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Electronic cleansing for dual-energy CT colonography based on material decomposition and virtual monochromatic imaging

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Abstract

CT colonography (CTC) uses orally administered fecal-tagging agents to enhance retained fluid and feces that would otherwise obscure or imitate polyps on CTC images. To visualize the complete region of colon without residual materials, electronic cleansing (EC) can be used to perform virtual subtraction of the tagged materials from CTC images. However, current EC methods produce subtraction artifacts and they can fail to subtract unclearly tagged feces. We developed a novel multi-material EC (MUMA-EC) method that uses dual-energy CTC (DE-CTC) and machine-learning methods to improve the performance of EC. In our method, material decomposition is performed to calculate water-iodine decomposition images and virtual monochromatic (VIM) images. Using the images, a random forest classifier is used to label the regions of lumen air, soft tissue, fecal tagging, and their partial-volume boundaries. The electronically cleansed images are synthesized from the multi-material and VIM image volumes. For pilot evaluation, we acquired the clinical DE-CTC data of 7 patients. Preliminary results suggest that the proposed MUMA-EC method is effective and that it minimizes the three types of image artifacts that were present in previous EC methods.

Keywords

Colon; virtual cleansing; dual-energy CT; random forest; virtual colonoscopy

1. Introduction

Early detection and removal of the benign precursor lesions of colorectal cancer would prevent the development of the cancer. Recently, CT colonography (CTC) has been recommended by the American Cancer Society as an option for colon cancer screening¹. The CTC provides a safe and accurate method for examining the complete region of the colon.

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Residual fluid and feces in the colon may obscure or imitate polyps on CTC images, thereby reducing the accuracy of CTC. Therefore, orally administered positive-contrast fecal-tagging agents are often used to enhance fecal materials on CTC images². This also makes it possible to perform electronic cleansing (EC) that subtracts the tagged fecal materials from CTC images for unobstructed visualization of the colon surface in virtual colonoscopy views³.

However, current EC methods produce routinely subtraction artifacts that distract image interpretation and may reduce detection accuracy. A majority of these EC methods have been developed for single-energy CTC, where the image interpretation is based on x-ray attenuation measurements only and the EC is not able to differentiate soft tissues reliably from partial-volume tagging effects and unclearly tagged regions due to their similar attenuation values⁴⁻⁷. Dual-energy CTC (DE-CTC) may be used to improve the performance of EC, because it is able to identify distinct materials and their partial-volume effects on CTC images. However, current EC methods for DE-CTC that include material-specific thresholding⁸ and level-set segmentation⁹ of the dual-energy images require time-consuming case-based manual ad-hoc parameter adjustments for precise delineation of different colonic materials. They also tend to produce subtraction artifacts, and they have not been validated with clinical cases.

In this study, we developed a novel multi-material EC (MUMA-EC) method that uses the material decomposition and virtual monochromatic (VIM) images of DE-CTC for minimizing the types of image artifacts that were present in the previous EC approaches. The method includes a machine-learning component that optimizes the required features and parameters automatically based on input images. Therefore, the MUMA-EC method presents a practical approach for performing EC in large-scale CTC screening programs. For pilot evaluation, we assessed the feasibility of the method in minimizing subtraction artifacts by use of clinical DE-CTC cases.

2. Methods

2.1 Calculation of material decomposition and virtual monochromatic (VIM) images

Figure 1a shows an overview of the calculation of input images for the application of EC. First, we perform a material decomposition of the DE-CTC images into water and iodine images by expressing their linear attenuation coefficients as a linear combination of the mass-attenuation coefficients of the basis materials by¹⁰

$$\mu(E) = \left(\frac{\mu}{\rho}\right)_1(E)\rho_1 + \left(\frac{\mu}{\rho}\right)_2(E)\rho_2, \quad (1)$$

where E is the dual-energy level (140 kVp or 80 kVp). The mass densities of the two basis materials are obtained by solving of the two linear equations.

