

Chapter 11

A Model-Driven Bayesian Method for Polyp Detection and False Positive Suppression in CT Colonography Computer-Aided Detection

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ABSTRACT

This chapter presents an automated method to identify colonic polyps and suppress false positives for Computer-Aided Detection (CAD) in CT Colonography (CTC). The method formulates the problem of polyp detection as a probability calculation through a unified Bayesian statistical approach. The polyp likelihood is modeled with a combination of shape, intensity, and location features, while also taking into account the spatial prior probability encoded by a Markov Random Field. A second principal curvature PDE provides a shape model; and partial volume effect is incorporated in the intensity model. When evaluated on a large multi-center dataset of colonic CT scans, the CAD detection performance as well as the volume overlap ratio demonstrate the potential of the proposed method. The method results in an average 24% reduction of false positives with no impact on sensitivity. The method is also applicable to generation of initial candidates for CTC CAD with high detection sensitivity and relatively lower false positives, compared to other non-Bayesian methods.

1. INTRODUCTION

Colorectal Cancer (CRC) is the second leading cause of cancer related death in western countries. Early detection and removal of polyps has been associated with reduction in the incidence

of colorectal cancer (Winawer, et al., 2003). As a new minimally-invasive screening technique, Computed Tomography (CT) Colonoscopy (CTC), also more popularly known as Virtual Colonoscopy (VC), uses CT imaging and dedicated interactive three-dimensional (3D) and two-

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dimensional (2D) imaging software to evaluate the colon. CTC has shown several advantages over the traditional Optical Colonoscopy (OC) for screening (Pickhardt, et al., 2003). Clinical studies suggest CTC can provide similar detection performance as colonoscopy but has a reduced risk of complication (Kim, et al., 2007). The CT scan is performed in supine and prone positions during a breath-hold acquisition. No sedation or analgesics are required.

Although CTC has been demonstrated to be an effective alternative colorectal screening approach (Johnson, et al., 2008), the manual interpretation of the CT data sets is very time-consuming due to the large quantity of data generated (typically 800-2000 images per patient) and some key factors (such as reader experience and specific skills) can affect the quality of CTC interpretation. Computer-Aided Detection (CAD) for CTC has been developed for the automated detection of polyps in order to overcome the difficulties of manual CTC interpretation. CAD offers the radiologist a second opinion, and has been shown to reduce the variability of the procedure. The clinical impact of CAD is being investigated. CTC CAD has been suggested as an effective second reader and may enhance the efficacy of CTC examinations through increased sensitivity of CTC examinations (Lawrence, et al., 2010).

1.1. Background

As a promising technology for CTC screening, colon CAD has received considerable research interest. Early effort of CTC CAD started with the work of Vining *et al.* (1999), who identified polyps based on colonic wall thickness. Since then, several polyp detection methods were developed. To date, typical approaches to CTC CAD can be classified as *shape-based*. Most sessile and pedunculated polyps protrude from the colon lumen and can be identified by their shape, which is part or totally spherical. Shape-based methods often rely on shape features derived from either

first order differential geometric quantities, such as Gradient Concentration (GC) (Yoshida, et al., 2001), Surface Normal Overlap (SNO) (Paik, et al., 2004), etc; or from second order quantities computed using Hessian matrices (Koenderink, et al., 1992; Yoshida, et al., 2001; Summers, et al., 2005), such as principal, mean, or Gaussian curvatures, etc. Yoshida & Nappi (2001; 2002) compute shape index and curvedness from principal curvatures to find initial candidates, which are then clustered and classified using quadratic discriminant analysis. They also add Gradient Concentration (GC) and Directional Gradient Concentration (DGC) features in the CAD in order to improve performance. GC and DGC calculate the confluence of gradient vectors toward a common point, while Paik *et al.* (2004) apply surface normal overlap method which is similar to the gradient orientation calculation but with statistic shape formulation. The work of Summers *et al.* (2005) utilizes mean curvature computed at voxels on the mucosal surface, which are then clustered and classified using quadratic discriminant analysis, whereas Kim *et al.* (2007) rely on eigenvalues of the Hessian matrix. Instead of computing curvature information on the voxel grid, Sundaram *et al.* (2008) apply a geometry processing approach directly on a mesh-based representation of the colon. Van Ravesteijn *et al.* (2010) use the second principal curvature in a differential equation that is solved explicitly on a mesh or implicitly on the image grid to identify polyp candidates. Jerebko *et al.* (2006) extended the work of Bogoni *et al.* (2005) by analyzing the symmetry of curvature patterns of raised objects in the colonic lumen.

Shape based methods have made steady progress in achieving high detection sensitivity and relatively low false positive regions (FPs). This is because the shape features take advantage of the fact that polyps tend to have rounded shapes or contain at least local spherical elements; while colonic folds are elongated shapes. However, in practice, polyps are often abnormal growths that exhibit varying morphology, and shape-based

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