A probabilistic method for virtual colonoscopy cleansing

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ABSTRACT

Currently, virtual colonoscopy examinations require extensive bowel preparation because residual materials can occlude lesions or can be misinterpreted as polyps. Our goal is to investigate a probabilistic method to segment contrast enhanced residual materials and remove them from the rendering.

The region around a sample position is modeled to contain mixtures of air, tissue and tagged intraluminal remains. For each image sample a probability vector is calculated expressing the probability that the materials of interest are present. A probability space is defined using the probabilities for pure materials as base vectors. Mixture vectors are constructed at 45-degree angles between the pure material vectors. The probability vectors are compared to the base vectors and the mixture vectors to classify them into material mixtures. Consider the layer between air and tagged fluid. Image intensities are similar to tissue. The scale at which the Gaussian averaged probability is calculated is increased until convergence: two successive scales result in the same classification.

The Bayesian classification method shows good results with relatively large objects. However, edges of small or thin objects are likely to be misclassified: a too large environment is needed for convergence.

Keywords: Automatic cleansing, CT colonography, virtual colonoscopy (VC), probabilistic segmentation

1. INTRODUCTION

Virtual colonoscopy (also referred to as CT-colonography) is an emerging technique for the detection of polyps in the colon. It offers several advantages compared to colonoscopy, which is today considered as the gold standard: a larger range of exploration, less patient discomfort, no sedation, no risk of perforation and lower costs [1,3,4]. First the patient's bowel has to be cleansed. Conventionally a patient is asked to drink a laxative two days before the colonography. Subsequently a 3-dimensional CT volume is acquired through which the physician can inspect the virtual colon. The invasive colonoscopy then is only necessary if a significant polyp is found. It has been demonstrated that follow up of unresected colorectal polyps up to 9 *mm* in diameter is safe [2].

Extensive colon preparation is necessary because intraluminal remains (stool and fluid) can easily be mistaken for polyps or vice versa. Therefore, it is important to thoroughly remove all these remains before scanning. This cleansing is very burdensome for the patient.

To allow a less strict cleansing regime and still be able to distinguish polyps from intraluminal remains, stool tagging was introduced [5,6]. In this preparation step the patient drinks a radio-opaque contrast material, enabling to differentiate the denser intraluminal remains from hypodense polyps (Figure 1).

Our goal is to investigate a probabilistic method to segment the opacified residual materials and remove them from the rendering ('Automatic colon cleansing'). Such a method allows a better colon surface segmentation and visualization with a more patient friendly bowel preparation.

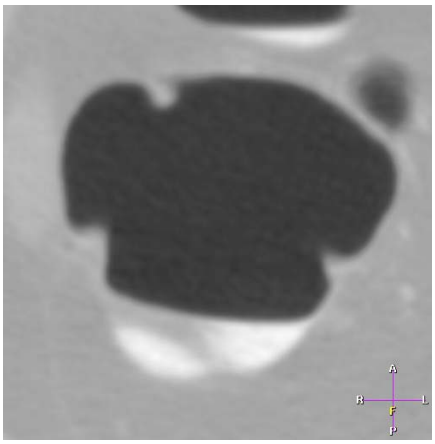

Figure 1: Typical CT image: Stool is visible in white, air in black, soft tissue in grey.

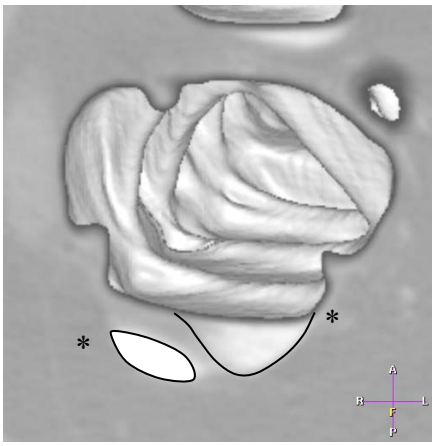

Figure 2: Straightforward isosurface visualization with transparent air and opaque contrast material. Some sections* are not segmented as desired.

To properly segment the colon surface from the volumetric data we have to deal with partial volume effects: a grey value in a CT data volume denotes the absorption of radiation in a region convolved with the Point Spread Function (PSF) of the acquisition process. This region can contain more than one material type, mixed by the measurement process.