The resulting water and iodine images, D_W and D_I provide the material fractions of lumen air, soft tissue, and iodine at each voxel. We also calculate their gradient images, ∇D_W and ∇D_I , that provide information about the partial-volume boundaries between different

materials. Finally, we synthesize two VIM images at 120 keV and 160 keV from the basis material images by reapplication of Equation (1). In principle, the VIM images are free of beam-hardening artifacts and provide quantitatively more accurate attenuation measurements than do conventional CTC images ¹¹.

2.2 The MUMA-EC method

Figure 1b shows an overview of the proposed method. After the calculation of input image data, we reconstruct a multi-material (MUMA) image volume that indicates the spatial locations of different colon materials and their partial-volume boundaries on the CTC images. The electronically cleansed images are synthesized from the MUMA and VIM image volumes.

To calculate the MUMA volume, we calculate statistical features (mean, standard deviation, skewness, and kurtosis) of local volumetric regions of interest (VOIs) of the eight input image volumes (the 80 kVp and 140 kVp, D_W , D_I , ∇D_W , ∇D_I , and the 160 keV and 120 keV VIM image volumes). Based on the values of these features, a random-forest classifier ¹² is used to classify each voxel into one of five groups that consist of three homogeneous groups (H-groups) and two partial-volume boundary groups (P-groups). The H-groups include lumen air (H_a), soft tissue (H_s), and tagging (H_t). The P-groups include the partial-volume boundaries between air and tagging (P_{at}) and those between soft tissue and tagging (P_{st}). The random forest is used to reconstruct a MUMA volume by assigning each voxel to the L-label of the H- or P-group that has the highest likelihood at the voxel.

The final electronically cleansed images are reconstructed from the MUMA and VIM image volumes. First, any remaining partial-volume fecal-tagging artifacts are eliminated from the MUMA image volume by the application of a statistical rule-based method that updates the labels of voxels with $L = P_{st}$ into $L = H_s$ or $L = H_t$ based on the statistical distribution of the labels within the local 26-neighborhood. Next, the electronically cleansed image volume is synthesized from the MUMA and VIM image volumes by

$$\nu = \begin{cases} v_M, L \in \{H_s\} \\ -1024 \text{ HU}, L \in \{H_a, H_t, P_{at}\} \end{cases}, \quad (2)$$

where v_M is the VIM-CT value. The final colon surface is reconstructed by the applications of three-dimensional Sobel gradient and Gaussian smoothing on the cleansed lumen region ⁴.

2.3 Evaluation

Seven patients were prepared for a DE-CTC examination with reduced bowel cleansing by 18 g of magnesium citrate and fecal tagging by means of 50 ml of orally ingested iodine. The DE-CTC scans were performed with a dual-energy CT scanner (SOMATOM Definition Flash Siemens Healthcare, Erlangen, Germany) at 140 kVp and 80 kVp energies with 0.6 – 0.7 mm slice thickness.

A pilot evaluation was performed both visually and quantitatively. For quantitative evaluation of the effect of dual-energy features, we compared the performance of the MUMA-EC method with those of a comparable single-energy EC method (only single-energy image features were used) and a dual-energy EC method (only the features of input dual-energy images were used).

To optimize the EC parameters, one of the DE-CTC cases was held out randomly to prepare a teacher image volume. Each voxel of the teacher volume was assigned manually to one of the five L-labels of the H-groups and P-groups (see Section 2.2). The parameters of the random-forest classifier and the rule-based method (see Section 2.2) were then optimized automatically by comparison of the manually assigned labels with the corresponding local input image features.

