Random Forests on Hierarchical Multi-Scale Supervoxels for Liver Tumor Segmentation in Dynamic Contrast-Enhanced CT Scans

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Context

We tackle **multi-label tissue classification** covered through supervised ensemble learning towards accurate **tumor segmentation** :

- high diversity in shape, location and size
- wide appearance heterogeneity
- severe class overlap in feature space
- ambiguous boundaries

Recent approaches capture long-range spatial context but are limited in their ability to deal with **spatial adaptivity** & **appearance heterogeneity**

Our motivation. Enable random forest (RF) [1] to find itself the best data sampling by:

- combining RF and **hierarchical multi-scale** tree resulting from recursive supervoxel decomposition
- describing each leaf supervoxel as a sequence of supervoxels belonging to its ascendant hierarchy

Application

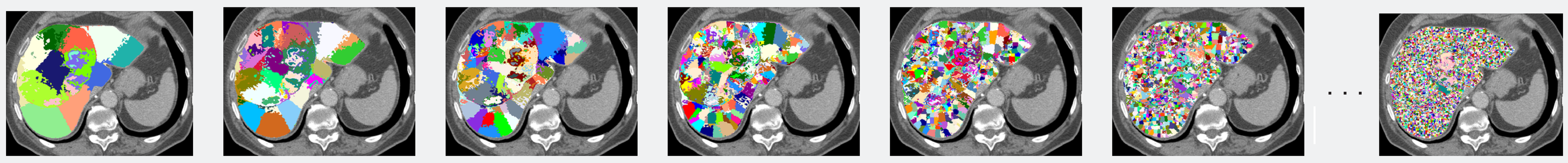
Clinical management of *hepatocellular carcinoma* (HCC) [2], most common type of liver cancer :

- requires the segmentation of healthy liver, tumoral active and necrotic tissues
- from dynamic contrast-enhanced (DCE) CT scans: HCC characterized by arterial enhancement followed by venous washout in response to contrast agent injection

WI AR EV LV liver mask

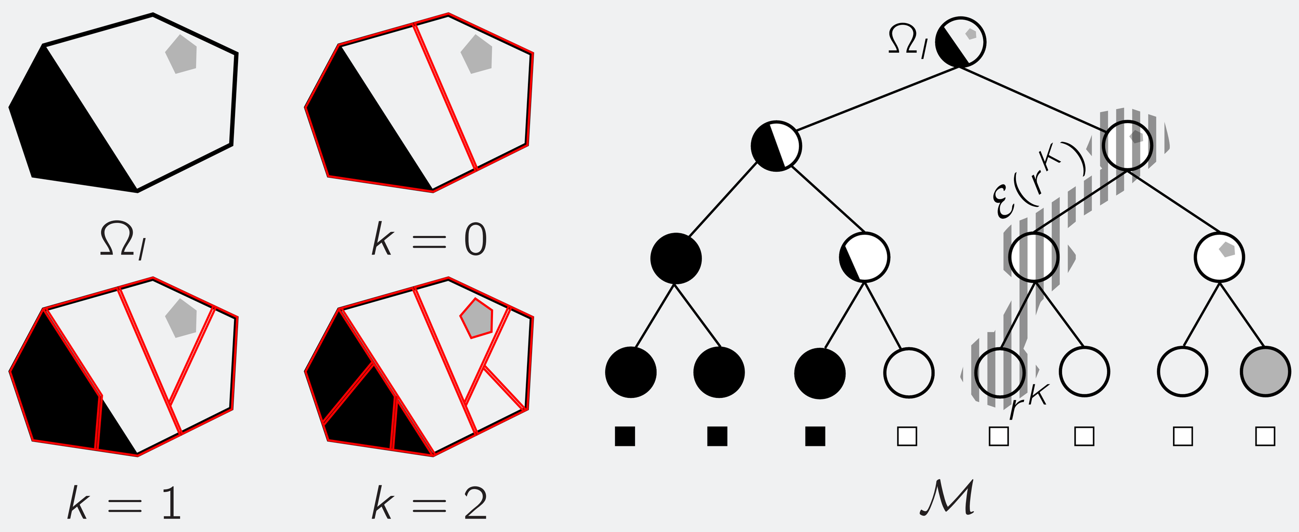
Contributions

Hierarchical multi-scale supervoxel representation | following [3]



scale $k=0$ $k=1$ $k=2$ $k=3$ $k=4$ $k=5$ ... K

- liver area Ω_l decomposed into a set of $K+1$ partitions $\mathcal{P}^k$
- $\mathcal{P}^k$ is a collection of SLIC [4] compact 3D supervoxels $\{\mathbf{r}_i^k\}$ such that $\mathbf{r}_i^k \cap \mathbf{r}_{j\neq i}^k = \emptyset$ and $\bigcup_i \mathbf{r}_i^k = \Omega_l$
- $\{\mathcal{P}^k\}$ encoded in the layers of a multi-resolution tree $\mathcal{M} = \{\mathcal{M}^k\}$



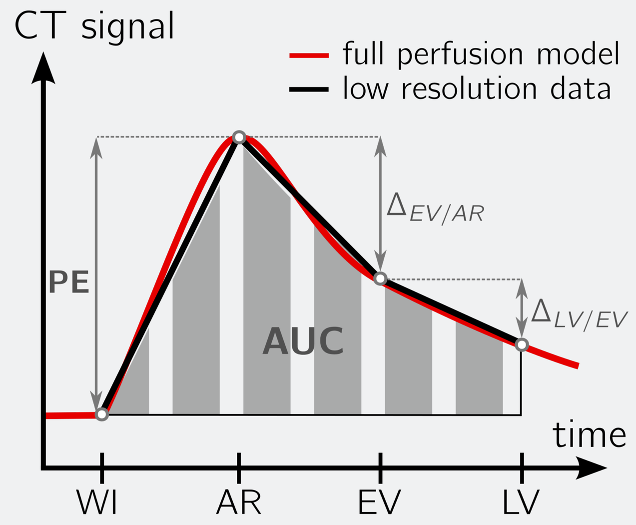
- $\mathcal{M}^k$ maps each supervoxel $\mathbf{r}_i^k \in \mathcal{P}^k$ to a set of child supervoxels $\{\mathbf{r}_j^{k+1}\} \subset \mathcal{P}^{k+1}$ s.t. $\mathbf{r}_i^k = \bigcup_j \mathbf{r}_j^{k+1}$

Hierarchical multi-scale supervoxel-based RF | extends [5] from single to multi-scale since intrinsic tissue properties may emerge at different scales for different tissues

① Build hierarchical multi-scale tree $\mathcal{M}$

② Assign visual features $\theta(\mathbf{r}^k)$ to all supervoxels $\mathbf{r}^k$ in each partition $\mathcal{P}^k$ with $k \in \{0,\dots,K\}$

Related to	Features	Nb
Intensity	mean intensity + 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



③ Associate to each supervoxel $\mathbf{r}^K$ at finest scale K all the supervoxels of decreasing scale belonging to its ascendant hierarchy including itself: $\mathcal{E}(\mathbf{r}^K) = \{\mathbf{r}^k\}_{k\in[0,\dots,K]}$

④ Define a new feature vector $\gamma(\mathbf{r}^K)$ associated to each $\mathbf{r}^K \in \mathcal{P}^K$ as the concatenation of all visual features assigned to supervoxels of $\mathcal{E}(\mathbf{r}^K) \Rightarrow$ **powerful multi-scale description of finest scale supervoxels**

⑤ Tissue classification based on supervoxels of scale K carried out via standard RF [1]

