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A unified EM approach to bladder wall segmentation with coupled level-set constraints

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Abstract

Magnetic resonance (MR) imaging-based virtual cystoscopy (VCys), as a non-invasive, safe and cost-effective technique, has shown its promising virtue for early diagnosis and recurrence management of bladder carcinoma. One primary goal of VCys is to identify bladder lesions with abnormal bladder wall thickness, and consequently a precise segmentation of the inner and outer borders of the wall is required. In this paper, we propose a unified expectation-maximization (EM) approach to the maximum-*a-posteriori* (MAP) solution of bladder wall segmentation, by integrating a novel adaptive Markov random field (AMRF) model and the coupled level-set (CLS) information into the prior term. The proposed approach is applied to the segmentation of T₁-weighted MR images, where the wall is enhanced while the urine and surrounding soft tissues are suppressed. By introducing scale-adaptive neighborhoods as well as adaptive weights into the conventional MRF model, the AMRF model takes into account the local information more accurately. In order to mitigate the influence of image artifacts adjacent to the bladder wall and to preserve the continuity of the wall surface, we apply geometrical constraints on the wall using our previously developed CLS method. This paper not only evaluates the robustness of the presented approach against the known ground truth of simulated digital phantoms, but further compares its performance with our previous CLS approach via both volunteer and patient studies. Statistical analysis on experts' scores of the segmented borders from both approaches demonstrates that our new scheme is more effective in extracting the bladder wall. Based on the wall thickness calibrated from the segmented single-layer borders, a three-dimensional virtual bladder model can be constructed and the wall thickness can be mapped on to the model, where the bladder lesions will be eventually detected via experts' visualization and/or computer-aided detection.

Keywords

Virtual cystoscopy; Bladder wall segmentation; EM algorithm; MAP solution; Markov random field; Coupled level-set

1. Introduction

According to the up-to-date statistics from American Cancer Society, bladder cancer has become the fourth most commonly diagnosed cancer and the eighth leading cause of cancer-

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related deaths among males in the United States. Approximately 72,570 new cases and 15,210 deaths for bladder cancer were estimated in the United States in 2013, which have increased by 26% and 22%, respectively in the past decade (Jemal *et al.*, 2003, Siegel *et al.*, 2013). Early detection of bladder abnormalities is crucial to effectively cure the disease and reduce the death rate. Because the recurrence rate after resection of the tumors is reported as high as 80% (Lamm and Torti, 1996), an appropriate follow-up procedure is also essential to detect bladder abnormalities.

While fiberoptic cystoscopy is currently believed to be the most accurate diagnostic procedure to detect bladder lesions, it is invasive, expensive and uncomfortable, with a limited field-of-view (FOV) and high risk of urinary track bleeding and infection following the invasive procedure (Aa *et al.*, 2009; Mariappan and Smith, 2005). Recent developments in medical imaging technologies render virtual cystoscopy (VCys) as a potential alternative (Duan *et al.*, 2012, 2011; Gohseth and Lerner, 2009; Kim *et al.*, 2005; Song *et al.*, 2001). Although most previous VCys studies are based on computed tomography (CT) technology, magnetic resonance (MR) imaging proves to be a better modality not only because it does not use ionizing radiation but it is also fully non-invasive, safe and cost-effective (Chen *et al.*, 2000; Liang *et al.*, 1999).

In clinical applications of VCys, image segmentation serves the ultimate goal of extracting the whole bladder wall, where the majority of clinical information resides. Early effort of using deformable model to delineate the bladder shape from CT images has shown good results (Costa *et al.*, 2007; Rousson *et al.*, 2005), but those works used CT images and did not segment both the inner and outer borders. Our previous work on MR-based VCys (Li *et al.*, 2008, 2004, 2003b) has shown promising results for the segmentation of the inner bladder wall, where a mixture-based segmentation algorithm with Markov random field (MRF) model-based prior is employed to segment multispectral MR images. Nevertheless, the segmentation of the outer bladder wall was not resolved until the introduction of a coupled level-set (CLS) approach on T_1 -weighted MR images (Duan *et al.*, 2010). Recently, Chi *et al.* (2011) applied a geodesic active contour (GAC) model in T_2 -weighted image to segment the inner bladder wall, and then coupled the constraint of maximum wall thickness in T_1 -weighted image to segment the outer wall. The limitation of their work arose from the difficulty to register the slices between two sequences. Ma *et al.* (2011) segmented the inner boundary in T_2 -weighted images using a modified GAC model and the outer boundary using a shape-guided Chan-Vese model, but the procedure of image smoothing before segmentation may cause the loss of true information of the bladder wall. Qin *et al.* (2012) proposed a coupled directional level set model to segment bladder wall boundaries from T_2 fast spin-echo MR images, however, the robustness of their model for three-dimensional (3D) segmentation had not been investigated.

In short, none of these methods is unifying information from both statistical and deformable models. Based on our tentative work of the adaptive MRF model-based image segmentation (Han *et al.*, 2013), we hereby propose a hybrid bladder wall segmentation approach by taking fully advantage of both the MRF model-based expectation-maximization (EM) algorithm (Li *et al.*, 2003a; Zhang *et al.*, 2001) and the CLS framework (Duan *et al.*, 2010; Paragios 2002; Zeng *et al.*, 1999, 1998). In that sense, our new approach not only accounts for the local distributional information provided by the random field model, but also naturally preserves the global shape information utilized in the level set method. It has been shown that the presented segmentation approach significantly reduces the influence of the artifacts in MR images and the complex background outside the bladder.

Different from most pre-existing works of focusing on T_2 -weighted MR images, this work considers T_1 -weighted images instead. Because the wall signal in T_1 -weighted images is

enhanced while the inside lumen and outside soft tissues are suppressed, the partial volume (PV) effect going from wall toward the lumen is less visible. However, in T₂-weighted images, the lumen signal is enhanced and the PV effect goes from the lumen into the wall, which can “swallow” small abnormal growth on the inner boundary (Lammle *et al.*, 2002; Liang *et al.*, 1999). Typical examples of T₁- and T₂- weighted bladder MR images are illustrated in Fig. 1.

The remainder of this paper is organized as follows: A general but brief review of the CLS method, the main steps of our proposed approach to bladder wall segmentation, and the evaluation methods on the segmentation quality are presented in Section 2. Section 3 reports the experimental results and quantitative evaluations for both phantom and clinical studies, especially the performance comparison with our previously proposed CLS approach. The conclusion and future work are provided in Section 4.

