

A Comparison of Virtual Colonoscopy Methods for Colon Cleansing

Mehrnaz Mostafavi¹, Mahtab Shaabani², Hossein Beigi Harchegani³

¹Faculty of Paramedical science, Shahid Beheshti University of medical sciences, Tehran, Iran

²Loghman Hakim Hospital, Shahid Beheshti University of Medical Sciences, Tehran, Iran

³Iranian Academic Center For Education AndResearch (ACECR), Khuzestan branch, Iran

*Corresponding author: Mehnaz Mostafavi, Faculty of Paramedical science, Shahid Beheshti University of medical sciences, Tehran, Iran, Tel: 989124766808; Email: mz_mostafavi@sbmu.ac.ir

Received date: April 11, 2021; Accepted date: September 03, 2021; Published date: September 13, 2021

Citation: Mostafavi M (2021) A Comparison of Virtual Colonoscopy Methods for Colon Cleansing. Colorec Cancer Vol: 7 No: 5.

Abstract

Electronic colon cleansing (ECC) attempts to segment the colon lumen from a patient's abdominal image collected for colonic content marking using an oral contrast agent. There are numerous algorithms and ECC methods.

Some benefits, drawbacks and technological aspects of their approaches were explained in the reviewed papers of this study, and we briefly describe some of the important techniques used in practical terms to ease the comparison of ECC techniques for researchers interested in studying this sector.

Keywords: Electronic colon cleansing; Virtual Colonoscopy; Polyp detection; CT Colonography

Introduction

CT Colonography (CTC), also known as virtual colonoscopy (VC), is now a promising method for early detection of colon cancer because of the latest developments in computed tomography (CT) technology [1-3], even with more than 57,000 colon cancer deaths each year in the United States.[4,5].CT colonography (CTC) is recommended as the radiological examination of choice for the diagnosis of colorectal neoplasia. It is indicated in patients with incomplete or contraindicated colonoscopy and serves as a diagnostic option to screen for colorectal cancer and adenomas. It's based on a low-dose, thin-section CT scan of the cleansed and distended colon in both the supine and prone positions.[6]

CTC is a minimally invasive procedure that measures colorectal polyps and masses based on distended colon CT scans. Approximately four phases are used in the new system. Next, in a way similar to that of optical colonoscopy, the patient's colon is cleansed and inflated with CO₂. Second, a helical abdominal CT scan of the patient is taken so that it covers the whole colon.[7,8]

The scan generates several hundred resolutions of 512x512 slices. These slices are reconstructed into a 3D volume of 100-250 MB in the third stage[9]. This volumetric data is then

subjected to a series of pre-processing phases needed for the virtual navigation operation. The exact segmentation of the colon lumen, which is the interior of the colon, from the origin, is the most important of these processes.

In the final stage, to detect polyps, we use precise volume rendering for virtual navigation across the inside of the colon. Electronic colon cleaning (ECC) of the colon is the first step of the CT data processing in VC, especially if other means have not been taken to extract fecal contents from the colon [4,10,11].

Both modern techniques in colonoscopy, including virtual colonoscopy, require a clean lumen of the colon for effective polyp identification. It was possible to mistake residual materials within the colon as part of the colon. Several various computer algorithms were proposed for the ECC in order to eliminate voxels reflecting contrast and residual nutrients.

They vary with the steps of image pre-processing, local image characteristics, feature dimensionality reduction procedure, applied modeling, the use of segmentation techniques and methods of classification[4,10]. This paper aims to briefly present the advantages, disadvantages and technical aspects of its methods.

Thresholding

The thresholding operation principle depends on the division of voxels into two classes that use a predefined threshold value.

$$M(x, y, z) = \begin{cases} 1 & \text{for } I(x, y, z) \geq T \\ 0 & \text{for } I(x, y, z) < T \end{cases}$$

Where: M(x,y,z) is a binary mask (1 - indicates an object, in this case a colon, 0 -background), and I(x,y,z) indicates a CT. Typically, the threshold value is calculated on the basis of a CT histogram or general knowledge of the values assigned to anatomical structures.

