

# Joint Classification-Regression Forests for Spatially Structured Multi-Object Segmentation

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## Joint Classification-Regression

Learning Objective

$$p(y|x) \quad x \in \mathbb{R}^m: \text{feature space} \\ y \in \mathcal{O}: \text{prediction space}$$

Categorical-Continuous Prediction

$$y = (c, r) \quad \left. \begin{array}{l} c \in \mathcal{C}: \text{classification space} \\ r \in \mathbb{R}^n: \text{regression space} \end{array} \right\} \mathcal{O} = \mathcal{C} \times \mathbb{R}^n$$

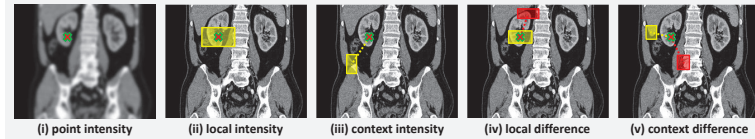
Tree Training: Information Gain

$$\mathcal{S} = \{(x_k, y_k)\}_{k=1}^K \quad I(\mathcal{S}_l, \mathcal{S}_l^L, \mathcal{S}_l^R) = H(\mathcal{S}_l) - \sum_{j \in \{L, R\}} \frac{|\mathcal{S}_l^j|}{|\mathcal{S}_l|} H(\mathcal{S}_l^j)$$

Joint Entropy

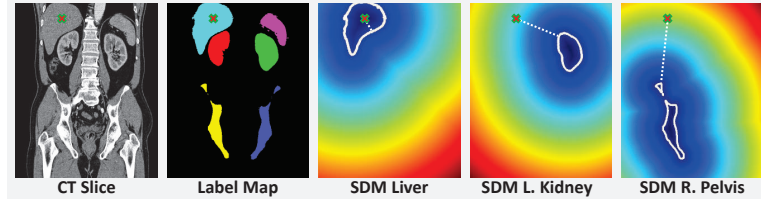
$$H(\mathcal{S}) = - \sum_{c \in \mathcal{C}} \int_{r \in \mathbb{R}^n} p(c, r|x) \log p(c, r|x) dr \\ = \underbrace{- \sum_{c \in \mathcal{C}} p(c|x) \log p(c|x)}_{\text{Shannon Entropy: } H_c} + \underbrace{\sum_{c \in \mathcal{C}} p(c|x) \left( - \int_{r \in \mathbb{R}^n} p(r|c, x) \log p(r|c, x) dr \right)}_{\text{Weighted Differential Entropy: } H_{r|c}}$$

Features: Capture local and contextual appearance



## Motivation: Class + Spatial Consistency

Exploit rich nature of label maps



Spatial Consistency via Distance Regression

Predictor

$$p(r|c, x) \cong \mathcal{N}(r; \mu_{r|c}, \Sigma_{r|c}|c, x)$$

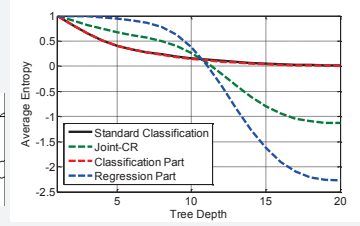
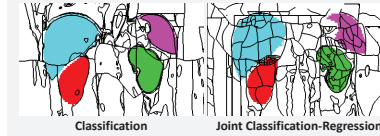
Entropy

$$H_{r|c} = \sum_{c \in \mathcal{C}} p(c|x) \left( \frac{1}{2} \log[(2\pi e)^n |\Sigma_{r|c}|] \right)$$

Entropy Normalization

$$H(\mathcal{S}) = \frac{1}{2} \left( \frac{H_c(\mathcal{S})}{H_c(\mathcal{S}_0)} + \frac{H_{r|c}(\mathcal{S})}{H_{r|c}(\mathcal{S}_0)} \right)$$