2. Method

2.1. Overview of Level Set Method

The classical level set method (Osher and Sethian, 1988), as an edge-based deformable model to detect objects in a given image, has been used extensively by the image segmentation community. Mathematically, a level set function (LSF) $(x_1, x_2, \dots, x_n) : D \rightarrow \mathbb{R}$ defined on an n -dimensional data domain D has real positive values inside and negative values outside the implicit surface of $\Phi = 0$ (i.e., the ZLSS: zero level set surface). At an artificial time t , the dynamics for the evolution of the ZLSS are introduced in its normal direction by:

$$\frac{\partial \Phi}{\partial t} + F|\nabla \Phi| = 0 \quad (1)$$

where $F = \text{div}(\frac{\nabla \Phi}{|\nabla \Phi|})$ is the curvature force to detect edges. Starting with a surface around the object to be detected, the LSF evolves and terminates its ZLSS on the boundary of the object. To segment regions without or with weak edges, the Chan-Vese (C-V) model (Chan and Vese, 2001) using both edge- and region-based image forces was proposed to improve the classical one.

Segmenting thin, elongated structures like the bladder wall is a peculiar task that often requires dedicated approaches, and the CLS method (Duan *et al.*, 2010) is one of the solutions for such applications. Two level set functions, i.e., inner LSF (ILSF) and outer LSF (OLSF), are utilized to segment the inner and outer bladder wall borders simultaneously. As shown in Fig. 2, two ZLSSs from ILSF Φ_1 and OLSF Φ_2 , respectively, are used to represent the two borders. The basic idea in the CLS method is that, instead of evolving each LSF to its convergence individually, coupling the information from both LSFs makes the extraction of both borders more stable and more accurate.

2.2. A Unified EM Approach with Coupled Level-Set Constrains

The proposed bladder wall segmentation framework can be described as follows. Firstly, upon manually initializing the ZLSS of the ILSF inside the bladder lumen, the ZLSS of ILSF is evolved outwards until reaching the boundary between lumen and wall, where we obtain a preliminary segmentation of the inner border. Secondly, an OLSF is initialized by expanding the ZLSS of the current ILSF outwards for certain layers via morphological dilation followed by further evolutions to reach the boundary between wall and outside tissues. Thirdly, through iteratively interleaved operations of the maximum-*a-posteriori* EM (MAP-EM) classification and the according evolution of CLS functions, the bladder wall inner and outer borders (i.e., the ZLSSs of the CLS functions) are further refined. Finally,

the bladder wall thickness is measured as the length of the electric field path from a point on the inner border to the outer border, and bladder lesions with abnormal thickness and wall textures can be detected via either experts' visualization or ideal observers (i.e., computer-aided detection and diagnosis - CAD). The proposed pipeline is depicted in Fig. 3.

2.2.1. Initialization of inner and outer level set functions—As the image intensity in bladder lumen is relatively homogeneous, it is easier to firstly distinguish the inner border rather than the outer border of the bladder wall. We initialize the ZLSS of ILSF as a spherical surface inside the bladder lumen. By modifying the C-V model from global to local operations in the image energy (Duan *et al.*, 2010), the ILSF Φ_1 is evolved by the following Euler-Lagrange equation:

$$\frac{\partial \Phi_1}{\partial t} = -\delta(\Phi_1(x))[(I_x - c_{in})^2 - (I_x - c_{out})^2] - \delta(\Phi_1(x))\lambda_1 + \int_D K(y-x)\{\gamma_1 H(\Phi_1(y-x)) - \gamma_2 [1 - H(\Phi_1(y-x))]\} dy \quad (2)$$

where the first term is a region-based image force generated from the local intensity difference inside and outside of the ZLSS, and the last two terms are the edge-based geometry forces. In the first term of Equation (2), c_{in} and c_{out} denote the local intensity mean values calculated from the inward and outward voxels close to the ZLSS of Φ_1 , where the distance from those voxels to the ZLSS is less than a narrow band width B . By setting Φ_1 to be negative in the second term, the ZLSS expands outwards step-by-step. The last two terms together, called the bent rate term, play the role of controlling the smoothness of the ZLSS. $H(\cdot)$ is the Heaviside step function, whose value is 1 when $\cdot > 0$ and 0 if $\cdot \leq 0$, and $\delta(\cdot) = dH(\cdot)/d\cdot$ denotes the 1D Dirac measure. $K(y-x)$ is also a step function whose value is 1 if $|y-x| \leq T$ and 0 otherwise, with T being a predefined positive constant to control the effective region of the bent rate. By setting $\Phi_1 = \Phi_2$, the bent rate term prevents the ZLSS from over bended. As a result, a preliminary segmentation of the inner bladder wall can be obtained when the ZLSS of ILSF reaches the boundary where the image intensity is sharply increased in T_1 -weighted MR images due to a transition from lumen to wall.

In our previous work, the OLSF Φ_2 is initialized based on an assumption that the outer border usually has a similar global shape as the inner border. However, this is not really the case in the presence of bladder lesions of higher stages. For instance, the shape of the inner border for a heavily diseased bladder may differ a lot from the shape of the outer border. To overcome this issue, we first expand the ZLSS of ILSF outwards for certain layers case-by-case via the operation of morphological dilation, which aims to mitigate the geometry discrepancy between the inner and outer borders. As illustrated in Fig. 4, compared with the original ZLSS of ILSF, the dilated ZLSS is much closer to the appearance of the outer bladder wall.

When $t = 0$, the ZLSS of OLSF is initialized as the dilated ZLSS of ILSF. Then only the geometry force for the ILSF Φ_1 , i.e., the last two terms in Equation (2), is adapted to evolve the OLSF Φ_2 for a preliminary segmentation of the outer border by

$$\frac{\partial \Phi_2}{\partial t} = -\frac{I_x}{1 + |\nabla I_x|^2} \{\delta(\Phi_2(x))\lambda_2 - \int_D K(y-x)[\gamma_3 H(\Phi_2(y)) - \gamma_4 (1 - H(\Phi_2(y)))] dy\} \quad (3)$$

where I_x represents the image gradient at location x , and $I_x/(1 + |\nabla I_x|^2)$ serves as an edge indicator to properly terminate the evolution at the boundary of the bladder wall and outside soft tissues. Same as Equation (2), Φ_2 is set to be negative which expands the ZLSS of OLSF outwards step-by-step, and a similar bent rate of $\gamma_3 = \gamma_4$ is adopted.

2.2.2. Statistical model for bladder wall segmentation—Since the ZLSSs of ILSF and OLSF from the preliminary segmentation have been placed near the inner and outer bladder wall borders, respectively, it is straightforward to define a shell-shaped volume of interest (VOI) containing the bladder wall, which is usually set to be 3 or 5 layers thicker from both sides of the volume enclosed by the ZLSSs of coupled LSFs. As the segmentation target has been switched from the entire MR volume to the defined VOI, our goal is to segment the VOI into $L = 3$ classes, labeled $l = 1$ (bladder lumen), 2 (bladder wall), or 3 (other tissues outside the wall), respectively.

