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Integration of 3D Scale-based Pseudo-enhancement Correction and Partial Volume Image Segmentation for Improving Electronic Colon Cleansing in CT Colonography

Hao Zhang^{a,b}, Lihong Li^c, Hongbin Zhu^a, Hao Han^a, Bowen Song^a, and Zhengrong Liang^{a,b,*}

^aDept. of Radiology, State University of New York at Stony Brook, NY 11794, USA

^bDept. of Biomedical Engineering, State University of New York at Stony Brook, NY 11794, USA

^cDept. of Engineering Science & Physics, City University of New York at Staten Island, NY 10314, USA

Abstract

Orally administered tagging agents are usually used in CT colonography (CTC) to differentiate residual bowel content from native colonic structures. However, the high-density contrast agents tend to introduce pseudo-enhancement (PE) effect on neighboring soft tissues and elevate their observed CT attenuation value toward that of the tagged materials (TMs), which may result in an excessive electronic colon cleansing (ECC) since the pseudo-enhanced soft tissues are incorrectly identified as TMs. To address this issue, we integrated a 3D scale-based PE correction into our previous ECC pipeline based on the maximum *a posteriori* expectation-maximization partial volume (PV) segmentation. The newly proposed ECC scheme takes into account both the PE and PV effects that commonly appear in CTC images. We evaluated the new scheme on 40 patient CTC scans, both qualitatively through display of segmentation results, and quantitatively through radiologists' blind scoring (human observer) and computer-aided detection (CAD) of colon polyps (computer observer). Performance of the presented algorithm has shown consistent improvements over our previous ECC pipeline, especially for the detection of small polyps submerged in the contrast agents. The CAD results of polyp detection showed that 4 more submerged polyps were detected for our new ECC scheme over the previous one.

Keywords

CT colonography; electronic colon cleansing; pseudo-enhancement correction; partial volume image segmentation; computer-aided detection

I. Introduction

According to statistics from the American Cancer Society, colorectal cancer is the third most commonly diagnosed cancer and the second leading cause of death from cancer in the United States [1]. Fortunately, most colon cancer arises from polyps, which can take 5–15 years for malignant transformation. Thus, early detection and removal of those colonic polyps can effectively decrease the incidence of colon cancer [2–4]. Computed tomography colonography (CTC) has the potential to be a minimal-invasive, cost-effective screening method for detection of colon polyps [5–9]. But the residue stool and colonic fluid survived

*Authors to whom correspondence should be addressed. jerome.liang@sunysb.edu.

after routine bowel preparation [10] would jeopardize the detection of polyps since the residue stool could mimic polyps and increase false positive (FP) rate, while the colonic fluid might bury polyps resulting in false negatives (FNs) [11]. Therefore, in current CTC studies, tagging agents are usually used to opacify the residual colonic materials for differentiation of the residues from colon wall and polyps [12].

However, the use of high-density contrast agents tend to introduce pseudo-enhancement (PE) effect on neighboring soft tissues and elevate their observed CT attenuation value toward that of the tagged materials (TMs). This artificial elevation may result in an excessive electronic colon cleansing (ECC) where the pseudo-enhanced soft tissues are incorrectly identified as TMs according to the reports by Nappi *et al.* [13] and Nappi and Yoshida [14]. Based on the scale-based image filtering strategy [20], Liu *et al.* [21] proposed a two-dimensional (2D) scale-based PE correction method that minimizes the PE effect in CTC data by subtracting the estimated PE components from the observed CT values. Their results indicated that computer-aided detection (CAD) with this PE correction as a preprocessing step can yield a higher sensitivity and a lower FP rate. Besides of the PE effect, a mixed tissue distribution or partial volume (PV) effect also impose several challenges for ECC, resulting in either excessive (over-complete) or incomplete colon cleansings especially for colon mucosa area [15–18]. In the past decade, various research studies of PV effects via modeling tissue mixture inside each voxel have been reported [24–26]. The authors have developed a maximum *a posteriori* expectation-maximization (MAP-EM) PV image segmentation algorithm which simultaneously estimates tissue mixture percentages within each image voxel and statistical model parameters for the tissue distribution [16, 19]. In our previous work [11], the PV effect was properly resolved and the ECC pipeline had shown promising results. However, due to insufficiently dealing with the PE effect, our previous work showed some limitations in CTC examination performance, especially for the severely pseudo-enhanced regions and the subsequent CAD tasks.