The reduced resolution of the detectors and the soft property of the reconstruction kernel is the product of a boundary between contrast and tissues (see fig. 1b), undesirable but typically acquired after threshold operation[4].

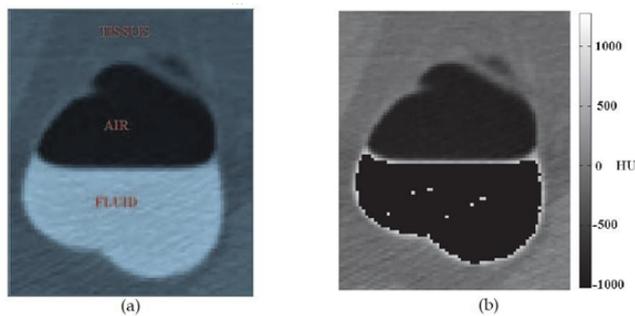


Figure 1: 2D slices of: a) 3D CT data; b) 3D CT data after classical thresholding operation.

While thresholding offers the fastest performance, the following list has several drawbacks. Thresholding, first, would not erase partial voxel length. Fig. Fig. 1b displays the profile of strength from top to bottom along a vertical line. Voxels whose intensities do not balance any of the two regions lie at the boundaries of two regions with separate intensities.

This voxels are unacceptable because when thresholding is used, they are improperly categorized. For instance, in Figure 2, the voxels lie in the soft-tissue range between the fluid and the air. Therefore, they are numbered and can not be removed as soft-tissue voxels. The adverse impact on segmentation is apparent instantly.[12,13]

While the fluid/stool with high density has been removed, a thin soft-tissue-like boundary also remains, and in fact is not present.

Second, for each severity spectrum, the threshold is very sensitive. A small change to these thresholds, specifically the contour of the inner surface of the colon, may lead to a change in the outcome of the segmentation.

Although the fluid/stool of high density was third, thresholding often gave rise to aliasing effects at the inner boundary of the colon. When anyone takes a closer glance at the segmented volume, it is instantly clear. The pressure values change dramatically from the spectrum of soft tissue to the air-range. From the volume rendering point of view, this is undesirable.[4,12]

The loss of the thin colonic mucosa that is found on the inner surface of the colon also indicates a sharp border. A barrier to the diagnosis of the polyps is the colonic mucosa, so its removal is undesirable.

Markov random field model Image segmentation

The algorithm is based on the framework of maximum posterior probability (MAP), including a priori neighborhood membership information defined by the randomly filed Markov (MRF) theory [6,13].

It iteratively estimates the model parameters in an interleaved manner through the expectation maximization (EM) algorithm and segments the voxels by MAP, converging to a solution where the parameters of the model and voxel labels are

arestabilized within a given criterion. The algorithm's implementation consists of two steps: parameter estimation and segmentation of the MAP[13].

Initial parameters

(Figure 2) is a standard histogram derived from a picture of a patient. The distinctive features of all abdominal CT images are expressed in this diagram. The three peaks refer, respectively, to the air inside the intestine, soft tissue and muscle. Beyond the muscle, the strengthened stool, fluid, and bone collapse into a small peak. [14,15]

Many partial volume effects arise between the air and the soft tissue and between the muscle and the stimulation products in those pressure ranges.

It is possible to obtain the initial parameter estimate for classification from the histogram based on thresholds. It is heuristic, however.

Instead, this solution suggested a simple approach to segmentation of online vector quantization that has a special property of independence of initial values. For the local feature vectors of each voxel, this method is based on a primary component analysis. In compliance with the nearest neighbor norm, feature vectors are then categorized into a class.

As the initial parameter calculation, the vector quantization approach gives us a tentative segmentation result. This approach then focuses on segmenting the tagged stool/fluid area using the secret MRF model to solve the problems of non-uniformity[15,17].