In general, the signal-to-noise ratio (SNR) for bladder MR images is usually much larger than 2. Hence, it is reasonable to assume the noise imposed on the image signal follows the Gaussian distribution (Gudbjartsson and Patz, 1995). Suppose a voxel x in the VOI comes from a tissue type $l = x$ with intensity mean μ_x and variance ν_x , the observed voxel intensity I_x is assumed to follow a Gaussian probability density function:

$$p(I_x | \mu_{\omega_x}, \nu_{\omega_x}) = \frac{1}{\sqrt{2\pi\nu_{\omega_x}}} \exp\left[-\frac{(I_x - \mu_{\omega_x})^2}{2\nu_{\omega_x}}\right]. \quad (4)$$

By the Bayesian theory, without prior knowledge of voxel x belonging to which class, the likelihood of observing voxel x with intensity I_x can be described as a finite Gaussian mixture model with the voxel label ω_x as a latent variable:

$$p(I_x) = \sum_{l=1}^L p(I_x | \mu_l, \nu_l) p(\omega_x = l). \quad (5)$$

The likelihood $p(I_x)$ implicitly depends on the tissue type ω_x that voxel x belongs to, and such uncertainty on voxel labeling is called the *a priori* probability, which can be formulated in the following functional, as described in (Duan *et al.*, 2010):

$$p(\omega_x) = \beta \exp[-\alpha_1 U(\omega_x) - \alpha_2 V(\omega_x)], \quad (6)$$

where β , α_1 , and α_2 are positive constant values.

Intuitively, the ZLSSs from the initialized ILSF and OLSF can provide prior knowledge of the bladder wall structure as well as the relative position of the inner border to the outer border, which can prevent the two borders from overlapping or crossing. Therefore, a level set potential term $U(\omega_x)$ is introduced in Equation (6), which is defined as:

$$U(\omega_x) = |\omega_x - \omega_{LS,x}| \min(|\Phi_1(x)|, |\Phi_2(x)|), \quad (7)$$

where $\omega_{LS,x}$ denotes the label of voxel x determined by both the ILSF ω_1 and the OLSF ω_2 evaluated at location x :

$$\omega_{LS,x} = \begin{cases} 1, \Phi_1(x) > 0 \\ 2, \Phi_1(x) < 0 \& \Phi_2(x) > 0 \\ 3, \Phi_2(x) < 0 \end{cases}. \quad (8)$$

As shown in Fig. 2, a voxel is classified as the bladder lumen ($\omega_{LS,x} = 1$) when it is inside the ZLSS of ILSF, and is classified as tissues outside the bladder wall ($\omega_{LS,x} = 3$) if it is

outside the ZLSS of OLSF. When the voxel is located outside the ZLSS of ILSF and inside the ZLSS of OLSF simultaneously, it is determined as the bladder wall ($L_{S,x} = 2$).

The commonly used MRF model is incorporated into the prior term of Equation (6) as well, where $V(x)$ is the newly proposed adaptive MRF (AMRF) potential:

$$V(\omega_x) = \sum_{y \in N_x^s} \frac{w_y}{d_y} \cdot [1 - \delta(\omega_y - \omega_x)]. \quad (9)$$

Here δ is an indicator function defined by $\delta(0) = 1$ or $\delta(\neq 0) = 0$, and N_x^s represents the scale-adaptive neighborhood of voxel x . The adaptive weight associated with each neighboring voxel y is w_y/d_y , where d_y denotes the Euclidean distance from voxel y to the central voxel x , and w_y as the normalized labeling difference within the clique (x, y) is defined by (Wang *et al.*, 2009):

$$w_y = \frac{|\omega_y - \omega_x|}{\max_{y \in N_x^s} |\omega_y - \omega_x|}. \quad (10)$$

To determine a scale-adaptive MRF size for each image voxel, we first introduce the object scale $s(x)$ at voxel x as the radius of the largest digital ball centered at that voxel, such that all voxels inside the ball satisfy a predefined intensity homogeneity criterion (Zhang *et al.*, 2012). By denoting $B_r(x)$ as a set of voxels within a digital ball of radius r centered at voxel x , the corresponding fraction of object (FO) that indicates the degree of intensity homogeneity for voxels on the outermost layer of digital ball $B_r(x)$ is formulated as:

$$FO_r(x) = \frac{\sum_{y \in B_r(x) - B_{r-1}(x)} G_\psi(I_x - I_y)}{|B_r(x) - B_{r-1}(x)|}, \quad (11)$$

where $|B_r(x) - B_{r-1}(x)|$ corresponds to the number of voxels in the volume of $B_r(x) - B_{r-1}(x)$. $G(\cdot)$ is a homogeneity function defined in the form of a unnormalized Gaussian kernel:

$$G_\psi(d) = e^{-\frac{d^2}{2\sigma_\psi^2}}. \quad (12)$$

Please refer to Saha and Udupa (2001) on how to select the appropriate homogeneity parameter (i.e., the standard deviation) for the Gaussian kernel.

Let the radius of a digital ball centered at each concerned voxel x be initialized as one, the fraction of object $FO_r(x)$ is calculated by increasing the ball radius r by a step of one each time. When the first time that the $FO_r(x)$ falls below a predefined threshold (usually 85% (Saha and Udupa, 2001)), we assume the largest radius of an intensity-homogeneous ball is reached and set the scale $s(x)$ to be $r - 1$. Subsequently, the order of neighbors to be considered in the AMRF model can be adaptively chosen based on the corresponding scale at the concerned voxel. Fig. 5 shows our scale-based neighborhood selection strategy. For each scale value, the neighborhood is constructed to be spherically symmetric in the 3D spatial domain based on the spatial resolution of the volumetric image.

2.2.3. Model fitting via the CLS integrated MAP-EM approach—In the proposed statistical model, the image intensity I is observable while the image labeling ω is unknown.

Thus, this is an incomplete data problem, where I is called the incomplete data while (I, ω) together forms the complete data. Since it is intractable to directly solve this model estimation problem, an EM algorithm, as the most widely used technique for solving the incomplete data problem, is desired.

We hereby employ an AMRF model-based MAP-EM algorithm to iteratively update the model parameters and voxel labels. A preliminary classification of the VOI, by using the well-known K -means clustering (Tou and Gonzalez, 1974), is available to initiate the label $\omega_x^{(0)}$ for each voxel x as well as the model parameters $\{\mu_l^{(0)}, \nu_l^{(0)}\}$ for each tissue type l , which is the very first step of the following iterative procedure.

The E-step computes the conditional expectation of the complete data likelihood $P(I, \omega | \Theta)$ penalized by the prior of voxel-wise labeling $P(\omega)$, given the observed data I and current parameter estimates $\Theta^{(n)} = \{\mu_l^{(n)}, \nu_l^{(n)}, \omega_x^{(n)}\}$:

$$Q(\Theta | \Theta^{(n)}) = E_{\Omega}[\ln(P(I, \Omega | \Theta) \cdot P(\Omega)) | I, \Theta^{(n)}]. \quad (13)$$

The M-step finds the new estimate of Θ which maximizes the Q -function:

$$\Theta^{(n+1)} = \arg \max_{\Theta} Q(\Theta | \Theta^{(n)}). \quad (14)$$

The detailed derivations on parameter estimation by the MAP-EM algorithm are provided in the Appendix A. It is shown that the model parameters for each class $l = 1, 2, 3$ can be updated iteratively by

$$\begin{cases} \mu_l^{(n+1)} = \frac{\sum_{x \in VOI} Z_{xl}^{(n)} I_x}{\sum_{x \in VOI} Z_{xl}^{(n)}} \\ \nu_l^{(n+1)} = \frac{\sum_{x \in VOI} Z_{xl}^{(n)} (I_x - \mu_l^{(n+1)})^2}{\sum_{x \in VOI} Z_{xl}^{(n)}} \end{cases} \quad (15)$$

where $Z_{xl}^{(n)}$ represents the conditional probability at current step that voxel x belongs to class l given its intensity I_x , and by Bayes' rule it can be calculated as:

$$Z_{xl}^{(n)} = \frac{p^{(n)}(\omega_x = l) p(I_x | \mu_l^{(n)}, \nu_l^{(n)})}{\sum_{l=1}^L p^{(n)}(\omega_x = l) p(I_x | \mu_l^{(n)}, \nu_l^{(n)})}. \quad (16)$$

Updating the voxel labels simultaneously while maximizing the Q -function is equivalent to updating the label ω_x voxel-by-voxel via the MAP criterion:

$$\omega_x^{(n+1)} = \arg \max_{l \in \{1, 2, 3\}} [p(I_x | \mu_l^{(n+1)}, \nu_l^{(n+1)}) \cdot p_{GS}^{(n)}(\omega_x = l)]. \quad (17)$$

Now recall the *a priori* probability defined by Equations (6), (7) and (9), their formulations have a clear interpretation. Mathematically, the maximization of the prior $p(x)$ in Equation (17) is equivalent to the minimization of its potential terms. The minimization of potential term $U(x)$ not only encourages voxel x to have the same label as it is determined by the LSFs via the term $|x - L_{S,x}|$, but also addresses the uncertainty of the classification for those voxels around the boundaries by minimizing the term $\min(|\Phi_1(x)|, |\Phi_2(x)|)$, i.e., the distance from x to the nearest ZLSS. While the minimization of $V(x)$ encourages the continuity of class labels between the central voxel x and its neighbors y .

In order to speed up the convergence of the MAP-EM algorithm, the *a priori* probability in Equation (17) is calculated under the Gauss-Seidel (GS) updating strategy (Sauer and Bouman, 1993), which takes advantage of available labeling information one step ahead. Once the label for each voxel in the VOI is updated via the above MAP-EM classification, a new level set energy function can be constructed from the updated labels as follows:

$$E^{MAP-EM} = \int_{x \in VOI} p(\omega_x=1|I_x)H(\Phi_1(x))H(\Phi_2(x))dx - \int_{x \in VOI} p(\omega_x=2|I_x)[1-H(\Phi_1(x))]H(\Phi_2(x))dx \\ - \int_{x \in VOI} p(\omega_x=3|I_x)[1-H(\Phi_1(x))][1-H(\Phi_2(x))]dx \\ + \gamma_5 \iint_D K(y-x)\Phi_1(y-x)[2H(\Phi_1(y-x))-1]dydx + \gamma_6 \iint_D K(y-x)\Phi_2(y-x)[2H(\Phi_2(y-x))-1]dydx \quad (18)$$

where γ_5 and γ_6 are adjustable parameters to control the bent rate. The first three integrations in Equation (18) represent the image energy while the last two integrations correspond to the geometry energy. The image energy is formulated as the negative of the cumulative probability of voxels in the VOI belonging to each specific class $l = 1, 2, 3$.

Minimization of this energy encourages the updated labeling $\omega_{LS,x}^{(n+1)}$ determined by the updated CLS functions to agree with the MAP-EM classification result.

By minimizing the energy function E^{MAP-EM} with respect to Φ_1 and Φ_2 , respectively, we have the following Euler-Lagrange equations accordingly:

$$\frac{\partial \Phi_1}{\partial t} = \delta(\Phi_1) \{ [p(\omega_x=1|I_x) - p(\omega_x=2|I_x)]H(\Phi_2) - p(\omega_x=3|I_x)[1-H(\Phi_2)] \} + \gamma_5 \int_D K(y-x)[2H(\Phi_1(y-x))-1]dy \quad (19)$$

$$\frac{\partial \Phi_2}{\partial t} = \delta(\Phi_2) \{ p(\omega_x=1|I_x)H(\Phi_1) - [p(\omega_x=2|I_x) - p(\omega_x=3|I_x)][1-H(\Phi_1)] \} + \gamma_6 \int_D K(y-x)[2H(\Phi_2(y-x))-1]dy \quad (20)$$

Hence, the current step ILSF Φ_1 and OLSF Φ_2 can be further evolved by the forces generated from Equations (19) and (20). A new $L_{S,x}$ estimate of the label for each voxel x can be determined by both the updated ILSF $\Phi_1^{(n+1)}$ and OLSF $\Phi_2^{(n+1)}$, which makes it ready to trigger the next interleaved operation of the MAP-EM classification and the CLS evolution.

This iterative interleaved procedure stops when the number of updated voxels is less than one tenth of the total number of voxels on the ZLSS within one time step. To put it in another way, an optimal segmentation of the bladder wall is achieved when the classification by the MAP-EM algorithm converges to the solution via the CLS evolution. The entire proposed procedure is depicted as followings:

1. $n = 0$, initiate the to-be-estimated parameter $\Theta^{(0)} = \{\mu_l^{(0)}, v_l^{(0)}, \omega_x^{(0)}\}$ from a preliminary classification of the VOI by using the K -means clustering, and initiate

the level set determined label $\omega_{LS,x}^{(0)}$ based on the initialized CLS functions $\Phi_1^{(0)}$ and $\Phi_2^{(0)}$.

2. Calculate the posterior probability by

$$Z_{xl}^{(n)} = \frac{p^{(n)}(\omega_x=l)p(I_x|\mu_l^{(n)},\nu_l^{(n)})}{\sum_{l=1}^L p^{(n)}(\omega_x=l)p(I_x|\mu_l^{(n)},\nu_l^{(n)})}$$

where the prior probability is

$$p^{(n)}(\omega_x=l) = \beta \exp\{-\alpha_1 |l - \omega_{LS,x}^{(n)}| \min(|\Phi_1^{(n)}(x)|, |\Phi_2^{(n)}(x)|) - \alpha_2 \sum_{y \in N_x^s} \frac{w_y}{d_y} [1 - \delta(l - \omega_y^{(n)})]\}$$

3. Update the tissue model parameters by

$$\mu_l^{(n+1)} = \frac{\sum_{x \in VOI} Z_{xl}^{(n)} I_x}{\sum_{x \in VOI} Z_{xl}^{(n)}} \quad \nu_l^{(n+1)} = \frac{\sum_{x \in VOI} Z_{xl}^{(n)} (I_x - \mu_l^{(n+1)})^2}{\sum_{x \in VOI} Z_{xl}^{(n)}}$$

4. Update the label for each voxel by the MAP estimation

$$\omega_x^{(n+1)} = \arg \max_{l \in \{1,2,3\}} [p(I_x|\mu_l^{(n+1)},\nu_l^{(n+1)}) \cdot p_{GS}^{(n)}(\omega_x=l)].$$

5. Evolve coupled LSFs $\Phi_1^{(n+1)}$ and $\Phi_2^{(n+1)}$ to minimize the new energy constructed from the updated labeling $\omega_x^{(n+1)}$.
6. Update the level set determined label $\omega_{LS,x}^{(n+1)}$ based on the updated LSFs.
7. $n \leftarrow n+1$, repeat from 2 until a stopping criterion has been met.

2.3. Segmentation Quality Indexes

To quantitatively measure the robustness of a segmentation method against the known ground truth, the following segmentation quality indexes were employed in our digital phantom studies. The accuracy of our proposed approach was evaluated by calculating the segmentation error rate (ER) with respect to each tissue type $l = 1, 2$, or 3 as a ratio of the bias of segmented volume V_l to the true volume V_l :

$$ER_l = \left| \widehat{V}_l - V_l \right| / V_l. \quad (21)$$

On the other hand, the repeatability was assessed by the coefficient of variation (CV), which is defined as a ratio of the standard error to the mean of the segmented volume for each tissue type l :

$$CV_l = S_{\widehat{V}_l} / \widehat{V}_l. \quad (22)$$

Furthermore, the overall segmentation quality could be measured by the commonly used miss classification rate (MCR), which is interpreted as:

$$MCR = \frac{\text{Number of miss classified voxels}}{\text{Total number of voxels}}. \quad (23)$$

For the study on diseased bladder phantoms, we particularly emphasized the segmentation precision on the cancer lesion instead of on each tissue type, which can be quantitatively measured by the Dice similarity index (DSI):

$$DSI(V_s, V_g) = \frac{2|V_s \cap V_g|}{|V_s| + |V_g|}, \quad (24)$$

where $|V_s|$ represents the estimated tumor volume based on the segmentation result and $|V_g|$ represents the known ground truth of the tumor volume. The DSI measures the degree of matching between the ground truth and the segmentation result, and its value changes from 0 (the worst) to 1 (the best).

3. Results and Discussion

3.1. Experiment Setting

At the beginning of the proposed bladder wall segmentation approach, the ZLSS of ILSF was manually drawn as a sphere (with different positions and radii for different lumen volumes) inside the bladder lumen through a graphical user interface. For the evolution of LSFs, the time and spatial steps were both fixed at 1. We empirically fixed the narrow band width B for level set construction to be 5, and the effective region T and smoothing parameters for bent rate calculation to be 8 and 10, respectively. The number of layers for the dilation of ILSF ranged from 0 to 3 depending on the minimum wall thickness. While for the MAP-EM classification, tunable parameters are the weights α_1 and α_2 for calculating the *a priori* probability. In order to make the novel AMRF model play a dominating role in the prior term, we usually set $\alpha_1 = 0.2$ and $\alpha_2 = 0.8$, empirically.

3.2. Robustness Evaluation of Our Approach via Digital Phantom Studies

To mimic the anatomical structure around the bladder wall, a three tissue-type digital phantom was generated for our simulation studies. Based on statistical analysis of the intensity distribution of clinical bladder MR images, we generated the soft tissue (ST) outside bladder wall with a mean intensity value of $\mu_1 = 500$, the bladder wall (BW) with a mean intensity value of $\mu_2 = 1000$, and the bladder lumen (BL) inside wall with a mean intensity value of $\mu_3 = 750$. Meanwhile, white noises with zero mean and standard deviations σ_i ($i = 1, 2, 3$) were imposed on each tissue type, where the noise level σ_i/μ_i was set to be varying from 1% (small noise) to 9% (large noise). To evaluate the robustness of our method, five scans/images with $128 \times 128 \times 128$ array size and 1mm cubic voxel size were simulated as replicates at each specific noise level.

Taking the simulated phantom with a medium noise level (5%) as an example, Fig. 6 illustrates a cross section of the digital phantom and the corresponding segmentations from both the CLS and the presented approaches. Though the visual difference is subtle as expected, the segmentation from the proposed method with an MCR of 1.32% is superior to that from our previous CLS method with an MCR of 3.53%. To better understand their performance, the convergence speed of the proposed MAP-EM algorithm in comparison to the regional adaptive clustering algorithm (RACA), which inherits the idea of (Pappas, 1992) and was proposed in the previous CLS work (Duan *et al.*, 2010), is shown in Fig. 7.

We can see that the proposed algorithm converges fast and becomes stable after less than ten iterations, while the convergence of the RACA algorithm is relatively slow not to mention its large MCR.

As an iterative approach, the robustness of the proposed algorithm can be evaluated from two aspects. On one hand, we validated its robustness to initial estimates of to-be-estimated parameters. Table 1 summarizes the MCR for the segmentation of phantom shown in Fig. 6, allowing the initial tissue model parameters $\{\mu^{(0)}, \sigma^{(0)}\}$ with various deviations (increasing or decreasing) from their true values. Given distributional parameters for each class, the corresponding initial classification $\{c^{(0)}\}$ can be obtained through intensity thresholding. The uniform MCRs in Table 1 show that our algorithm is insensitive to initial estimates. On the other hand, the robustness of our approach to the segmentation of phantoms with various noise contaminations was also examined. As shown in Fig. 8, despite of the varying noise level, the overall ER of the presented approach is less than 1% and the overall CV is below 0.4%. Therefore, both the accuracy and repeatability of the proposed segmentation scheme are satisfactory. Besides focusing on the measure of ER and CV for each segmented tissue type, it is more reasonable to measure the performance of our approach using the overall MCR. The averaged MCR at each noise level are listed in the second row of Table 2, where the overall MCR is below 3% and an expected increasing trend of the MCR is observed with an increase of noise levels.

Furthermore, to examine the robustness of our method to the segmentation of irregularly shaped bladder walls, studies on diseased bladder phantoms were conducted as well. Fig. 9 demonstrates one typical example of the diseased bladder phantom with a tumor embedded on the inner wall, where there is a high level noise contamination of 9%, and the MCR over the entire volume is reduced from 3.39% of the CLS method to 2.18% of the proposed method. Instead of evaluating the accuracy on the segmented bladder wall, we focused on the precision of tumor size estimation which is more clinically oriented. As shown in Fig. 10, our approach is able to obtain a reasonable segmentation of the tumor with the DSI value above 94% across different noise levels. Meanwhile, it is noted that the overall MCR is also satisfactory and boosts with the increment of noise level as shown in the last row of Table 2.