A successful ECC of the CT colonography images is critical for the following study. In this work, we aim at developing a new ECC scheme which takes into account both the PE and PV effects that commonly appear in CTC images. Major contributions of this paper are as follows: 1) We expanded the scale-based PE correction method to a 3D space to better estimate the PE effects in CTC images; 2) We adopted the scale strategy for adaptively selecting the local neighborhood information in implementing the MAP-EM PV image segmentation algorithm; and 3) We further integrated the 3D scale-based PE correction into our previous MAP-EM PV image segmentation algorithm for improving the performance of ECC. It was expected that after correction for both the PE and PV effects, an improved performance of ECC scheme shall be observed.

The remainder of this work is presented as follows. Section II introduces the scale-based PE correction method and the MAP-EM PV image segmentation algorithm, followed by Section III which presents the new ECC pipeline. Section IV evaluates the new ECC pipeline using 40 selected CTC datasets with comparison to our previous ECC results. Finally, Section V draws conclusions of this study and also discusses future research directions.

II. Overview of the Correction Method and Segmentation Algorithm

In this study, we extended the scale-based PE correction method [21] to 3D space where the parameters of the associated scale function were derived from the object scale at each voxel. The related scale component was then calculated by convolving the original CT image values with the corresponding scale function. Following that, we adapted the MAP-EM PV image segmentation algorithm for colon wall extraction and lumen cleansing where the

scale-based strategy was also utilized to adaptively select the neighborhood system. The correction method and segmentation algorithm are demonstrated below.

A. 3D Scale-based PE Correction Method

A.1. Computation of object scales—The distance between voxels is defined as the Euclidean distance in 3D space herein. Meanwhile, the scale at each image voxel is defined as the radius of the largest hyperball centered at that voxel so that all voxels within the ball satisfied a predefined image intensity homogeneity criterion [20, 21]. Specifically, for each voxel i in the image, a digital ball of radius r centered at i is a set of voxels $B_r(i)$. Then, the fraction of object $FO_r(i)$, which indicates the portion of the ball boundary occupied by a region that is adequately homogeneous with i , is defined by:

$$FO_r(i) = \frac{\sum_{j \in B_r(i) - B_{r-1}(i)} W_\Psi(Y_i - Y_j)}{|B_r(i) - B_{r-1}(i)|}, \quad (1)$$

where $|B_r(i) - B_{r-1}(i)|$ is the number of voxels in the voxel set of $B_r(i) - B_{r-1}(i)$. Y_i and Y_j are the intensities of voxels i and j respectively, and W_Ψ is a homogeneity function defined by:

$$W_\psi(x) = \exp\left(-\frac{x^2}{2\sigma_\psi^2}\right), \quad (2)$$

where σ_ψ is the region-homogeneity parameter and computed following the method as in Saha and Udupa [20].

In summary, the scale $K(i)$ at each image voxel i , can be computed with the pseudo-code shown in Table I [20]. The computed scale $K(i)$ will be used later not only to correct for the PE effect in CTC images but also to adaptively select the neighborhood system in our segmentation algorithm.

A.2. Calculation of pseudo-enhanced components and correction of PE effect

—After the scale value at each voxel is obtained, the associated distribution of pseudo-enhanced components Y_s at the concerned voxel is estimated by convolving the observed CT image Y_i with an adaptive 3D scale function $SF(i)$. That is, $Y_s = Y_i \otimes SF(i)$. The 3D adaptive scale function is defined as:

$$SF(i) = \left(\frac{1}{\sqrt{\pi}\sigma}\right)^3 \exp\left\{-\frac{[(x-u)^2 + (y-v)^2 + (z-w)^2]}{\sigma^2}\right\}, \quad (3)$$

where (x, y, z) represents the coordinates at image voxel i . Whereas the parameters of the scale function, u, v, w , and σ , are adaptively set as the transformed scale values derived from the above computations, in other words,

$$\sigma = S_i - K(i), \quad (4)$$

$$u = v = w = (S_i - K(i))/2, \quad (5)$$

where S_i is the maximum scale value to be set initially for the scale calculation.