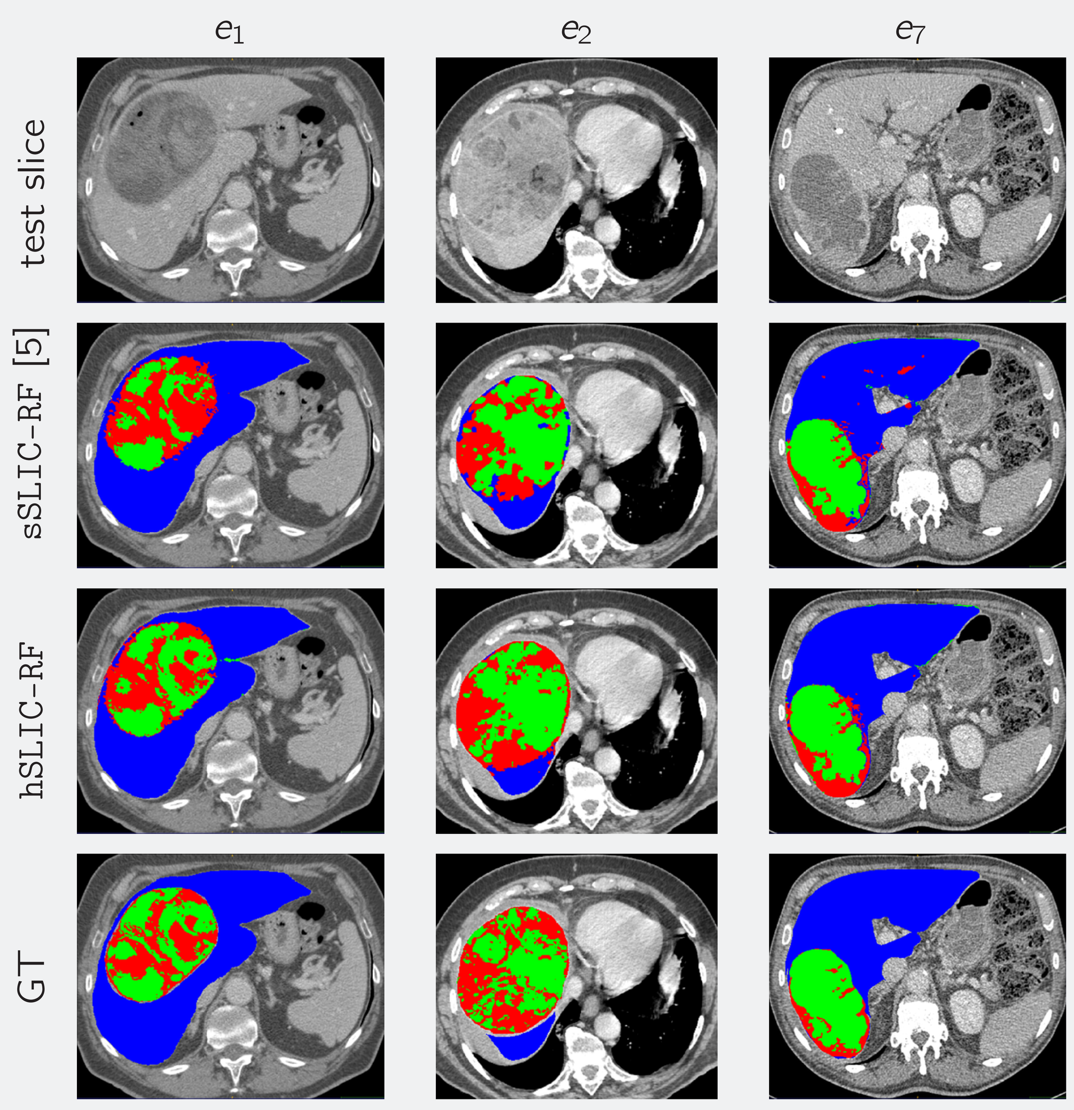
Results

Dataset. 8 examinations $\{e_1,\dots,e_8\}$ stemming from patients with HCC with 6 equally reparted 2D axial slices labeled by 4 experts in hepato-digestive surgery.

Experiments. Comparison between hierarchical multi-scale supervoxel-based RF (hSLIC-RF) and single-scale supervoxel-based RF [5] (sSLIC-RF) with optimal shared and e_i-dependent supervoxel resolutions.

methods	optimized sSLIC-RF [5]		hSLIC-RF
resolution	shared	e_i-dependent	multi-scale
$\text{DICE}_{\text{activ}}$	76.5 ± 10.1	78.7 ± 9.18	$\mathbf{80.4} \pm 8.81$
$\text{DICE}_{\text{necro}}$	85.3 ± 12.5	$\mathbf{86.9} \pm 9.51$	$\mathbf{86.9} \pm 10.5$
$\text{DICE}_{\text{prcm}}$	94.3 ± 4.12	94.9 ± 3.85	$\mathbf{95.5} \pm 3.56$
$\text{DICE}_{\text{tumor}}$	88.9 ± 8.51	89.4 ± 6.12	$\mathbf{91.0} \pm 6.99$

- significant impact of scale selection in single-scale context
- hSLIC-RF outperforms the upper bound reachable by sSLIC-RF $\Rightarrow$ confirms the benefits of our **adaptive data sampling scheme**
- stronger spatial regularization inherited from the capacity of multi-scale SLIC supervoxels to adhere to image boundaries



Further work

- multi-examination training to make our strategy becoming fully automatic
- HCC management $\Rightarrow$ correlation between tumor necrosis rate and survival rates
- longitudinal liver tumor study
- extension to other tumor types, organs and modalities

References

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