3.3. Comparison with the Previous CLS Approach on Clinical Data

Under informed consent, two normal volunteer and three patient subjects were scanned using a Philips Achieva 2.6 MR scanner. A 3D THRIVE (T_1 High Resolution Isotropic Volume Examination) pulse sequence was employed to acquire T_1 -weighted images covering the FOV of the whole bladder with 10° flip angle, T_R of 6.23ms, T_E of 3.87ms, 1mm slice thickness, the image size of 256×256 , and the total slice number of 84. The acquisition time for an image volume of each subject was less than 20 minutes. The voluntary motions were mitigated by instructing the subject to keep still and with the help of a belt motion suppression system. Moreover, post image processing to compensate for the motion and deformation of the bladder wall during data acquisition was also considered (Lin *et al.*, 2011).

3.3.1. Volunteer studies—The two healthy volunteers (male) were with an average age of 28. Fig. 11 shows one example of T_1 -weighted MR image from a volunteer dataset, where a noticeable weak intensity area is observed on the bladder wall as indicated by the arrow in Fig. 11(c). It results in a connection between lumen and outside tissues, which places a challenge to the capacity of segmentation algorithms in preventing the ZLSS from leaking out of a weak wall area. As shown in Fig. 11(f) and Fig. 11(i), the previous CLS approach failed to avoid such leakage, while our new approach, with more accurate detection of the weak edge between lumen and wall, effectively prevented the leakage. Of

note, in order to prevent the previous CLS approach from a severe leakage outside the bladder, the maximum evolution number of ILSF was defined which inevitably resulted in an insufficient evolution of the ILSF as can be seen from Fig. 11(d) and Fig. 11(e). Fig. 12 illustrates another example from the other volunteer dataset. The presented method apparently has a better delineation of the inner and outer borders compared with the CLS method. The CLS method failed to determine the bladder-prostate interface but our new method succeeded as shown in Fig. 12(h) and Fig. 12(i). Even for the relatively easy task of inner border segmentation, the outcome from the CLS approach shows unsatisfactory results because it is sensitive to inhomogeneities within the bladder lumen (e.g., near the arrows in Fig. 12(a) and Fig. 12(b)).

3.3.2. Patient studies—The three patients (2 male and 1 female) were with an average age of 75. Fig. 13 shows the slice views of a male patient dataset, where there is a large tumor embedding on the inner mucosa layer. The proposed approach correctly outlined the outer bladder wall while the CLS approach failed as indicated by the up arrow in Fig. 13(d). The third column of Fig. 13 demonstrates that the presented approach is more sensitive to weak edges of the bladder wall, which ensures an accurate calculation of the wall thickness. Fig. 14 and Fig. 15 illustrate the segmentation results from another two patient datasets using the previous and the presented approaches, respectively. Since the wall contrast to its outside surrounding soft tissues varies noticeably as shown in Fig. 14, the previous CLS method failed severely at the relatively low contrast areas marked by the arrows, but the proposed approach succeeded because tissue model parameters in the MAP-EM algorithm are estimated based on the global rather than local information. Now refer to Fig. 15 of a female patient scan, the presented method obviously outperformed the CLS method in terms of preserving the expected structure of the bladder wall. Part of the bladder wall looks even fuzzy as marked in Fig. 15(c), and the presented approach was still able to prevent the outer zero level set from overlapping with the inner zero level set.

3.3.3. Quantitative evaluation of the segmented results—In order to quantitatively evaluate the difference between our new approach and the previous CLS method, five experts were asked to score the segmented inner and outer borders from the three patient and two volunteer datasets. By comparing to the corresponding bladder MR raw images slice by slice, scores were given in the range from 0 (worst) to 10 (best) for each method to correlate with the clinical utility. This expert evaluation study was a blinded process, because we set the display order of segmentation results to be random and the experts had no knowledge of which method was used for each display.

Fig. 16 shows the pair-wise scatter plots of experts' scores on our new method against the old method for the segmentation of either the inner (Fig. 16(a)) or the outer (Fig. 16(b)) border. To visualize duplicate points with identical values, all the scores were jittered by adding into some sufficiently small random noises. For the evaluation of segmented inner border, there are 18, 3, and 4 out of 25 pairs of scores that the presented method was given greater, equal, and smaller scores than the previous method, respectively. The 4 pairs of scores under the 45 degree concordance line correspond to the cases where the segmented inner border from the new method is not as smooth as that from the old method (e.g., as indicated by the left arrow in Fig. 13(d) and Fig. 13(g)), and such deficit can be overcome by increasing the smoothing radius for the level set evolution. Since most of the data points in Fig. 16(a) and all of the points in Fig. 16(b) fall above the concordance line, we can conclude that our new method is superior to the old method.

In addition, the scores were further analyzed using a linear mixed-effects model (Littell *et al.*, 2006). There exist the two-level random effects, including a random subject effect and a random border effect nested within subject, and the fixed effects, including three main

effects of expert, border, and method, as well as one interaction effect of border-by-method. The statistical analysis demonstrates that the newly proposed approach generates highly-significant higher scores than the old CLS approach for either the segmented inner border ($p < 0.001$) or the outer border ($p < 0.0001$). The corresponding differences between the scores of these two methods and their 95% confidence intervals are 1.40 (0.74, 2.07) for the inner border and 3.70 (3.03, 4.37) for the outer border. Furthermore, the expert effect is not statistically significant ($p = 0.808$) which can be concluded that the scores from different experts are consistent in ranking these two methods.

3.3.4 Visualization of the segmented bladder wall—Given the segmented single-layer inner and outer borders, the wall thickness for each voxel positioned on the inner border can be expressed as the integration of the electric field path from the concerned voxel to the outer border. The electric field path is assured to be perpendicular to both borders. Since the two borders are treated as two iso-surfaces, one and only one electric field path can be traced from each voxel on one surface to the other (Zhao *et al.*, 2011). Bladder lesion areas with abnormal wall thickness are detected via machine learning. Finally, 3D rendering of the segmented bladder wall, with pseudo colors representing different wall thicknesses, can be generated for the purpose of urologists' further diagnosis and inspection. Fig. 17 shows the rendering results for a volunteer and a patient datasets. The dotted circle in Fig. 17(a) indicates a leakage of the inner border caused by an inaccurate segmentation from the previous CLS approach as already shown in Fig. 11(f). Overall, the 3D bladder model rendered from our new segmentation results not only captures the expected structure of the bladder wall but also provides a more visually appealing interface for VCys.

4. Conclusion and Future Work

In this paper, we have presented a clinical data-driven approach for segmenting the bladder wall in T_1 -weighted MR volumes. The proposed approach is an integration of the CLS method and the AMRF model-based MAP-EM algorithm. As an iterative approach, it demonstrates good performance such as fast convergence, robustness to initial estimates, and robustness against noise contaminations as well as local shape variations of the bladder wall. To prove the gain of the presented method, we compared its performance with our previously developed CLS method via both phantom and clinical studies. Promising improvement was observed. The breakthrough of our new approach is in five folds.

First of all, triggered by the motivation to improve our previous CLS framework, an AMRF model-based MAP-EM algorithm is introduced as a substitute of the RACA clustering procedure. Comparing to the RACA strategy which usually yields a biased estimation of the underlying statistical model parameters, the new algorithm yields accurate estimation of the model parameters and thus generates the robust classification outcomes. Moreover, the speed of the convergence of the proposed MAP-EM algorithm is faster than that of the previous RACA algorithm.

Secondly, different from our previous CLS framework, the presented algorithm updates the model parameters, regional labels, as well as the level set functions simultaneously within one iteration step, which makes the interleave of the MAP-EM classification and the CLS evolutions in a real unified manner.

Thirdly, while the conventional MRF model considers a fixed order of neighbors, our AMRF model adopts the scale-based adaptive neighborhoods to construct the MRF penalty. The neighborhood for each voxel is adaptively determined according to the degree of intensity homogeneity around that voxel. When the local intensity distribution tends to be uniform, a larger neighborhood for the MRF prior is considered to enlarge the penalty

difference between distinct tissue types, as it is believed that voxels with similar intensities are likely to fall into the same class. On the contrary, when the local intensity distribution is complicated (e.g., near the outer bladder wall), a smaller MRF neighborhood reduces the misclassification rate by mitigating the disturbance from nearby major classes, and thus preserves the boundary sharpness and fine structures.

Fourthly, instead of using the conventional distance-based MRF weights, the MRF coefficients utilized in our AMRF model are more adaptive, in the sense that it makes the subsequent MAP classification more discriminative by stratifying the labeling difference between neighboring voxels and the central voxel.

Last but not least, it is unrealistic for the previous CLS approach to assume that the outer border of the bladder wall has a similar shape as the inner border. For instance, the inner border of a diseased bladder may vary a lot in shape from the outer border. Our previous work initiates the evolution of OLSF directly from the ZLSS of ILSF, however, the OLSF may be inadequately evolved in the presence of a large discrepancy between the shape of the ZLSS of ILSF and the shape of the outer border. In this paper, we propose an efficient way to initialize the OLSF via an operation of morphological dilation from the ZLSS of ILSF followed by further evolutions to reach the outer border. The gain of this manipulation is that not only the ZLSS of OLSF can be placed more closely to the outer bladder wall, but also it can avoid unexpected termination of the OLSF at the inner border when the ILSF is inadequately initialized.

Nevertheless, considering the PV effect around bladder wall borders, further research on classifying each voxel as a mixel with different tissue proportions via the mixture-based MAP-EM algorithm (Li *et al.*, 2004; Liang and Wang, 2009) is under progress to minimize the PV effect. In addition, bias field correction (Li *et al.*, 2008) can be incorporated into the proposed MAP-EM algorithm to accommodate the commonly existed inhomogeneity effect in MR images. More importantly, future work is needed to appraise the impact of the presented segmentation approach for the detection of bladder abnormalities by either experts' visualization or ideal observers (i.e., CAD).

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Appendix A. Derivation of the MAP-EM Solution

This section provides the derivation for the EM approach to the MAP solution of the proposed statistical model, where $\Theta = \{\mu, v\}$ is the to-be-estimated parameter. Based on the chain rule and the fact that $P(\Theta | I) = 1$, we have $P(I, \Theta) = P(I | \Theta) \cdot P(\Theta) = P(I | \Theta) \cdot P(\Theta)$. Hence, Equation (13) in the E-step of the EM algorithm can be rewritten as:

$$Q(\Theta | \Theta^{(n)}) = E_{\Omega}[\ln(P(I | \Omega, \Theta) \cdot P(\Omega)) | I, \Theta^{(n)}]. \quad (A.1)$$

According to the conditional independence assumption of the image intensity I_x and of the labeling ω_x for each voxel x , Equation (A.1) can be further expressed as:

$$\begin{aligned} Q(\Theta | \Theta^{(n)}) &= E_{\Omega} \left[\sum_{x \in VOI} \ln(p(I_x | \mu_{\omega_x}, v_{\omega_x}) \cdot p(\omega_x)) | I, \Theta^{(n)} \right] \\ &= \sum_{x \in VOI} E_{\omega_x} [\ln(p(I_x | \mu_{\omega_x}, v_{\omega_x}) \cdot p(\omega_x)) | I, \Theta^{(n)}] \\ &= \sum_{x \in VOI} \sum_{l=1}^L [\ln(p(I_x | \mu_l, v_l) p(\omega_x=l)) \cdot p(\omega_x=l | I, \Theta^{(n)})], \end{aligned} \quad (A.2)$$

where L is the predefined number of classes for the VOI.

Of note, given infinite realizations of the entire image intensity configuration, it is computationally infeasible to calculate the labeling probability $P(\omega_x = l | I, \Theta^{(n)})$ of a single voxel x . However, the Markov random field assumption ensures that the labeling of a single voxel is merely influenced by its own intensity and its neighbors' labeling configuration. For simplicity, we use the symbol $Z_{xl}^{(n)}$ to represent the current estimate of the posterior probability $P(\omega_x = l | I_x, \Theta^{(n)})$.

Substituting $Z_{xl}^{(n)}$ into Equation (A.2) and expanding the probability density functions, we have

$$Q(\Theta|\Theta^{(n)}) = \sum_{x \in VOI} \sum_{l=1}^L \left[-\frac{1}{2} \ln(2\pi\nu_l) - \frac{(I_x - \mu_l)^2}{2\nu_l} - \alpha_1 U(l) - \alpha_2 V(l) \right] \cdot Z_{xl}^{(n)}. \quad (\text{A.3})$$

The M-step aims to find the solution of $\Theta^{(n+1)} = \{\mu_l^{(n+1)}, \nu_l^{(n+1)}, \omega_x^{(n+1)}\}$ which maximizes the Q -function. By setting the first-order partial derivatives of $Q(\Theta|\Theta^{(n)})$ with respect to μ_l and ν_l to be zero, respectively, we can solve the following system of equations:

$$\begin{cases} \frac{\partial Q}{\partial \mu_l} = \sum_{x \in VOI} \frac{(I_x - \mu_l)}{\nu_l} Z_{xl}^{(n)} = 0 \\ \frac{\partial Q}{\partial \nu_l} = \frac{1}{2} \sum_{x \in VOI} \frac{\nu_l - (I_x - \mu_l)^2}{\nu_l^2} Z_{xl}^{(n)} = 0 \end{cases}, \quad (\text{A.4})$$

which yields the new estimates of tissue model parameters:

$$\begin{cases} \mu_l^{(n+1)} = \frac{\sum_{x \in VOI} Z_{xl}^{(n)} I_x}{\sum_{x \in VOI} Z_{xl}^{(n)}} \\ \nu_l^{(n+1)} = \frac{\sum_{x \in VOI} Z_{xl}^{(n)} (I_x - \mu_l^{(n+1)})^2}{\sum_{x \in VOI} Z_{xl}^{(n)}} \end{cases}. \quad (\text{A.5})$$

According to Bayes' rule, the current step posterior probability $Z_{xl}^{(n)}$ in Equation (A.5) can be calculated by:

$$Z_{xl}^{(n)} = \frac{p^{(n)}(\omega_x = l) p(I_x | \mu_l^{(n)}, \nu_l^{(n)})}{\sum_{l=1}^L p^{(n)}(\omega_x = l) p(I_x | \mu_l^{(n)}, \nu_l^{(n)})}, \quad (\text{A.6})$$

where $p^{(n)}(\omega_x = l) = \exp[-\alpha_1 \cdot U^{(n)}(l) - \alpha_2 \cdot V^{(n)}(l)]$ is the current estimate of the *a priori* probability.