At the end, the PE effect is corrected by subtraction of the estimated 3D pseudo-enhanced components from the original CT image at each voxel. That is, for the newly corrected CT

image Y_c , $Y_c = Y_i - Y_s$. The subtraction can be repeated in a similar manner as an iterative process. It is expected that the repeated process shall converge to a stable solution. This expectation will be reported later in the section of Results.

B. Partial Volume Image Segmentation Algorithm

Let the image intensity $\mathbf{Y}$ after PE correction be represented by a column vector in the form of $\{Y_i, i = 1, \dots, I\}$, where I denotes the total number of voxels in the image and each Y_i is an observation of an individual random variable with mean $\bar{Y}_i$ and variance σ_i^2 at voxel i . (In this study, $\mathbf{Y}$ shall be the image data after the above PE correction). Assume the image contains M tissue types. Let the contribution of tissue type m to the observation of Y_i in

voxel i be denoted by X_{im} , $i = 1, \dots, I$; $m = 1, \dots, M$. Then, we have $Y_i = \sum_{m=1}^M X_{im}$. Each X_{im} is an unobservable random variable with mean X_{im} and variance σ_{im}^2 . Let Z_{im} be the fraction of tissue type m in voxel i , contributing Y_i , under conditions of $\sum_{m=1}^M Z_{im} = 1$, $0 \leq Z_{im} \leq 1$. Let μ_m and ν_m be the mean and variance of tissue type m fully filling in voxel i . Assume all M tissue types contribute to Y_i independently, we have $X_{im} = Z_{im}\mu_m$, $\sigma_{im}^2 = Z_{im}\nu_m$, $\bar{Y}_i = \sum_{m=1}^M Z_{im}\mu_m$, and $\sigma_i^2 = \sum_{m=1}^M Z_{im}\nu_m$.

The E-step of the EM algorithm [22] computes the conditional expectation of the unobservable variable distribution given image $\{Y_i\}$ and current iteration estimates

$\{\mu_m^{(n)}, \nu_m^{(n)}, Z_{im}^{(n)}\}$ [19]:

$$Q(\Theta|\Theta^{(n)}) = -\frac{1}{2} \sum_{i,m} \{\ln(2\pi) + \ln(Z_{im}\nu_m) + \frac{1}{Z_{im}\nu_m} [(X_{im}^{(n)})^2 - 2X_{im}^{(n)}Z_{im}\mu_m + Z_{im}^2\mu_m^2] + \beta U(Z_{im})\} \quad (6)$$

where Y_i was assumed to follow a normal distribution, which is valid in many clinical applications of CT and magnetic resonance imaging (MRI). Parameter set Θ represents the tissue fractions $\{Z_{im}\}$ and tissue model parameters $\{\mu_m, \nu_m\}$, and $X_{im}^{(n)}$ and $(X_{im}^{(n)})^2$ are the conditional expectations of X_{im} and X_{im}^2 respectively, i.e.,

$$X_{im}^{(n)} = E[X_{im}|Y_i, \Theta^{(n)}] = Z_{im}^{(n)}\mu_m^{(n)} + \frac{(Z_{im}^{(n)}\nu_m^{(n)})}{\sum_{j=1}^M (Z_{ij}^{(n)}\nu_j^{(n)})} \cdot (Y_i - \sum_{j=1}^M Z_{ij}^{(n)}\mu_j^{(n)}), \quad (7)$$

and

$$(X_{im}^{(n)})^2 = E[X_{im}^2|Y_i, \Theta^{(n)}] = (X_{im}^{(n)})^2 + (Z_{im}^{(n)}\nu_m^{(n)}) \cdot \frac{\sum_{j \neq m}^M (Z_{ij}^{(n)}\nu_j^{(n)})}{\sum_{j=1}^M (Z_{ij}^{(n)}\nu_j^{(n)})}. \quad (8)$$