Spatial Regularization



Robust Parameter Estimation

Parent nodes provide prior on Gaussian parameters

$$\mu_{r|c}^{\text{child}} = \frac{|\mathcal{S}_{r|c}^{\text{child}}|}{\kappa + |\mathcal{S}_{r|c}^{\text{child}}|} \mu_{r|c}^{\text{child}} + \frac{\kappa}{\kappa + |\mathcal{S}_{r|c}^{\text{child}}|} \mu_{r|c}^{\text{parent}} \quad \Sigma_{r|c}^{\text{child}} = \frac{|\mathcal{S}_{r|c}^{\text{child}}|}{Z} \Sigma_{r|c}^{\text{child}} + \frac{\nu + n - 1}{Z} \Sigma_{r|c}^{\text{parent}} + \text{mean correction term}$$

## Experimental Evaluation

Setup

- 80 3D-CT scans, 6 major organs
- 2-fold cross-validation (40/40 train/test split)
- 50 trees, depth 20: trained on 10% of image points
- 100 features per node from a pool of 1000 features
- Greedy optimization over 10 uniform thresholds

Forest Predictions

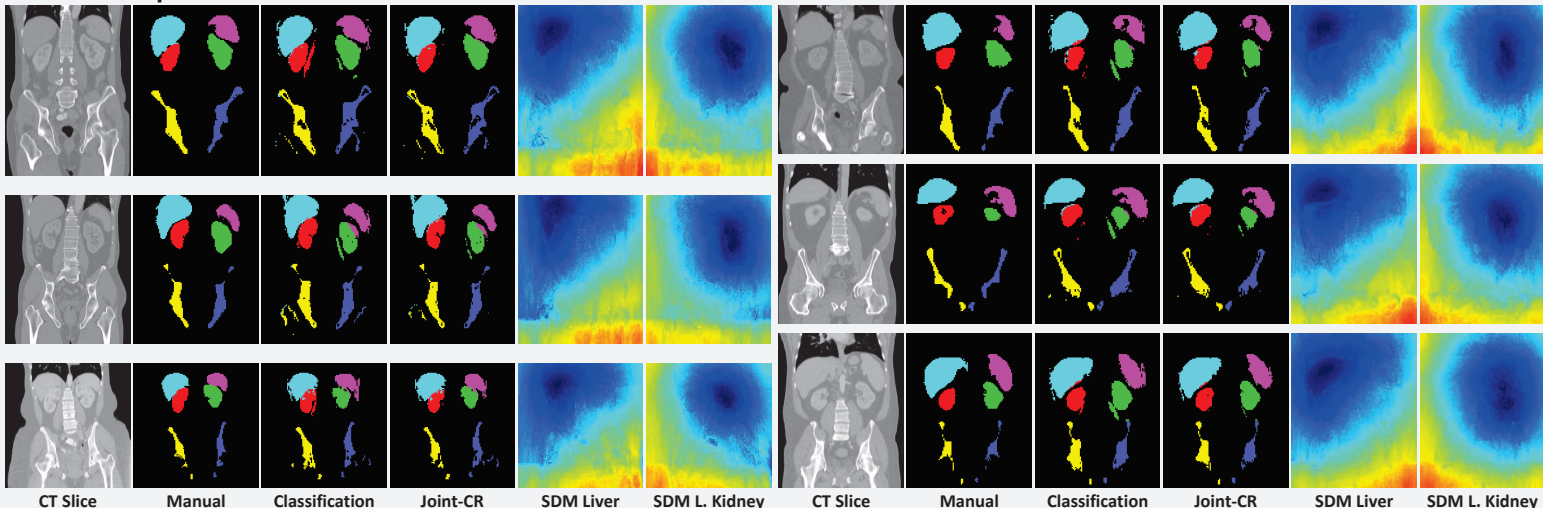
Classification MAP estimate

$$\hat{c} = \arg \max_{c \in \mathcal{C}} p(c|x)$$

Regression mixture mean estimate

$$\tilde{r} = \sum_{c \in \mathcal{C}} p(c|x) \mu_{r|c}$$

Visual Examples



Joint classification-regression yields class and spatial consistency

## Quantitative Results