Note that the model parameters μ_l and ν_l are continuous vectors but the label ω_x for each voxel is a discrete random variable. Recall Equation (A.2), when fixing the model parameters and the labeling of other voxels $\omega_{i \in VOI, i \neq x}$, the classification of voxel x which makes the Q -function maximized is actually equivalent to the MAP estimation:

$$\omega_x^{(n+1)} = \arg \max_{l \in \{1,2,3\}} [p(I_x | \mu_l^{(n+1)}, \nu_l^{(n+1)}) \cdot p_{GS}^{(n)}(\omega_x = l)]. \quad (\text{A.7})$$

In order to speed up the convergence of the classification process, the Gauss-Seidel (GS) updating strategy is utilized to calculate the *a priori* probability in Equation (A.7) by:

$$p_{GS}^{(n)}(\omega_x = l) = \beta \exp \{ -\alpha_1 [l - \omega_{LS,x}^{(n)} | \min(|\Phi_1^{(n)}(x)|, |\Phi_2^{(n)}(x)|)] - \alpha_2 [\sum_{y \in N_x^s, y < x} \frac{w_y}{d_y} (1 - \delta(l - \omega_y^{(n+1)})) + \sum_{y \in N_x^s, y > x} \frac{w_y}{d_y} (1 - \delta(l - \omega_y^{(n)}))] \}. \quad (\text{A.8})$$

Fig. 1.
Typical examples of T_1 -weighted (left) and T_2 -weighted (right) MR images of the bladder.
The bladder wall is more distinguishable in T_1 -weighted than T_2 -weighted scan.

Fig. 2.
An illustration of the CLS functions and their corresponding ZLSSs.

Fig. 3.
The proposed pipeline for the detection of bladder abnormalities via VCys.

Fig. 4.

A conceptual illustration on the gain of dilation from ILSF to the initialization of OLSF. The gray band denotes the bladder wall. The inner boundary of the white band denotes the ZLSS of initialized ILSF, while its outer boundary represents the dilated ILSF (i.e., the initialized OLSF) which, in shape, is much closer to the outer bladder wall.

Fig. 5.

An illustration of scale-based neighborhood selection. (a) Select the 2D first order neighborhood with 4 neighbors when the scale $s(x) = 0$; (b) select the 3D first order neighborhood with 6 neighbors when $s(x) = 1$; (c) select the 2D second order and 3D first order neighborhood with 10 neighbors when $s(x) = 2$; (d) select the neighborhood with 22 neighbors when $s(x) = 3$.

Fig. 6. Cross section of a healthy bladder phantom simulated at a medium noise level of 5%. (a) Original image; (b) Segmentation from the CLS approach; (c) Segmented image from the proposed approach.

Fig. 7.

The speed of the convergence comparison between the regional adaptive clustering algorithm (RACA) and the proposed MAP-EM algorithm, in terms of the miss classification rate for the segmentation of phantom shown in Fig. 6.

Fig. 8. (a) Error rate and (b) coefficient of variation of the proposed approach for the segmentation of bladder lumen (BL), bladder wall (BW), and soft tissue outside the bladder wall (ST) in healthy bladder phantoms simulated at different noise levels.

Fig. 9. Cross section of a diseased bladder phantom with a high noise level of 9%. (a) Original image; (b) Segmentation from the previous CLS approach; (c) Segmented image from the proposed approach.

Fig. 10.

Averaged Dice similarity index (DSI) with error bars for the segmented bladder tumor from the proposed method at different noise levels.

Fig. 11. Segmented borders (yellow curves) for the first volunteer dataset. (a) – (c) The original T_1 -weighted MR images; (d) – (f) Corresponding segmentation results from the previous CLS approach; (g) – (i) Corresponding segmentation results from our new approach.

Fig. 12. Segmented borders (yellow curves) for the second volunteer dataset. (a) – (c) The original MR images; (d)–(f) Corresponding segmentation results from the previous CLS approach; (g) – (i) Corresponding segmentation results from our new approach.

Fig. 13.

Segmented borders (yellow curves) for the first patient dataset. (a) – (c) The original MR images; (d) – (f) Corresponding segmentation results from the previous CLS approach; (g) – (i) Corresponding segmentation results from our new approach.

Fig. 14. Segmented borders (yellow curves) for the second patient dataset. (a) – (c) The original images; (d) – (f) Corresponding segmentation results from the previous CLS approach; (g) – (i) Corresponding segmentation results from our new approach.

Fig. 15. Segmented borders (yellow curves) for the third patient dataset. (a) – (c) The original MR images; (d) – (f) Corresponding segmentation results from the previous CLS approach; (g) – (i) Corresponding segmentation results from our new approach.

Fig. 16.

Scatter plot of experts' scores on the new method against the old method for the segmentation of (a) the inner border and (b) the outer border. The presented approach is scored significantly higher than the previous approach ($p < 0.001$), especially for the segmentation of the outer border ($p < 0.0001$).

Fig. 17.

3D visualization of a few segmented bladder walls. The outside view of the segmented inner border from the previous CLS approach (upper row) and our new approach (lower row) for the first volunteer dataset (left column) and the first patient dataset (right column). Potential lesion areas are highlighted by warm-colored patches in the 3D bladder model due to the abnormal wall thickness.

Robustness of the MAP-EM algorithm to initial estimates for the segmentation of phantom in Fig. 6 (Upper corner in each cell: given initial estimates larger than true values; Lower corner: smaller than true values).

Table 1

	0% deviation	20% deviation	40% deviation	60% deviation	80% deviation	99% deviation
MCR	1.32%	1.32%	1.31%	1.31%	1.32%	1.32%
		1.31%	1.31%	1.32%	1.32%	1.31%

Table 2

Robustness of the MAP-EM algorithm to the segmentation of phantoms with different noise contaminations.

	1% noise	3% noise	5% noise	7% noise	9% noise
MCR (healthy phantom)	1.256%	1.280%	2.084%	2.368%	2.836%
MCR (diseased phantom)	1.222%	1.238%	1.976%	2.552%	2.598%