Semantic Context Forests for Learning-Based Knee Cartilage Segmentation in 3D MR Images

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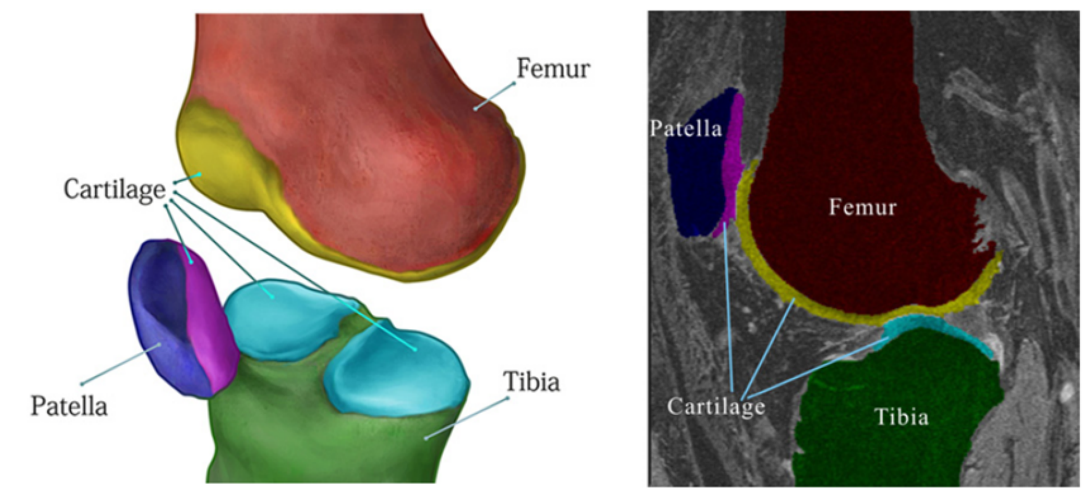
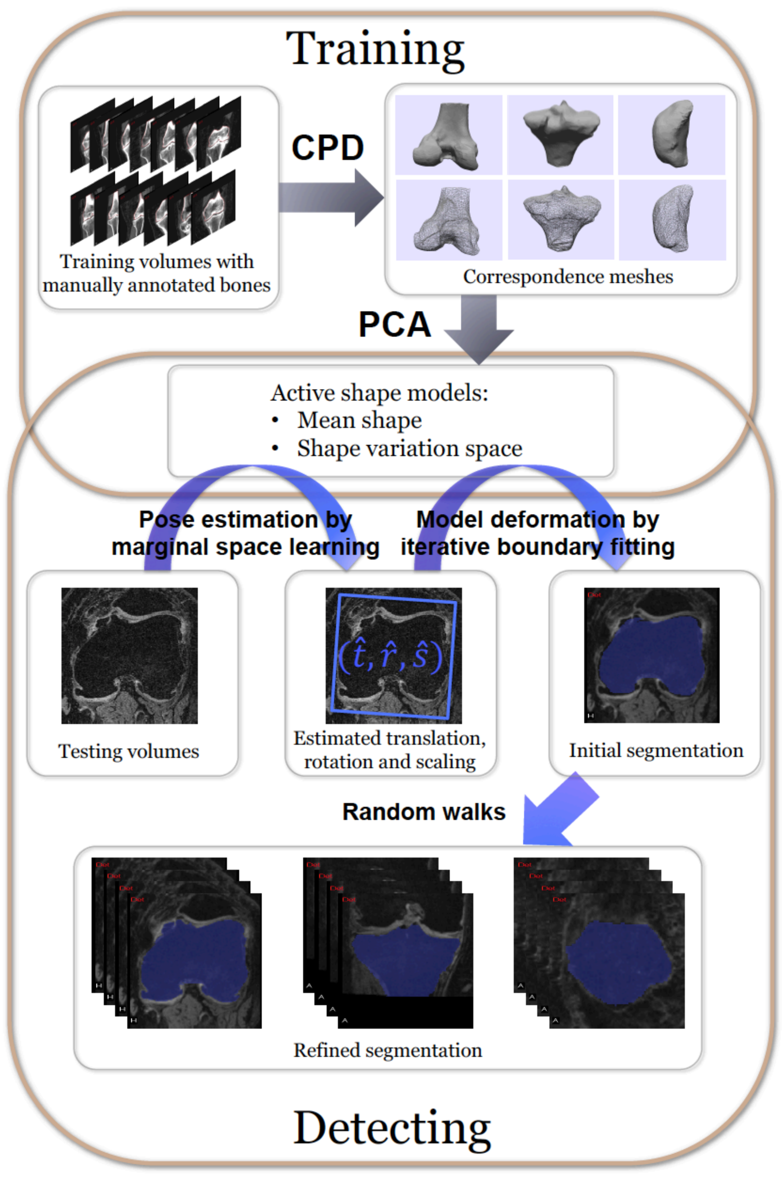
Abstract