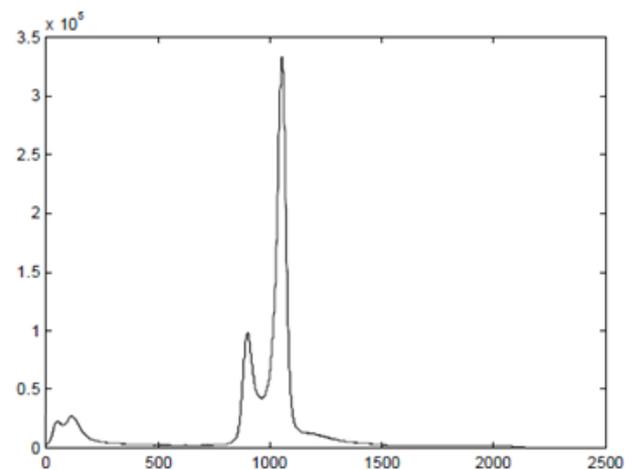


Figure 2: Histogram of a volume CT image from a patient.

Parameter estimation

Assume that an image consists of L classes (or tissue types) and each class l is characterized by a Gaussian parameter vector $\mu_l(\sigma_l, \mu_l)$. Let $P_l(Y_{ijk} | \mu_l)$ be the probability distribution of voxel Y_{ijk} which is associated with class l . The likelihood for each voxel Y_{ijk} , falling into L distinct classes, is described by a mixture functional as

$$\rho(Y_{ijk}|X, \theta) = \sum_{l=1}^L \rho(1|X_{N(ijk)}) \rho_l(Y_{ijk} | \theta_l)$$

Where $\rho(1|X_{N(ijk)})$ is the locally-dependent probability when X_{ijk} is equal to 1, and $X_{N(ijk)}$ reflects the labels of those nearby voxels.

Assuming a set of initial estimation $\{\mu^{(0)}, v_1^{(0)}\}_{l=1}^L$ and applying the EM algorithm, that have, at each iteration n,

$$Z_{ijk}^{(n)} = \frac{p^{(n)}(l|X_{N(ijk)}) p_l(Y_{ijk} | \theta_l^{(n)})}{\sum_{l=1}^L p^{(n)}(l|X_{N(ijk)}) p_l(Y_{ijk} | \theta_l^{(n)})}$$

$$\mu_l^{(n+1)} = \frac{\sum_{i,j,k=1}^{I,J,K} Z_{ijk}^{(n)} Y_{ijk}}{\sum_{i,j,k=1}^{I,J,K} Z_{ijk}^{(n)}}$$

$$v_l^{(n+1)} = \frac{\sum_{i,j,k=1}^{I,J,K} Z_{ijk}^{(n)} (Y_{ijk} - \mu_l^{(n+1)})^2}{\sum_{i,j,k=1}^{I,J,K} Z_{ijk}^{(n)}}$$

Where $Z_{ijk}^{(n)}$ is the conditional probability that voxel Y_{ijk} belongs to class l, which represents the tissue percentages within that voxel. The calculation of tissue percentages $\{Z_{ijk}^{(n)}\}$ within each voxel requires determination of the conditional probability $\rho^{(n)}(1|X_{N(ijk)})$ at the n-th iteration.

The determination of $\rho^{(n)}(1|X_{N(ijk)})$ requires estimation of the classlabels $\{l\}$, which can be obtained by the following MAP segmentation method.

MAP segmentation method

A MRF prior is constructed to reflect the neighborhood information. The assignment of labels over the voxel array is performed by the MAP criterion. A Markov random field prior can be constructed to reflect the neighborhood information by

To represent the neighborhood details, a prior MRF is constructed. The MAP criteria executes the distribution of labels over the voxel series[16,18]. A prior Markov random field can be constructed to represent the neighborhood data by

$$p(X) = \frac{1}{\alpha} \exp\left[-\frac{U(X)}{\beta}\right]$$

Where α is a constant of normalization and β is a constant parameter. The $U(X)$ energy function defines the degree of penalty levied on the neighbors and, in three dimensions, can be specified as

$$U(X) = \sum_{j=1}^N \left\{ \sum_{l \in c_1^j} [1 - \delta(l_i - l_r)] + \sum_{s \in c_2^j} [1 - \delta(l_i - l_s)] / \sqrt{2} \right\}$$

Where $\delta(0) = 1$, the voxel names of the neighbors are $\delta(\neq 0) = 0$ and $\{li\}$. The r index runs over the 6 neighbors of the first order and s runs over the 12 neighbors of the second order. The segmentation is carried out iteratively, where at the(n+1)-th iteration, the current voxel is allocated to the corresponding tissue type l by,

$$\{\max_{l \in L} p_l(Y_{ijk} | \theta_l) p(X_{ijk}^{(n+1)} = \theta_l | X_{N(ijk)}^{(n)})\}$$

Segmentation Using Segmentation Rays

Need for a Sophisticated Segmentation: After the latest bowel preparation, the CT data obtained is much more complicated than the one obtained from a pre-cleansed bowel. The complexity occurs due to the vast volume of fluid and stool inside the colon (fig 3). Although these unwanted residues have been improved, due to partial volume impact, they do not have a clear boundary.

The problem is further compounded by the CT scanner's finite resolution and poor contrast. Discuss the un-usability of naive methods to segmentation now.[12,13]

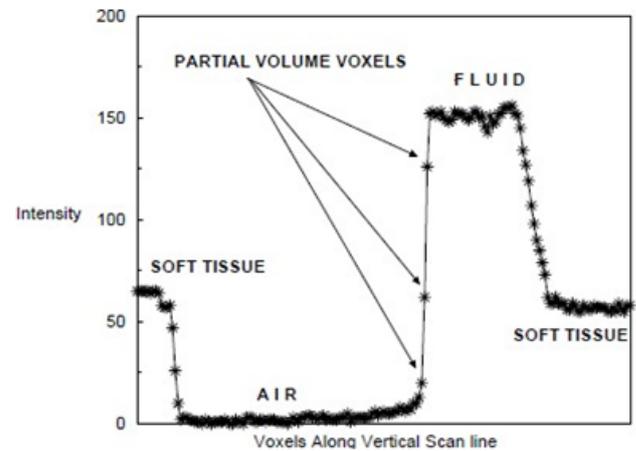


Figure 3: Intensity profile at the boundary of air and fluid.

The fundamental premise behind this approach is that there is a special property at the intersection of two distinct-density regions. As moved in a regular direction to the intersection, this property is the special strength profile at each intersection. While doing so, before reaching the other field, it went through the partial volume effect (PVE) voxels present at the junction. It can thus accurately recognize and remove these PVE voxels.

The individual strength profiles are analyzed and stored beforehand for various intersections. These have been shown to be the characteristics of the intersection of the two regions and do not depend on the protocol for CT scanning. [12]

The next step in this algorithm is to detect crossings on the basis of their characteristic properties. This is achieved by casting rays across the volume and comparing the graphs of the intensity profile along the ray to various intersections' intensity profiles. If a match occurs, the ray has found the intersection successfully.

These programmers of algorithms further refine their algorithm in order not to cast rays where they know for certain that there is no intersection. Here they exploit the fact that air is flooding the inside of the colon. The rough contour of the colonic interior is given by the application of the area developing on the air voxels from a seed point within the colon. [12,14]

A certain task is done until a ray senses an intersection. This mostly includes extracting the voxels of PVE present at the intersection by either classifying the voxels or changing their values of strength to reconstruct the mucosa. In the end, most of the PVE voxels were found and deleted by this algorithm.

It employs Volumetric Contrast Enhancement for the residual PVE voxels at the intersection of fluid and soft tissues, which is a volumetric variation of the contrast enhancement used in image processing. This results in mucosal regeneration, which was totally missed due to the high fluid density. The step also extracts the fluid left from the colon.[12,19]

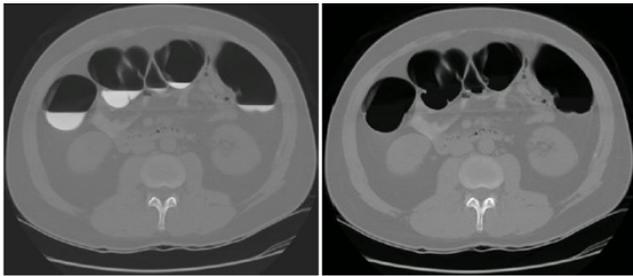


Figure 4: A traverse slice before (left) and after (right) electronic cleansing.

Using non-linear transfer function and morphological operations

The suggested ECC approach is based on non-linear value transformation combined with the processing of morphological voxels.

Second, if the CT data has non-offset Hounsfield Unit (HU) values, the voxel values are increased by 1024 and the unsigned 16-bit fixed-point integer data format is obtained, resulting in a substantial computation time reduction.[20,21].

One must locate them in the CT data to delete voxels reflecting contrast. This approach computes two binary masks in order to achieve this goal: a fluid mask and a residual mask. The fluid mask is generated by the thresholding operation described in section 3: value 1. is given to voxels with values greater than 1600.

This method searches for values greater than 1350 and equal to or smaller than 1600 in the case of the residual mask, as voxels representing stool and fluid remain within this range. Using regular hexahedrons of size 3, all masks are dilated. Voxels with masks equal to 1 are then processed by two transfer functions, as seen in Fig. 5, representing the Gaussian transformation of intensity:

$$I_{new}(x, y, z) = 1000 \cdot \exp\left(-\frac{(I(x, y, z) - 1000)^2}{2 \cdot \sigma^2}\right)$$

With $\sigma = 450$ for the fluid mask and 100 for the residual one. This operation is desirable due to necessity to keep smooth changes of intensity on the border between colon and soft tissues.

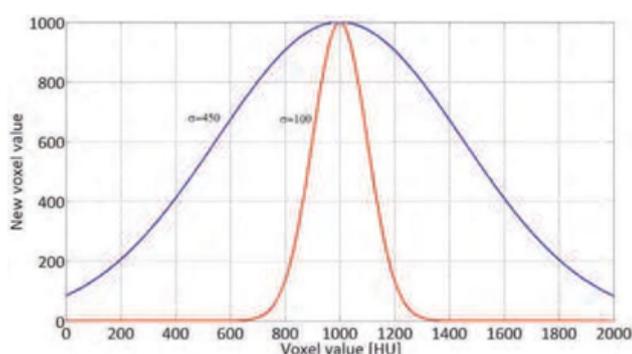


Figure 5: Gaussian transfer functions; blue line – for fluid mask $\sigma=450$, red line – for residual mask $\sigma=100$.

A binary data (MBin) of 0s for the air ($v < 300$) and 1s for the remaining sections is generated in the next step. Then a series of two morphological operations is carried out: 1) by means of a three-cubic matrix, a 3Derosion operation is applied on each volume, 2) a dilation operation is carried out on the data resulting from the erosion process.

Finally, it is also important to verify if the voxels obtained from the subtraction belong to the boundary. Since the patient lies on his back or abdomen during CT scanning, the boundary is often parallel to the surface of the body.

The following theorem will sum up the whole process.

$$M_{Bin} = \begin{cases} 1 & \text{for } I(x, y, z) \geq 300 \\ 0 & \text{for } I(x, y, z) < 300 \end{cases}$$

$$M_{Del} = \text{dilation}(\text{erode}(M_{Bin}))$$

$$M_{Pr_Border} = M_{Del} - M_{Bin}$$

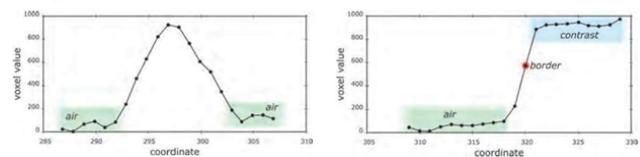


Figure 6: The intensity profiles for a voxel which cannot be removed (left) and must be removed (right).