Other problems are a non-uniform distribution of tagged material, non-uniform distribution of HU-values for colon tissue, and noisy data. In this paper we focus on the partial volume problem. We try to estimate the mixture of material types at a sample position, and use this mixture to remove the tagged material.

2. METHOD

Initially, a probability space is constructed using Bayesian probabilities. Subsequently these probabilities are convolved with a smoothing function to include the spatial context of a sample in the classification. These smoothed probabilities are used to remove the tagged material from the CT image.

2.1 DATA MODEL FOR ONE TISSUE

It is assumed that the image intensities for a material n are normally distributed around an average intensity value μ_n with standard variation σ which is the same for all materials in the area of interest. The probability of an intensity value z given a material n is written as:

$$p(z|n) = \frac{1}{\sigma_n \sqrt{2\pi}} \exp\left[-\frac{1}{2} \left(\frac{z - \mu_n}{\sigma_n} \right)^2 \right] \tag{1}$$

The method assumes that the data contains three tissue types: air (±-970 HU), tissue (±-50 HU) and tagged intraluminal remains (±300 HU) (Figure 1).

2.2 MIXTURE MODEL FOR MULTIPLE TISSUES

The imaging process is modeled by a convolution with a Point-Spread-Function (PSF) after which Gaussian noise is added. The shape of the PSF is assumed to be a Gaussian.

We want to solve the partial-volume problem at the boundaries between two materials. At the boundary the contribution of the different material types can be considered equal, and therefore the a priori probability p(n) is assumed to be equal for all materials.

To classify image intensities into mixtures of materials we use the Bayes' rule. The probability of a material *n* given an image-intensity *z* is estimated by:

$$p(n|z) = \frac{p(z|n)p(n)}{\sum_n p(z|n)p(n)} \tag{2}$$

The intensity distributions $p(z|n)$ are estimated from material regions in the neighborhood of edges.

2.3 PROBABILITY SPACE

For each sample position *r* a probability vector is calculated expressing the probability that the materials of interest are present. We define a three dimensional probability space (Figure 3):

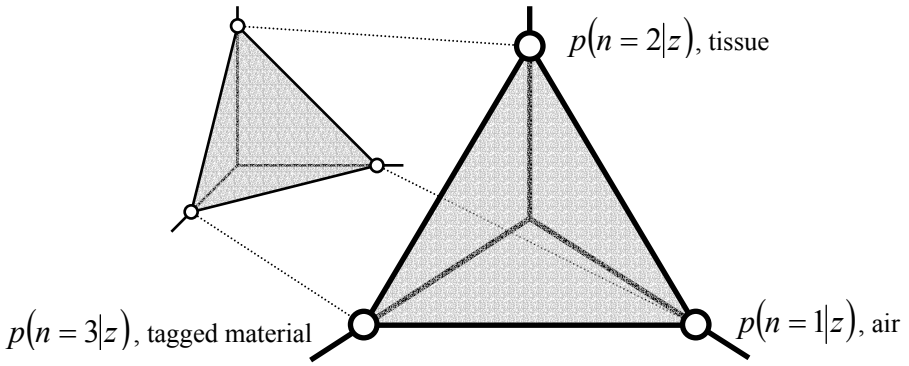

Figure 3: Material probability space with three materials.

We present the three Bayesian probabilities in a planar triangle of which the vertices denote the probability of pure material. The probability vector at a position *r* is defined by:

$$\vec{p}(\vec{r}) = \begin{bmatrix} p_1 \\ \cdots \\ p_N \end{bmatrix} \text{ with } p_n = p(n|z) \tag{3}$$

Mixture vectors in probability space are defined at 45-degree angles between the pure material vectors. This choice is supported by the fact that the probability of a material in a large environment of a sample position is 50 % for each of two materials in the neighborhood of an edge.

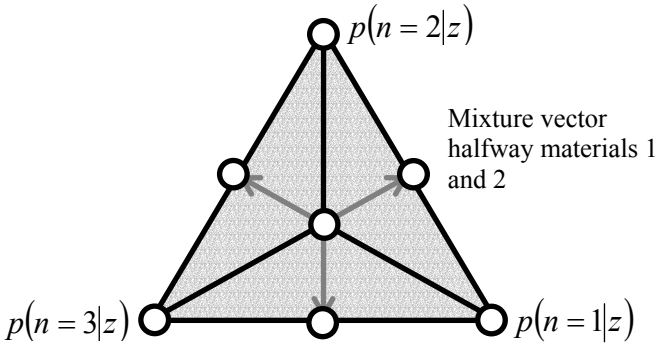

Figure 4: Material probability space with three materials and their mixtures.