For testing, VOIs (size: 16×16×16 voxels) were sampled from regions of the six testing cases that represented the three types of failures that were present in previous EC methods (Figure 2a). Type I (partial-volume artifact) included artificial partial-volume boundaries that imitate a non-existent soft tissue layer between air and tagging (top image of Figure 2a). Type II (three-material layer) included thin layers of soft tissue between air and tagging that can be removed erroneously by EC (middle image of Figure 2a). Type III (three-material mixture) included partial-volume three-material mixtures of air, soft tissue, and tagging (bottom image of Figure 2a). To provide a ground truth the voxels of each VOI were assigned manually to one of the six L-labels of the H-groups and P-groups (Figure 2b).

The accuracy of the EC methods was evaluated by the calculation of the overlap ratio (OR) of L-labels between those assigned automatically by the EC method and those assigned manually to the ground truth by

$$\delta = \frac{N(E)}{N(V)}, \quad (3)$$

where $N(E)$ is the number of voxels that were labeled correctly by the EC method, and $N(V)$ is the total number of voxels in the VOI. The statistical significances of the differences of ORs between the three EC methods were compared by use of the paired t -test.

3. Results

A total of 34 VOIs were used for a pilot evaluation. There were 4 Type-I VOIs, 11 Type-II VOIs, and 19 Type-III VOIs.

Visual evaluation indicated that the proposed MUMA-EC method can perform EC at high accuracy. Figure 3 shows two examples of the application of EC to submerged polyps. Column (a) shows 2D images of a 20-mm polyp (top row) and an 8-mm polyp (bottom row). Column (b) shows the corresponding virtual endoscopic images of the polyps before electronic cleansing. Column (c) shows the corresponding virtual endoscopic images after performing the proposed MUMA-EC. The images show how the application of the MUMA-

EC method enables precise subtraction of the obstructing fecal tagging while preserving the soft-tissue region of the polyp.

Table 1 shows the mean and standard deviation of the ORs between the manual and automated labels. The overall OR (all artifacts) is highest with the MUMA-EC and lowest with the single-energy EC method. For specific types of artifacts, the MUMA-EC has higher OR than dual-energy EC in the detection of thin soft-tissue layers between air and tagging, whereas the dual-energy EC yields slightly higher OR in the detection of artificial partial-volume layers.

Table 2 shows the statistical comparison of the differences of ORs between the EC methods. The overall differences between the single-energy EC and dual-energy/MUMA-EC methods were statistically significant ($p < 0.01$). The differences were also statistically significant between the dual-energy EC and MUMA-EC methods, except for the VOIs of three-material mixtures (Type III).

The visual differences between the automated labels of the EC methods can be seen in Figure 2. In comparison with the manually labeled ground truth (column b), the single-energy EC method (column c) and the dual-energy EC method (column d) are unable to detect thin soft-tissue layers between lumen air and tagging (white arrows). Furthermore, the single-energy EC method also detects artificial partial-volume regions incorrectly as soft tissue (yellow arrows). However, the proposed MUMA-EC method (column e) is able to resolve all of these situations correctly.

4. Discussion

Current EC methods for CTC are unable to differentiate soft-tissue structures reliably from partial-volume tagging artifacts and unclearly tagged stool, because their image interpretation is based largely on an analysis of single x-ray attenuation measurements within the target object. Therefore, they tend to produce subtraction artifacts that interfere with the interpretation of CTC images. In this study, we developed a MUMA-EC method that uses dual-energy information to produce material decomposition and VIM images to systematically differentiate soft-tissue materials from tagged materials and partial-volume artifacts. The use of a random forest classifier and a statistical rule-based method with a teacher CTC image volume facilitated automated parameter optimization of the method.

The pilot results indicate that the use of material decomposition and VIM images yielded significant improvements in the accuracy of MUMA-EC over those of using single-energy image features or dual-energy image features alone. The method was particularly effective in preserving thin soft-tissue layers between lumen air and fecal tagging while also being able to identify artificial partial-volume layers between lumen air and fecal tagging. These results indicate that the use of material decomposition and VIM image features provides meaningful information for distinguishing tagged fecal materials from soft tissue, thereby enabling effective virtual cleansing of tagged fecal materials without generating distracting image artifacts.