The automatic segmentation of human knee cartilage from 3D MR images is challenging due to the thin sheet structure of the cartilage with diffuse boundaries and inhomogeneous intensities. We present an iterative multi-class learning method to segment the femoral, tibial and patellar cartilage simultaneously, which effectively exploits the spatial contextual constraints between bone and cartilage, and also between different cartilages. High accuracy and robustness is achieved on 176 volumes from the OAI dataset.

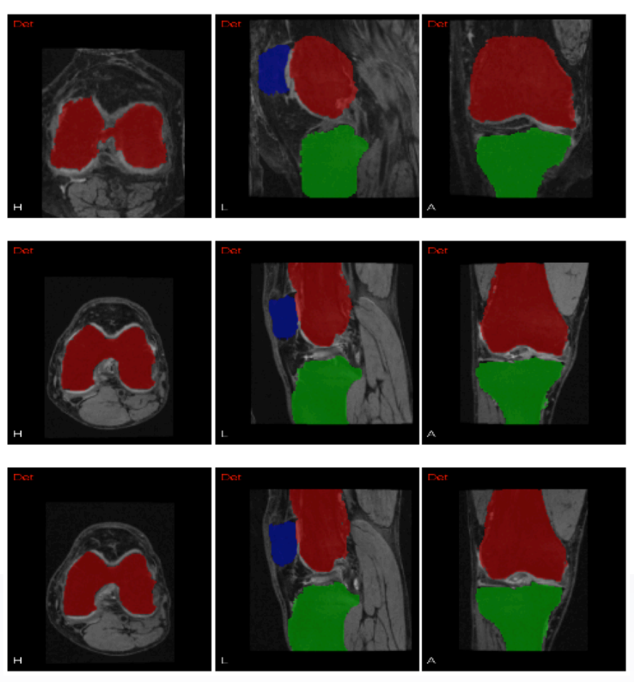


Bone Segmentation

We first segment knee bones using Marginal Space Learning (MSL) followed by random walks (RW) refinement.



	Femur DSC (%)	Tibia DSC (%)	Patella DSC (%)
Before RW	92.37±1.58	94.64±1.18	92.07±1.47
After RW	**94.86**±1.85	**95.96**±1.64	**94.31**±2.15



Resulting segmentation masks

Red: femur

Green: tibia

Blue: patella

Feature Extraction

For each voxel, we extract:

1. Intensity-based features.

$$f_1(\mathbf{x}) = I(\mathbf{x}),\ f_2(\mathbf{x}) = ||\nabla I(\mathbf{x})||$$

2. Distance to bone surface features and their linear combinations.

$$f_3(\mathbf{x}) = d_F(\mathbf{x}),\ f_4(\mathbf{x}) = d_T(\mathbf{x}),\ f_5(\mathbf{x}) = d_P(\mathbf{x})$$

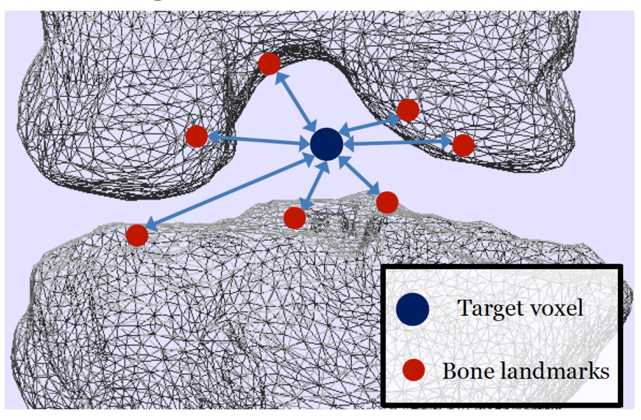
$$f_{6/7}(\mathbf{x}) = d_F(\mathbf{x}) \pm d_T(\mathbf{x})$$

$$f_{8/9}(\mathbf{x}) = d_F(\mathbf{x}) \pm d_P(\mathbf{x})$$

3. Distance to densely registered bone landmark features.

$$f_{10}(\mathbf{x}, \zeta) = ||\mathbf{x} - \mathbf{z}_\zeta||$$

This is a novel and effective way to combine shape-model-based methods and learning-based methods.



