# A New Adaptive Markov Random Field Model in a Coupled Level Set Framework for Bladder Wall Segmentation in MR

Images

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# Introduction

Bladder cancer has become the fourth most common diagnosed cancer and the fifth leading cause of cancer-related deaths in the United States [1]. Early detection is crucial to effectively cure the disease and reduce the death rate. Additionally, as the recurrence rate after resection of the tumors is reported as high as 80% [2], an appropriate follow-up procedure is also essential to detect bladder abnormalities. Magnetic resonance (MR) imaging-based virtual cystoscopy (VCys) [3] has shown its promising virtue for evaluation of the entire bladder and early diagnosis of bladder carcinoma because of its non-invasive, safe, and cost-effective nature.

# Purpose

One primary goal of VCys is to detect the bladder wall abnormal regions for urologists' further diagnosis, in which wall thickness is the key factor to identify abnormalities. To acquire such information for computer-aided detection, a precise 3-D bladder wall model is needed, which requires an effective segmentation of the inner and outer borders of the wall.

## Method

In this work, we propose a novel approach to integrate an adaptive Markov random field (MRF) model into a coupled level set (CLS) framework [4] for bladder wall segmentation using  $T_1$ -weighted MR images. Firstly, upon initializing an inner level-set function (ILSF) inside the bladder lumen, the ILSF is further evolved by using the modified Chan-Vese model to achieve a preliminary segmentation of bladder inner wall. Secondly, after expanding the current ILSF outwards for certain layers via morphological dilation, a preliminary segmentation of outer wall can be obtained by evolving the dilated ILSF surface. Thirdly, the inner and outer borders of the bladder wall are further refined through an interleaved iterative operation of the coupled level-set evolution and the proposed adaptive MRF model-based maximum a *posteriori* (MAP) classification as follows,

$$L_{x}^{(n+1)} = \arg \max_{l \in \{1,2,3\}} [p_{l}(I_{x} \mid \Theta_{l}^{(n+1)}) \cdot p(l \mid L_{N_{x}}^{(n)}, \Phi_{x}^{(n)})]$$

where *L* denotes the label set of ROI containing 3 classes (lumen, wall, and outside soft tissues),  $p(I | \Theta)$  is the Gaussian probability of image intensity *I* with parameter  $\Theta$ , and  $p(I | L_N, \Phi)$  represents the scale-adaptive MRF prior probability of class *l* given the current neighboring labels  $L_N$  and level set functions  $\Phi$ . Eventually, when the iterative process is converged for a finalized inner and outer borders, the bladder wall thickness can be measured as the integration of electric field path from each voxel on the inner border to the outer border.

### Results

As shown in Fig. 1 of patient studies, the proposed method obviously outperformed the previously reported CLS method in terms of preserving the true bladder wall structure. The bladder lesions with heated colors representing abnormal wall thicknesses were detected via 3-D volume rendering. Furthermore, experts were asked to score the segmented borders from both methods, which showed that our new approach generated highly-significant higher scores than the old approach on both segmented inner border (p < 0.001) and outer border (p < 0.0001), given that the scores from different experts were consistent (p = 0.808). To further evaluate the robustness of our method, simulated phantom studies were conducted as shown in Fig. 2, and Fig. 3 illustrates that both the misclassification rate (< 1%) and classification variation (< 0.4%) of proposed approach are satisfactory.



(d) (e) (f) Figure 1: Results from patient studies: (a)(d) the CLS approach, (b)(e) the new approach, and (c)(f) the corresponding 3-D rendering for each patient dataset.



Figure 2: Slice view of original and segmented image from a digital phantom.



Figure 3: Accuracy (left panel) and repeatability (right panel) evaluation of proposed segmentation scheme via digital phantoms at different noise levels.

#### Conclusion

We have presented a clinical data-driven approach for segmenting the bladder wall in  $T_1$ -weighted MR images. The new method has been evaluated by both phantom and patient studies. Since this framework takes full advantages of both the CLS method and the MRF model-based algorithm, promising improvement was observed over the previous CLS approach.

#### References

- [1] R. Siegel et al., CA: A Cancer J. Clin., 2012.
- [2] D.L. Lamm et al., CA: A Cancer J. Clin., 1996.
- [3] D.J. Vining et al., Am. J. of Roentgenology, 1996.
- [4] C. Duan et al., IEEE Trans. Med. Imaging, 2010.