Consequently, within the triangle of probabilities (Figure 5 and 6), areas are defined in which probabilities are classified as a pure material (dark areas) or as a mixtures or material types (light areas). Within the areas of the smallest distance to a mixture vector (light grey areas in Figure 5) probabilities are classified as a mixture of two materials. In figure 6 mixtures of three materials are also modeled.

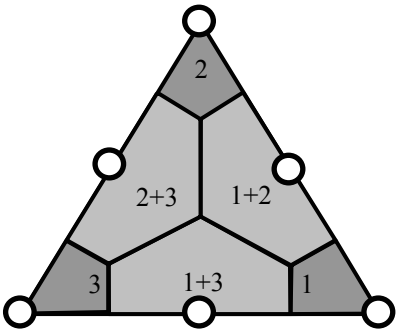

Figure 5: Classification areas for mixtures of two materials (light).

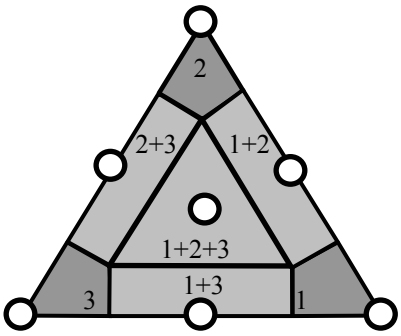

Figure 6: Classification areas for mixtures of two and three materials (light).

2.4 MULTISCALE CLASSIFICATION

To properly segment partial volume values into their mixtures of material types it is not sufficient to calculate probability vectors at a single sample location. It is essential to use the spatial context.

Consider the boundary between air and tagged intraluminal remains (Figure 7). Intensity values on the boundary can be similar to soft tissue intensities. The result would be a wrong material classification at the boundary if only one intensity value at the sample location r is used. At larger scales the probabilities in a volume around a sample position are weighted to classify the materials as a mixture of air and tagged fluid.

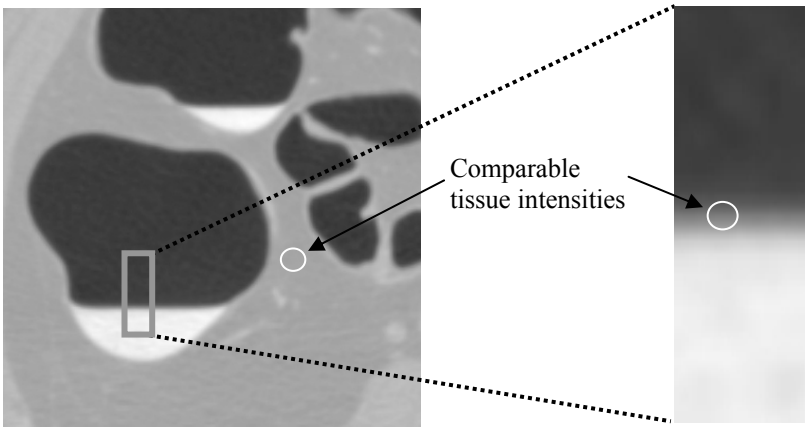

Figure 7: Intensity values on a boundary can be similar to single material intensities through convolving with the PSF.

Therefore, we smooth the probability vectors in $\vec{r}$ with a Gaussian $N(\vec{r},\sigma_p)$ at a range of scales σ_p to utilize the spatial context of a sample value:

$$\overrightarrow{p_{\sigma_p}}(\vec{r}) = \begin{bmatrix} p_{1,\sigma_p} \\ \cdots \\ p_{N,\sigma_p} \end{bmatrix} \text{ with } p_{n,\sigma_p} = p(n|z) \otimes N(\vec{r},\sigma_p) \tag{4}$$

The spatially smoothed probability vectors also form a probability space.

Notice that the probability space is convolved with a smoothing function. If the intensity values were convolved with such a function, than the material-boundary samples would be wrongly classified.

At an increasing range of scales probability vectors are calculated. We sample the probability scale-space using 3 samples per doubling of the scale parameter. Thus, the scale parameter σ_p will get the following values: 1.0 1.5 2.0 3.0 4.0 6.0 8.0. We start at $\sigma_p = 1$.

We increase the scale if:

- two scales do not result in the same classification;
- the sum of the probabilities in the denominator of Bayes' rule is too small;
- the scale is smaller than a maximum scale defined by the size of clinically significant polyps (corresponding to about 9 *mm* in diameter).

At the smallest scale at which two successive smoothed probabilities result in the same classification, the Bayesian probabilities are used to calculate the material mixtures.

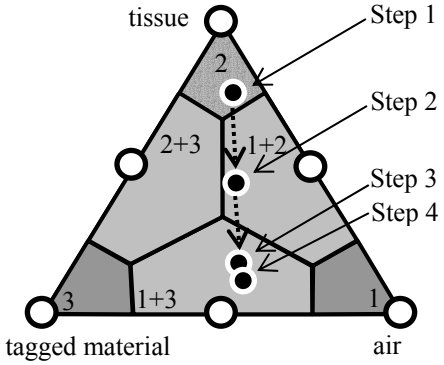

Figure 8: Multiscale probability trajectory.

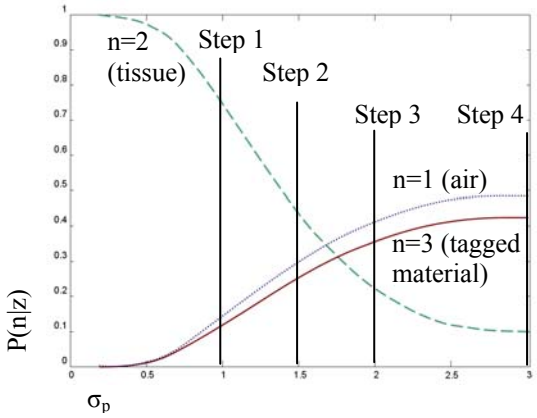

Figure 9: Multi scale Gaussian smoothed probabilities (Sigma in *mm*).

As can be seen from figure 8 and figure 9, by enlarging the scale the Bayesian probabilities on n=1 (air) and n=3 (tagged material) increase and the Bayesian probabilities on n=2 (tissue) decrease.

A simple decisive rule to classify the smoothed probability vector as a material mixture is computing the nearest predefined mixture-probability in the probability plane.

We can now calculate the volume percentages of a single material using the Bayesian probabilities at the most appropriate scale. We create a new image volume in which we use the Bayesian probability on colon tissue.

3. RESULTS

The probabilistic method is tested using CT data. One slice of the original data is depicted in figure 10.

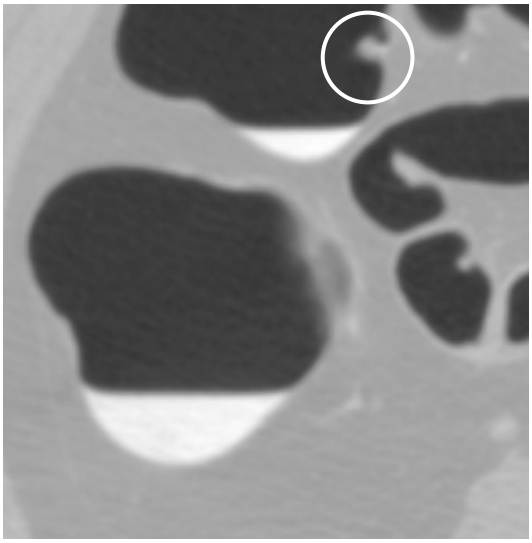

Figure 10: Typical CT image: Stool is visible in white, air in black, soft tissue in grey.

Figure 11 shows the classification result if only pure materials and mixtures of two materials are modeled. Figure 12 shows the classification result if the mixture of three materials is included in the model.

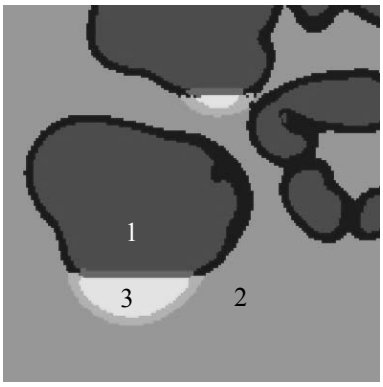

Figure 11: Typical classification result of the probabilistic method incorporating material mixtures of two materials.

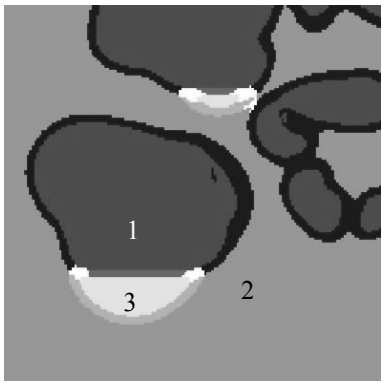

Figure 12: Typical classification result of the probabilistic method incorporating material mixtures of two and three materials.

Figure 13 and 14 depict the CT slices after colon cleansing: the opacified residual materials are removed from the 3-dimensional CT volume.

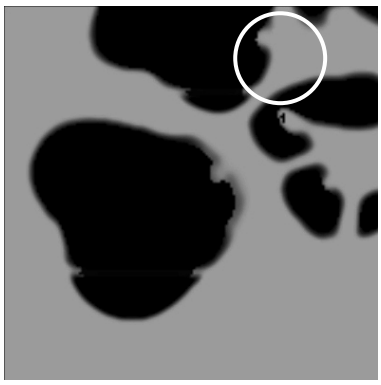

Figure 13: Typical cleansing result of the probabilistic method incorporating material mixtures of two materials.

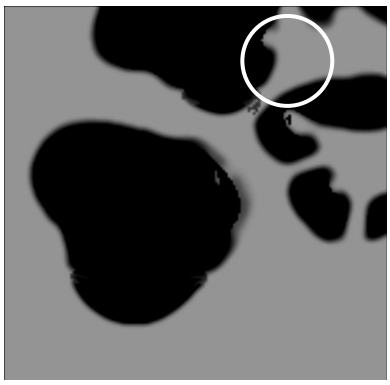

Figure 14: Typical cleansing result of the probabilistic method incorporating material mixtures of two and three materials.

Finally a typical classification problem is shown in figure 16 using the CT data depicted in figure 15 as input. This problem will be discussed in the following section.

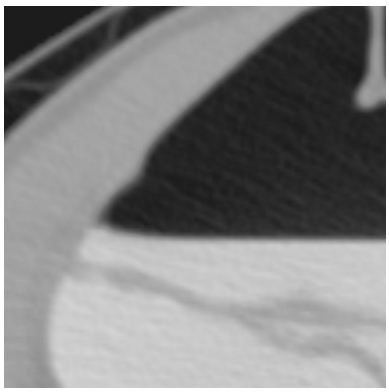

Figure 15: Typical CT image: Stool is visible in white, air in black, soft tissue in grey.

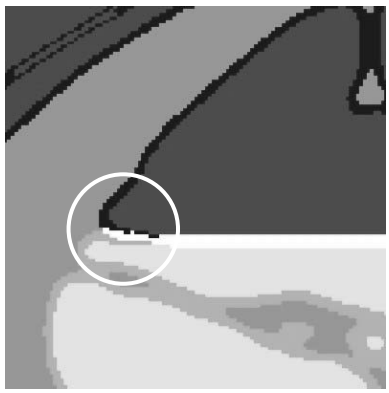

Figure 16: Typical classification result of the probabilistic method incorporating material mixtures of two materials.

4. CONCLUSIONS

The Bayesian classification method shows good results with relatively large objects. The cleansed CT output image can be analyzed slice by slice or by visualization of a 3-D iso-surface. Problems with this method can occur in the following cases:

- At edges of small or thin objects, a too large environment is applied for convergence.
- The example images (figures 13 and 14) demonstrate extensive blurring in highly curved regions (see the circles in the figures).
- Consider image samples at the boundary between air and tagged intraluminal remains. In figure 8 it can be seen that the multiscale probability trajectory could easily stabilize in the mixture area of materials one (air) and two (soft tissue). In that case a large environment is needed for convergence at the correct classification. Figure 16 demonstrates this problem using the CT data shown in figure 15 as input.
- Computing the classification using the proposed method is computationally expensive. At every sample position minimally two Bayesian probability vectors are needed.

Our research now focuses on solving the automatic colon cleansing problem using more sophisticated models. Currently we investigate a method applying two grey-level thresholds and one gradient-level threshold.

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