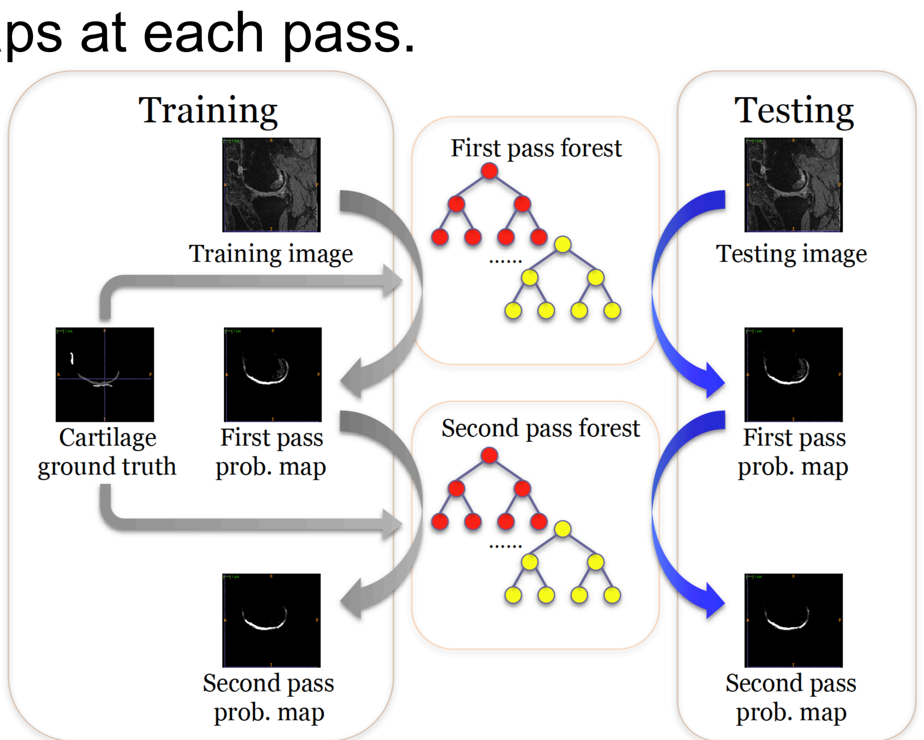
4. Context features.

$$f_{11}(\mathbf{x}, \mathbf{u}) = I(\mathbf{x} + \mathbf{u}) - I(\mathbf{x})$$

Context features capture the rich context information in the MR data.

Semantic Context Forests

We use auto-context alike cascaded random forests to improve the probability maps at each pass.

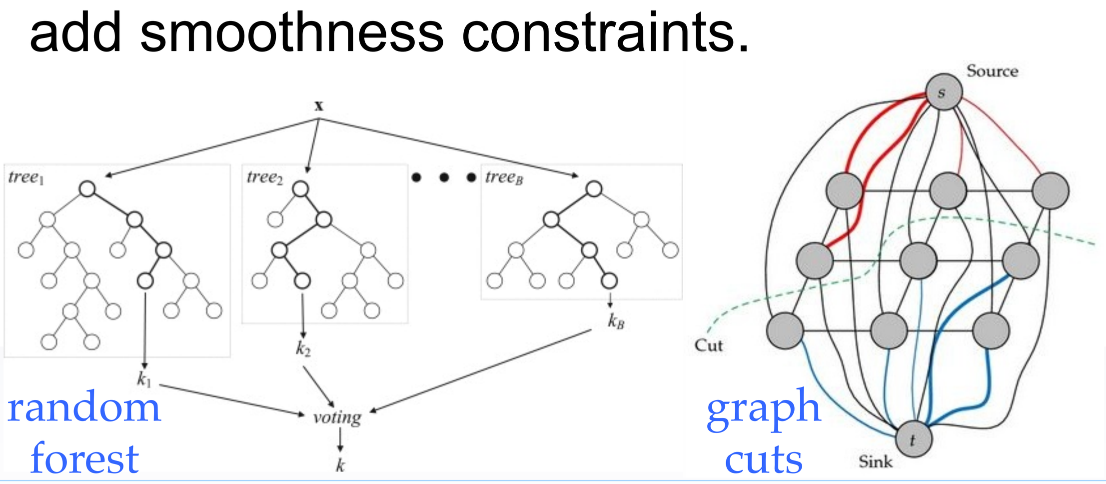


At each pass, we compute 6 new (groups of) features using probabilities from the previous pass:

$$f_{12}(\mathbf{x}) = P_F(\mathbf{x}),\ f_{13}(\mathbf{x}) = P_T(\mathbf{x}),\ f_{14}(\mathbf{x}) = P_P(\mathbf{x})$$

$$f_{15/16/17}(\mathbf{x}, \mathbf{u}) = P_{F/T/P}(\mathbf{x} + \mathbf{u}) - P_{F/T/P}(\mathbf{x})$$

Finally, we use multi-label graph cuts to add smoothness constraints.