A majority of current EC methods have been evaluated only with phantom studies or with a limited number of 2D images. We performed a three-dimensional evaluation using clinical CTC cases, which provide a greater challenge for the application of EC than simple phantoms or 2D images. Furthermore, we developed a scheme for automated parameter optimization based on a machine learning method, whereas current EC methods tend to require manual ad-hoc parameter adjustments that may also need to be repeated for new cases. Therefore, our approach based on machine learning provides a potential solution for consistent and reproducible automated application of EC in large-scale CTC screening programs.

This pilot study had some limitations. In particular, the number of evaluation cases and the number of VOIs was relatively small. Never the less, we were able to show statistically significant improvements in the accuracy of the proposed MUMA-EC method.

5. Conclusions

We developed a novel MUMA-EC method for DE-CTC that uses material decomposition and VIM image features with machine learning to produce artifact-free electronically cleansed CTC images. A pilot study was performed to evaluate the performance of the method and to compare the effect of single-energy and dual-energy image features in the EC using clinical DE-CTC cases. The results suggest that the proposed MUMA-EC method is effective in minimizing subtraction artifacts on electronically cleansed CTC images. Furthermore, the use of machine learning eliminates the need for case-specific ad-hoc parameter adjustments, thereby facilitating large-scale application of EC in CTC examinations.

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Figure 1. Overview of the proposed MUMA-EC method. (a) The calculation of material decomposition and VIM images from input DE-CTC images. (b) The calculation of electronically cleansed images by use of multi-material classification.

Figure 2.

Examples of the multi-material labeling of VOIs. (a) Original CT images. Yellow squares indicate regions that were used for the evaluation. (b) Manually labeled ground-truth images: blue color indicates lumen air, white color indicates fecal tagging, orange color indicates soft tissue, red color indicates partial-volume boundary of air and tagging, and pink color indicates partial-volume boundary of soft tissue and tagging. (c) Automated labeling by the single-energy EC method (arrows indicate artifacts). (d) Automated labeling by the dual-energy EC method without VIM features (arrow indicates an artifact). (e) Automated labeling by the proposed MUMA-EC method.

Figure 3.

Examples of the EC of submerged polyps. (a) Uncleansed VIM images show two polyps. (b) Virtual endoscopic images of the polyps before EC. (c) Virtual endoscopic images of the polyps after the application of MUMA-EC.

Paired sample statistics of the overlap ratios between manual labeling and automated labeling for each type of artifact.

Table 1

Type of artifact	n	Single		EC method Dual		MUMA	
		Mean	Std.	Mean	Std.	Mean	Std.
Artificial partial-volume (Type I)	4	0.79	0.04	0.89	0.06	0.87	0.06
Three-material layer (Type II)	11	0.89	0.04	0.89	0.05	0.92	0.02
Three-material mixture (Type III)	19	0.89	0.04	0.91	0.02	0.91	0.03
All artifacts	34	0.88	0.05	0.90	0.04	0.91	0.03

Abbreviations: Single = single-energy EC, Dual = dual-energy EC, MUMA = multi-material EC.

Table 2

Paired *t*-test of the statistical difference between the overlap ratios of the EC methods.

Pairs	Type of artifact	t	p-value
Single & Dual	Artificial partial-volume	-5.58	0.011
	Three-material layer	-0.41	0.688
	Three-material mixture	-2.80	0.012
	All artifacts	-3.47	< 0.01
Single & MUMA	Artificial partial-volume	-4.94	0.016
	Three-material layer	-3.20	0.010
	Three-material mixture	-4.20	< 0.01
	All artifacts	-5.93	< 0.01
Dual & MUMA	Artificial partial-volume	5.28	0.013
	Three-material layer	-2.71	0.022
	Three-material mixture	-1.08	0.296
	All artifacts	-2.08	0.046

Abbreviations: Single = single-energy EC, Dual = dual-energy EC, MUMA = multi-material EC.