After subtraction, with each voxel equal to 1 in the MPr-Border volume, the strength profile must be tested in the usual direction of the body surface (fig 6): if the profile includes voxels belonging to the stool or comparison, this voxel is omitted.

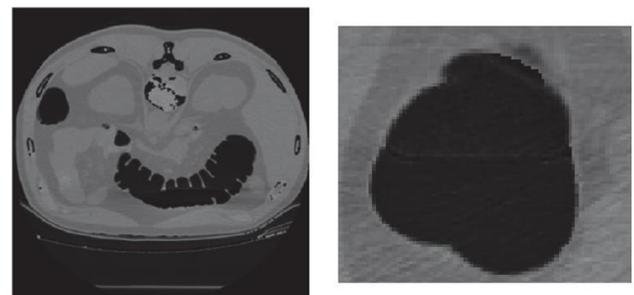


Figure 7: Exemplary results of usage of the proposed algorithm for colon cleansing.

Figure 7 demonstrates excellent performance from the implementation of the proposed algorithm for electronic colon cleansing.

Conclusion

Four of the essential electronic colon cleaning techniques, the first phase of virtual colonoscopy, were introduced in this article. Any strategies have some benefits and drawbacks that we constantly debate with them. Despite the method of thresholding, the quickest and shortest method has some drawbacks that are described.

Thresholding, first, would not erase partial voxel length. Second, for each severity spectrum, the threshold is very sensitive. Third, at the inner colon boundary, thresholding often gives rise to aliasing results. The algorithm models the tagged materials and colon objects in the Markov random field method by an isotropic Markov random field. Unlike the non-MRF methods, this spatial knowledge dependent on MRF was implemented into the EM algorithm to simultaneously approximate model parameters and segment voxels. The use of a concealed MRF model overcomes the problems of non-uniformity in the tagged fluid/stool regions, which are the biggest barrier to simulated colonoscopy without the traditional physical colon washing technique. In the identification of partial volume regions, the value of segmentation rays over other segmentation methods is. Segmentation rays can detect partial volume regions accurately and remove them if desired. If partial volume is removed, it is straight-forward to delete other unnecessary regions (e.g. tagged fluid) (e.g., by using thresholding). As it needs minimal computing, this approach to electronic cleansing is incredibly fast.

References

1. R. T. Greenlee, et al., "Cancer statistics," vol. 50, pp. 7-33, 2000.
2. H. B. Harchegani, et al., "NOVEL ALGORITHM FOR IMAGE PROCESSING TO DETECT CANCEROUS MORPHOLOGY," International Journal of Analytical, Pharmaceutical and Biomedical Sciences(IJAPBS), pp. 161-165, 2015.
3. "Cancer Facts and Figures," A. C. Society, Ed., ed, 2003.
4. Virtual Colonoscopy - Technical Aspects: InTech China, 2011.
5. Y. H. e. al., "Computer-aided Diagnosis Scheme for Detection of Polyps at CT Colonography," Radiographics, vol. 22, pp. 963- 979, 2002.
6. Mang, T., Bräuer, C., Gryspeerdt, S. et al. Electronic cleansing of tagged residue in CT colonography: what radiologists need to know. Insights Imaging 11, 47 (2020). <https://doi.org/10.1186/s13244-020-00848-9>
7. R. SL, et al., "Patient preferences for CT colonography, conventional colonoscopy and bowel preparation," Am J Gastroenterol, pp. 578–585, 2003.
8. L. PA, et al., " Dietary fecal tagging as a cleansing method before CT colonography 2002;224.," Radiology, vol. 224, pp. 393–403, 2002.
9. D. J. Vining, et al., "Technical feasibility of colon imaging with helical CT and virtual reality," Ann. Meeting Amer. Roentgen Ray. Soc, p. 104, 1994.
10. e. a. Cai W., "An Electronic cleansing method for inhomogeneously tagged regions in noncathartic CT colonography.," vol. 30, pp. 559-574, 2010.