Dataset

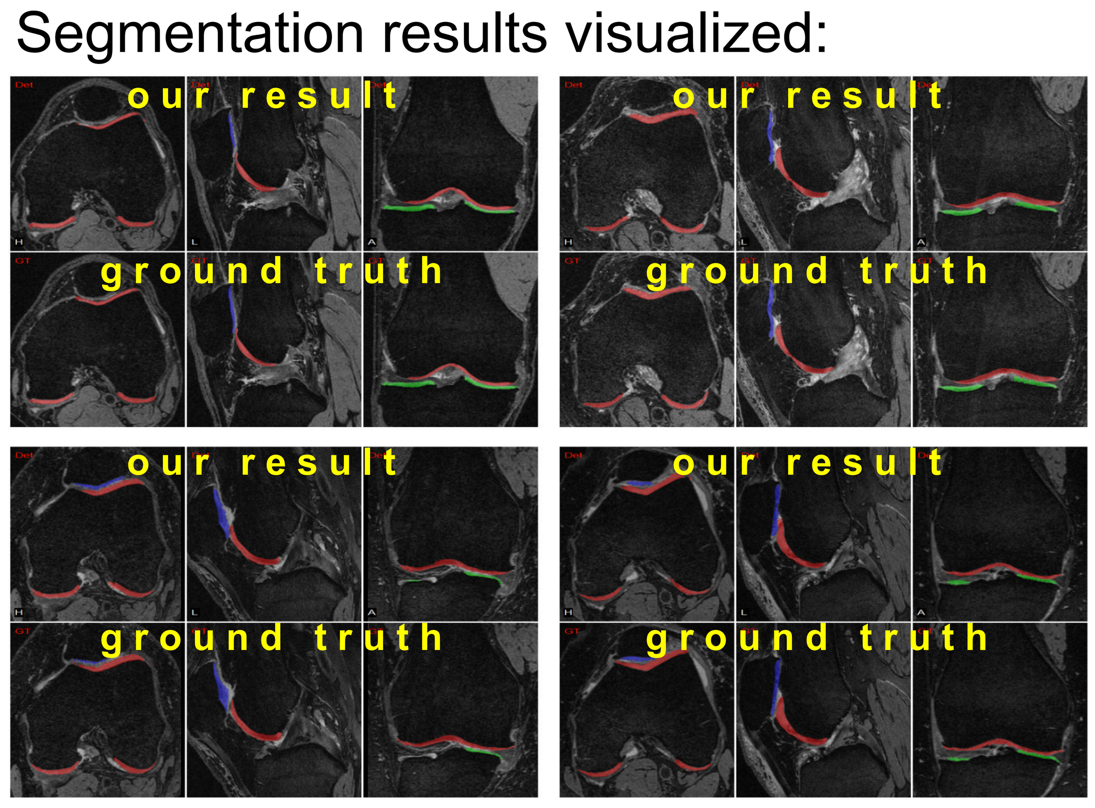
Our method is evaluated on 176 volumes from the Progression subcohort of OAI dataset. Image size is 384×384×160. We perform three-fold cross validation and report Dice Similarity Coefficient (DSC).

Experiment Results

Numerical evaluation using DSC:

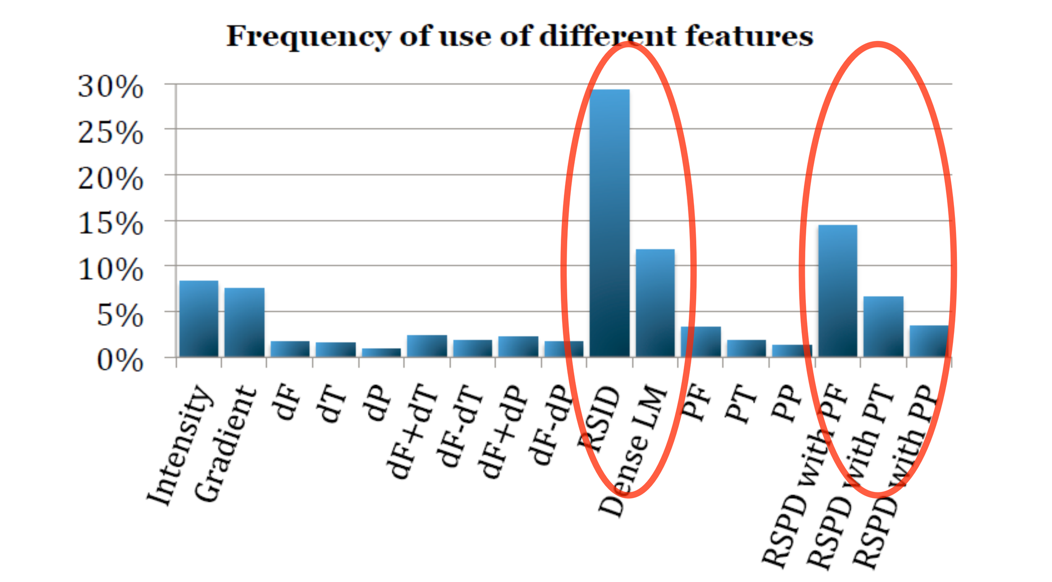
Author	Dataset	Fem. Cart. DSC Mean	Fem. Cart. DSC Std.	Tib. Cart. DSC Mean	Tib. Cart. DSC Std.	Pat. Cart. DSC Mean	Pat. Cart. DSC Std.
Shan [23]	18 SPGR images	78.2%	5.2%	82.6%	3.8%	–	–
Folkesson [2]	139 Esaote C-Span images	77%	8.0%	81%	6.0%	–	–
Fripp [4]	20 FS SPGR images	84.8%	7.6%	82.6%	8.3%	83.3%	13.5%
Lee [6]	10 images in OAI	82.5%	–	80.8%	–	82.1%	–
Yin [5]	60 images in OAI	84%	4%	80%	4%	80%	4%
Proposed method	OAI, D_1 subset (58 images)	85.47%	3.10%	84.96%	3.82%	78.56%	9.38%
	OAI, D_2 subset (58 images)	85.20%	3.65%	83.52%	4.08%	80.79%	7.40%
	OAI, D_3 subset (60 images)	84.22%	3.05%	82.74%	3.84%	78.12%	9.63%
	OAI, overall (176 images)	84.96%	3.30%	83.74%	4.00%	79.16%	8.88%

Segmentation results visualized:

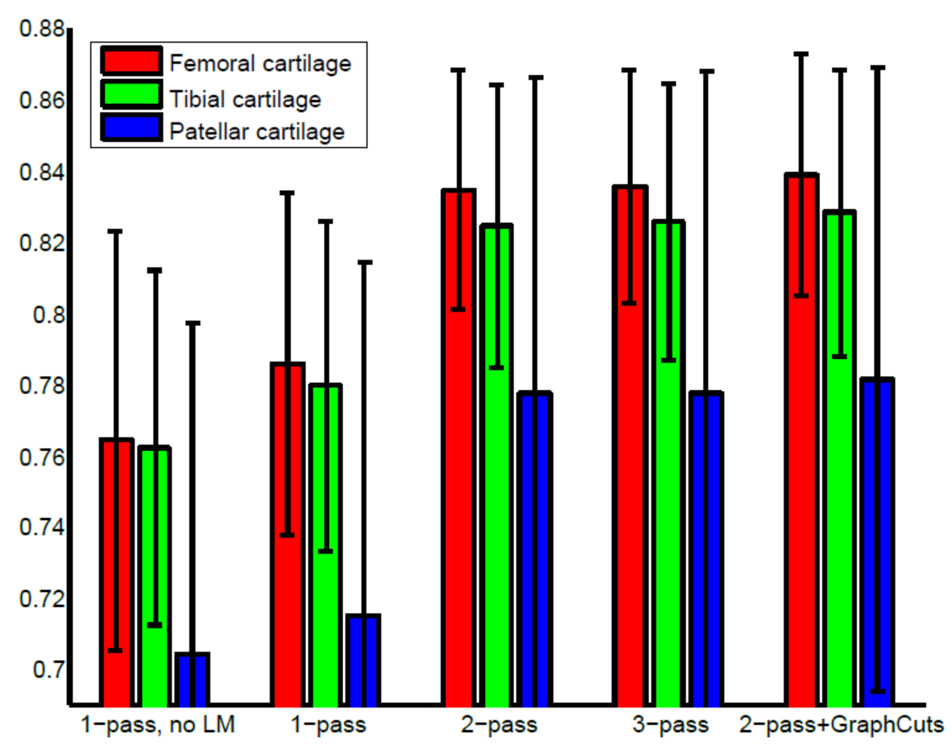


Red: Femoral cart. **Green:** Tibial cart. **Blue:** Patellar cart.

Feature frequency in random forests:



Comparative study:



Biggest improvement is from distance to bone landmark features and a second pass random forest.

Example prob. maps of femoral cartilage: