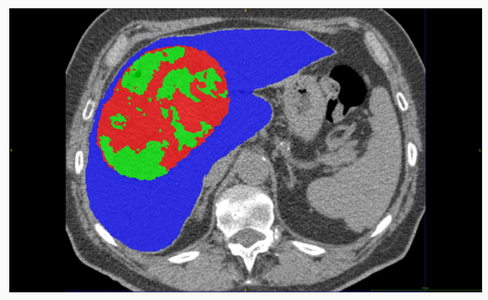
Training 3D supervoxel selection $\boldsymbol{S} = \{\boldsymbol{r}_j, c(\boldsymbol{r}_j)\}_{j \subset \{1,\dots,K_R\}}$

③ Training



Random forest [2] optimized using $\boldsymbol{S}$ to obtain a voxel/label mapping model

④ Prediction

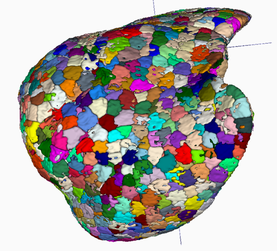


Prediction of label $c(\boldsymbol{r})$ assigned to each 3D supervoxel $\boldsymbol{r} \in \boldsymbol{R} \backslash \boldsymbol{S}$

⑤ TN rate estimation

$$\tau = \frac{\sum_{r_i \in \text{necro}} |\boldsymbol{r}_i|}{\sum_{r_i \in \text{tumor}} |\boldsymbol{r}_i|}$$

From voxels to semantic regions



Random forest performed on 3D supervoxels obtained with SLIC [1]:

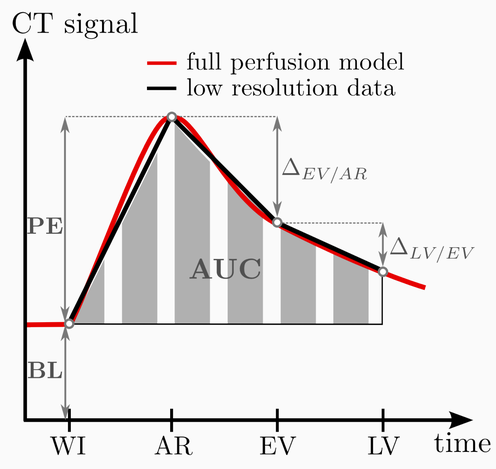
- introduces spatial consistency at a large spatial extent
- reduces interaction efforts: the practitioner has only to label a subset of $\boldsymbol{R}$ instead of brushing strokes on many voxels

Exploiting multi-phase input data

Multi-phase cluster-wise features assigned to supervoxels:

Related to	Features	Nb
Intensity	mean intensity including BL + std dev.	$4+4$
Gradient	mean gradient magnitude + std dev.	$4+4$
Multi-phase	peak enhancement (PE)	1
	inter-phase diff. $\Delta_{EV/AR}$, $\Delta_{LV/EV}$	2
	area under enhancement curve (AUC)	1

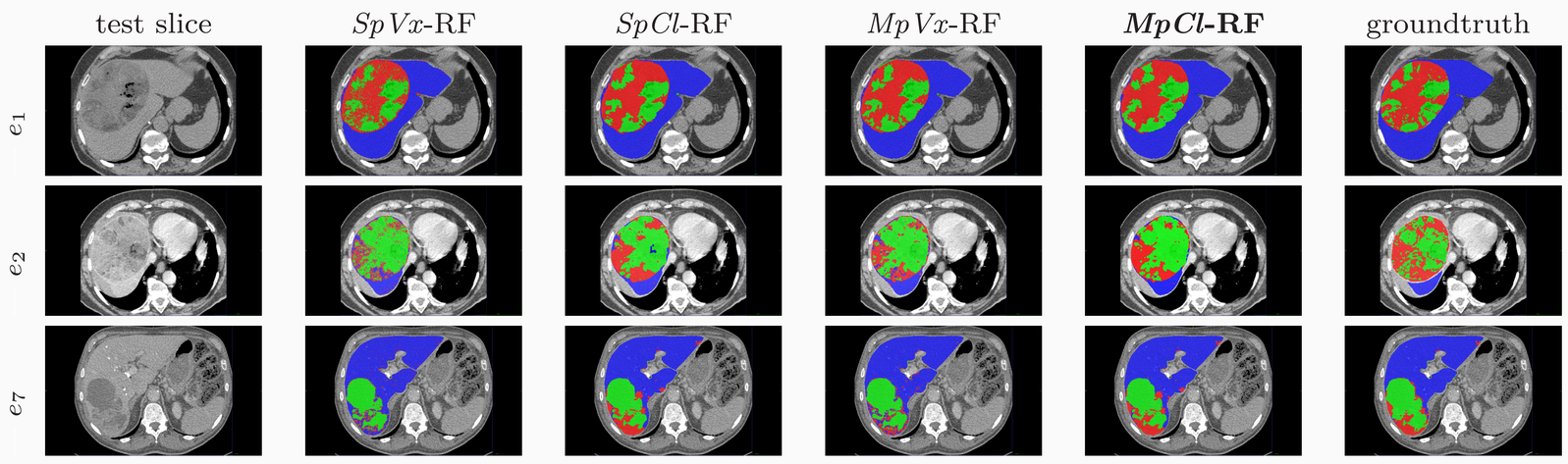
Multi-phase features discriminate supervoxels based on their own arterial enhancement and venous washout



Results

7 examinations with 6 equally reparted 2D axial slices labeled by 4 experts in hepato-digestive surgery whose annotations are fused using STAPLE [3]. We comparatively assess *single-phase voxel-wise* (*SpVx*), *single-phase cluster-wise* (*SpCl*), *multi-phase voxel-wise* (*MpVx*) and the proposed ***multi-phase cluster-wise*** (*MpCl*) **random forest** (RF).

methods	*SpVx*-RF	*SpCl*-RF	*MpVx*-RF	***MpCl*-RF**
TN rate error	6.40 ± 2.85	9.13 ± 4.78	6.60 ± 3.32	$\mathbf{5.26} \pm 3.90$
$\text{DICE}_{\texttt{activ}}$	54.3 ± 17.2	65.8 ± 15.3	65.5 ± 12.4	$\mathbf{74.4} \pm 12.6$
$\text{DICE}_{\texttt{necro}}$	65.0 ± 21.6	63.8 ± 25.8	71.8 ± 17.6	$\mathbf{71.9} \pm 19.5$
$\text{DICE}_{\texttt{prcm}}$	80.5 ± 13.1	89.7 ± 4.90	87.4 ± 9.00	$\mathbf{93.3} \pm 3.08$



Results confirm the benefits of exploiting dynamic information at a cluster spatial extent

Further work

- multi-examination learning to make our strategy becoming fully automatic
- longitudinal liver tumor study
- extension to other tumor types, organs and modalities

Acknowledgements

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References

[1] Radhakrishna A. *et al.*, SLIC superpixels compared to state-of-the-art superpixel methods. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 34(11):2274–2282, 2012.

[2] Breiman L. Random Forests. *Machine learning*, 45(1):5–32, 2001.

[3] Simon K.W. *et al.*, Simultaneous truth and performance level estimation (STAPLE). *IEEE Transactions on Medical Imaging*, 23(7):903–921, 2004.