The last term in Eq. (6) reflects a penalty on the normal distribution of the unobservable variables $\{X_{im}\}$ and β is an adjustable parameter controlling the degree of the penalty:

$$U(Z_{im}) = \sum_{l \in \varepsilon_i} w_{il} \cdot (Z_{im} - Z_{lm})^2 \quad (9)$$

where index l indicates the neighbors ε_i and w_{il} is a weighing factor for different orders of neighbors.

In this study, we adopted the 3D scale at voxel i , $K(i)$, into our definition of neighbors of ε_i to control the degree of penalty of *a priori* $U(Z_{im})$. By utilizing 3D scale at each voxel, we can adjust our neighborhood system and make it adaptive to the local information at each iteration [27]. Table II shows the selection of neighborhood based on the value of $K(i)$ at each voxel, and Fig. 1 illustrates how the first- and second-order neighbors are defined in 2D and 3D space.

Furthermore, the M-step of the EM algorithm determines the next iteration estimates

$\{\mu_m^{(n+1)}, \nu_m^{(n+1)}, Z_{im}^{(n+1)}\}$, which maximize the conditional expectation in Eq. (6). That is:

$$\frac{\partial Q}{\partial \mu_m} \Big|_{\mu=\mu^{(n+1)}}=0 \Rightarrow \mu_m^{(n+1)} = \frac{\sum_i X_{im}^{(n)}}{\sum_i Z_{im}^{(n)}} \quad (10)$$

and similarly

$$\nu_m^{(n+1)} = \frac{1}{I} \sum_i \frac{(X_{im}^{(n)})^2 - 2X_{im}^{(n)} Z_{im}^{(n)} \mu_m^{(n)} + (Z_{im}^{(n)} \mu_m^{(n)})^2}{Z_{im}^{(n)}}. \quad (11)$$

For the tissue mixture fractions $\{Z_{im}\}$, maximizing the conditional expectation (6) will

subject to the conditions of $\sum_{m=1}^M Z_{im}=1, 0 \leq Z_{im} \leq 1$ and will not generate a close-form solution for $Z_{im}^{(n+1)}$ in general. Since the solution for $Z_{im}^{(n+1)}$ is spatially localized to voxel i , a logic approach to the solution is to consider the neighborhood anatomical information in the acquired image. Specifically, in the CTC application, we consider four tissue types of (1) air inside the colon and lungs, (2) fat, (3) muscle, and (4) bone and TMs in the abdominal CTC images. Mostly we have two tissue types interface, e.g., the air may be neighbor to muscle or TMs. Three tissue types interface may occur at the interface of air, muscle and TMs. By considering the neighborhood anatomical information, $Z_{im}^{(n+1)}$ can be calculated by solving a polynomial equation [19].

As an iterative means, the MAP-EM PV image segmentation algorithm may converge to one possible solution of many in a feasible-solution region, depending on the initialization of the iterative process. In order to obtain an optimal estimate, an innovative initialization of the model parameters and tissue mixture fractions $\{\mu_m^{(n+1)}, \nu_m^{(n+1)}, Z_{im}^{(n+1)}\}$ was reported in [11].

It is worth mentioning that in this paper, we improved the neighborhood selection in the penalty term of E-step based on the extracted 3D object scale for the partial volume image segmentation algorithm. Details of parameter selection and algorithm implementation were illustrated in our previous study [11].

III. New ECC Pipeline

A new ECC pipeline via the above presented 3D scale-based PE correction and MAP-EM PV image segmentation algorithm is presented below. Fig. 2 shows the flowchart of the newly proposed ECC scheme.

The new scheme can be summarized as follows:

1. First, all image voxels were initially classified into four tissue types of air, fat, muscle, and bone (including TMs) via an adaptive thresholding strategy based on

CT image histogram. The thresholds were determined as those local optima by taking derivative along the histogram [15]. The histogram for different datasets can vary a little bit, and thus the thresholds also vary for different datasets. Therefore, our thresholding strategy is adaptive. Figure 3 illustrated the typical thresholds for the four tissue classes.

2. Then, the classified bone/TMs class regions were dilated 4–6 voxel-unit layers to form the region of interest (ROI) as shown in Fig. 4. The rationale behind of this is that these 4–6 voxel-unit layers are likely to have severer PE effects due to surrounding bone/TMs tissues.
3. Following that, the above presented 3D scale-based PE correction was applied to all the image voxels within the ROI. More specifically, we first computed the object scales for the voxels, and then calculated the pseudo-enhanced components based on the object scales. Finally, we subtracted the estimated pseudo-enhanced components from the original CT image at each voxel. The related algorithms are demonstrated in Sec II. A and an example of this process is illustrated in Fig. 4.
4. Then, the above presented MAP-EM PV image segmentation algorithm was applied to identify the image voxels in the lumen space and around the colon wall for ECC on the CT images. The implementation of the segmentation algorithm was illustrated in our previous study [11], and the difference herein is the scale-based adaptive selection of neighborhood in the penalty term.

IV. Experiments and Results

In this paper, we define *un-submerged polyps* as polyps that surrounded by luminal air, while polyps submerged in the contrast agents are referred as *submerged polyps*. The newly proposed ECC pipeline was evaluated on 40 patient CTC scans chosen from 338 patient scans according to the following criterion: they contain at least one submerged polyp whose size ranges from 5 to 10mm. Of these 40 CTC scans, 23 scans are at supine views while the other 17 scans are at prone views, and each scan is represented by a volume image of more than 400 slices of 512×512 array size. In these scans, the colon cleansing was performed with standard pre-colonoscopy cleansing or barium enema bowel preparation [10]. Oral tagging agents were used for the purpose of ECC. Single dose of 2% barium (500 ml) and Gastrografin (120 ml) were given to tag residual stool and fluid. Multi-slice CT scanners were used in helical mode to collect data with collimations of 1.25–5.0 mm, pitch of 1–2, reconstruction interval of 1.25–5.0 mm and the scanning protocol including modulated 50–200 mAs and 120–140kVp.

Our previous ECC pipeline without PE correction and scale-based adaptive selection of neighborhood system [11] was applied to these datasets and their results were set as the reference for comparison purposes.

A. Convergence Characteristics of the Scale-based PE Correction

As mentioned above, the scale-based PE correction consists of two steps of (1) estimation of scatter component due to the PE effect and (2) subtraction of the scatter component from the original CTC images. If the correction is effective, repeating the two steps shall converge to a stable solution. This expectation is shown by Fig. 5. Beyond one iterative cycle, the gain became moderate. Therefore, only one iteration was performed in this study for the 3D scale-based PE correction algorithm.

B. Capacity of Recovering Submerged Soft-Tissue Structures

A major contribution made by the scale-based PE correction is expected to be the recovery of pseudo-enhanced soft tissues which were partially or fully submerged into the TMs. Fig. 6 illustrates a comparison of ECC results between the previous and current ECC schemes in segmenting pseudo-enhanced soft tissues. The small boxes of dots indicate the locations of our concerned regions, where soft tissues are submerged in the contrast agents and PE effect is observed. It can be observed that the old ECC scheme induced over-cleansing of the pseudo-enhanced soft tissues, which are resulted from the inadequate treatment of PE effect. On the contrary, our new ECC scheme can better preserve the soft tissues by explicit PE correction.

C. Capacity of Preserving Shape and Texture of Polyps

Fig. 7 illustrates a comparison of the ECC results between the previous and current ECC schemes in segmenting the pseudo-enhanced polyps. It is noted that by our previous ECC scheme, the edge of polyps submerged in the contrast agents was partially over-cleansed, whereas the newly proposed ECC results preserved better the size of polyps. Most importantly, our new strategy corrects polyps' CT attenuation value by suppressing the pseudo-enhancement effects around submerged polyps. Thus, the shape and texture information of submerged polyps would be close to those of the un-submerged polyps. As a result, the new ECC scheme will facilitate the CAD of polyps, which will be demonstrated in the quantitative analysis section.

D. Evaluation of Image Quality by Observer Study

In an effort to quantitatively compare the ECC results from our previous and current pipelines, three radiologists were asked to score the results from 0 (worst) to 10 (best) on *cleansing tagged materials* and *preserving shape and texture of polyps/soft tissues*. For each scan, two ECC results were displayed on the screen slice-by-slice with randomized display position, i.e., one on the left and the other on the right, while the corresponding raw CTC images were shown above for reference. Therefore it is a completely blind procedure.

The pair-wise scatter plot of the scores for the 40 patient scans from three radiologists is illustrated separately (with different labels) in Fig. 8. The scatter plot used a Jitter plot technique (adding a small amount of random noises to the values) to avoid the overlap of multiple observations with the same plotted values [23]. The paired two samples *t*-test shows that the new ECC pipeline generated highly-significant higher scores than the previous ECC pipeline ($p < 0.0001$). In addition, the variability due to different radiologists was relatively small and the repeated measures of analysis of variance (ANOVA) indicate that the scores from the three radiologists are consistent ($p = 0.1747$). For the new ECC results, the scores (mean $\pm$ std) from three radiologists are 9.08 ± 0.42 , 8.45 ± 0.64 , and 8.18 ± 0.64 , respectively. While for the old ECC results, the scores from three radiologists are 6.05 ± 1.01 , 5.90 ± 0.96 , and 5.88 ± 1.68 , respectively. It is evident that the new ECC method is far better than the old one in terms of radiologists' scoring.

E. Quantitative Analysis

To further confirm the merits of the new pipeline, we performed CAD on the two groups of ECC results to quantitatively demonstrate the performances of the ECC pipelines. In the 40 CTC scans, a total of 72 polyps were confirmed with both optical and virtual colonoscopies (regarded as ground truth), of which 31 polyps are surrounded by luminal air, while the remaining 41 polyps are submerged in contrast agents, as shown in Table III.

With our CAD system, 66 true positives (TPs) and 1438 false positives (FPs) are detected for the old ECC results, while 70 TPs and 1454 FPs are detected for the new ECC results. Of note, there are 4 more TPs detection for our new ECC scheme while maintaining the similar level of FPs in the initial polyp detection. It is also worth mentioning that, after this initial polyp detection, feature extraction and support vector machine (SVM) classification steps can be applied to further reduce the FPs rate [28]. A closer look (Table III) at the CAD detection results reveal that, for the un-submerged polyps (polyps surrounded by luminal air), all of them can be detected by both the old and new ECC pipelines, since they are less likely to be affected by the PE effect and thus they do not affect the detection of initial polyp candidates (IPCs). On the contrary, for the polyps submerged in contrast agents which are more likely to be pseudo-enhanced, 4 more polyps are detected for our new ECC results, that is an approximately 10% increase over the previous one. To reveal the effect on variable polyp sizes, we divided the IPC detections by their sizes. Table IV shows all the un-submerged polyps of size equal or larger than 5 mm were detected. Table V reveals the improved detection of polyps with size from 5mm to 8mm. The new ECC pipeline improved 4 detections over the old pipeline for the small polyps (5 to 8 mm) which are more likely to be affected by the PE effect.

V. Discussion and Conclusions

In our previously developed ECC pipeline, the PV effect was fully considered while the PE effect was not sufficiently addressed, resulting in some over-complete ECC cases where pseudo-enhanced soft tissues and small polyps could be incorrectly identified as TMs. In this work, we integrated a scale-based PE correction component into our previously developed PV image segmentation-based ECC pipeline to minimize the PE effect for CTC. It takes into account the following effects that commonly appear in CTC images: (1) the PE effect due to orally administered high-density contrast agents; and (2) the PV effect across the mucosa layer around the colon wall.

In addition to utilizing the 3D adaptive scale at each voxel, $K(i)$, for correction of the PE effect, we also relieved the constraint of a predefined neighborhood system in our previous PV image segmentation. Instead, we employed the 3D scale $K(i)$ to adaptively define the neighbors of ε_i for effective control of the degree of the penalty, $U(Z_{im})$. Thus, the selection of the neighborhood system was adaptive and spatially variant according to the local information at each voxel.

The presented ECC scheme was first visually evaluated via 2D image demonstration, and the gain over the previous ECC scheme is observed. Then the new ECC scheme was quantitatively assessed by radiologists' rating (human observer) and CAD (computer observer). By comparing the CAD results with the radiologists' reports (the foremost standard for colon cancer analysis), 4 more submerged polyps were detected out of 41 submerged polyps by our new ECC scheme compared with the old ECC scheme, that is approximately 10% improvement. In short, the new ECC scheme has shown improved performance over the previous cleansing results, especially for the small polyps of size from 5 to 8 mm and submerged in the contrast agents.

In this work, we compared the two ECC schemes based on the MAP-EM PV image segmentation algorithm. A further comparison between the new ECC scheme with other prevailing segmentation algorithms can be an interesting research topic for an investigation in future.

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Fig. 1. Illustration of neighborhood systems for voxel i with different scale values: (a) $K(i) = 0$, (b) $K(i) = 1$, (c) $K(i) = 2$, and (d) $K(i) = 3$.

Fig. 2.
Flowchart of the newly proposed ECC scheme.

Fig. 3.
Typical example of three thresholds for the four tissue classes.

Fig. 4. Illustration of the PE correction process: (a) raw CTC data; (b) classified bone/TMs regions via the adaptive thresholding strategy; (c) dilation of (b) by 4 voxel layers to form the PE-affected ROI; (d) PE-corrected CTC data.

Fig. 5. Illustration of convergence performance of the 3D scale-based PE correction algorithm. The vertical axis denotes the intensity change with the iteration number. It should be noted that the intensity is the Hounsfield unit (HU) plus 1000, which scales all the intensity to non-negative value.

Fig. 6.

Comparison between the current ECC with PE correction and previous ECC without PE correction in recovering soft tissues which are submerged into the tagged materials. The pictures at the top row are the original CT images, while the ECC results from our previous pipeline are shown in the middle row and the ECC results obtained by the current pipeline are shown on the bottom row.

Fig. 7.

Comparison between the previous and current ECC schemes in segmenting pseudo-enhanced polyps: the original CTC images (above), the segmentation results from our previous ECC scheme (middle), and the segmentation results obtained by the current ECC scheme (below).

Fig. 8.
Radiologists' rating of the ECC results.

Table I

Pseudo-code for the object scale computation.

```
For each voxel  $i$ :  
begin  
   $r = 1$ ;  
  while  $FQ_r(i) > t_s$  (e.g., 85%)  
     $r = r+1$ ;  
  end  
   $K(i) = r-1$ ;  
end
```

Table II

Selection of neighborhood system based on 3D scale at each voxel.

$K(i)$	Neighborhood system	Number of neighbors
0	2D first-order	4
1	3D first-order	6
2	2D second-order and 3D first-order	14
3	3D second-order	22

Table III

Initial polyp candidates (IPCs) detection results

	Ground truth	Old method	New method
Un-submerged polyps	31	31	31
Submerged polyps	41	35	39

Table IV

IPCs detection results for the un-submerged polyps

Un-submerged polyps	Ground truth	Old method	New method
5 mm	3	3	3
6 mm	11	11	11
7 mm	7	7	7
8 mm	4	4	4
9 mm	1	1	1
10 mm	2	2	2
>10 mm	3	3	3

Table V

IPCs detection results for the submerged polyps

Submerged polyps	Ground truth	Old method	New method
5 mm	9	8	9
6 mm	11	9	10
7 mm	6	5	6
8 mm	7	5	6
9 mm	2	2	2
10 mm	6	6	6