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POLYP DETECTION IN COLON CAPSULE ENDOSCOPY BY USING TEXURE SEGMENTATION METHOD

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ABSTRACT:

Colorectal Cancer is one of the type of cancer caused in the region of colon. Current polyp detection method communicate heavily on curvature based characteristics to distinguish between abrasions these assume that the discrete triangulated surface, mesh or volume closely approximates a smooth continuous surface. Today's computer aided detection system for computed tomography colonography (CTC) enables automated detection and segmentation of colorectal polyps. We present a pattern move by proposing a method that measures the amount of protrudeness of entrant object in a scale adaptive fashion. One of the main result is that the performance of the candidate detection depends only on parameter the amount of protrusion.

KEYWORDS—Biomedical Image processing, Polyp detection, Colorectal cancer, Capsule Endoscopy

INTRODUCTION:

We identify a number of challenges that are associated with the detection of polyp candidates. First, optimization of the parameters is always complicated by the limited availability of preparation examples. This may lead to overtraining for a specific patient population, patient grounding, scanning hardware or scanning protocol. Thus, it is preferred to keep the number of restrictive criteria to a minimum. Second, to achieve good discrimination power and accurate measurement of lesion size, precise 'delineation' (or segmentation) of the candidate is needed. Although a number of methods are available for segmentation purposes , adding such a separate step would introduce more parameters to the CAD pipe and should be avoided. Fuzzy segmentation methods using sophisticated pattern recognition techniques might preclude this problem. A third challenge is associated with the computation of the first and second order products, which are needed to compute the principal curvatures and to characterize local shape. The derivative operators must act on a range of sizes and should not have optimal performance for a specific size only. Ideally, the scale should adapt to the underlying image structure..

We aim to introduce a new prototype for the detection of swelling regions on highly structured surfaces embedded in a 3D image. Polyps are assumed to have introduced a deformation to the originally healthy colon surface. We will describe a novel method to reconstruct the data without these protrusions. Effectively, the technique aims to _undo' the deformation by modifying the underlying intensities so that the protruding shape is no longer there. The proposed method does not require any assumptions on the lesion shape such as axial-symmetry, sphericity or lesion size, other than that it protrudes. It works well for highly irregular protruding objects. Lesion candidates are generated using only a single threshold. Small variations of the threshold affect the detection sensitivity of the smaller polyps first. Additionally, the resulting segmentations include the complete piece. In earlier work we proposed a scheme that operated on an explicit representation of the colon surface, which was obtained by a triangulation of the iso surface at - 650 HU. Only information of this particular isophote was used to estimate the structured surface without the protrusions. Possible beneficial information from other isophotes, with higher or lower intensities, was ignored. The scheme proposed in this paper differs fundamentally by acting on an implicit representation of the colon surface.

That is, it uses information from other isophotes as well. Consequently, there is no need for optimizing the intensity level of the iso surface. Another advantage of this method is that topological difficulties and complex mesh processing tasks, such as mesh generation and mesh smoothing, are avoided. We will compare both methods and validate that the two techniques are to some extent complementary. Moreover, exploiting the complementary aspects will be shown to lead to improved sensitivity.

IMAGING THE SMALL INTENSTINE:

WCE usually is performed in an ambulatory out patient setting. Abstaining or consumption of clear liquids only for10 to 12 hours is standard practice; some centers use a clear liquid diet for 24 hours before the study. Data are differing, but several studies suggest that use of a full or partial bowel preparation the night before the study yields improved visualization of the small intestine.1-4Atthe time of the procedure, the sensing system (eg, pads or a belt) is applied to the abdominal wall and connected to the data recorder that is worn by the patient. The capsule is activated by removal from a magnetic holder. After ingestion of the capsule, patients are instructed to keep a diary of indications and monitor the lights on the data recorder to confirm that the signal is being received. Patients are encouraged to avoid exercise or activities that may cause the sensors to detach. A diet of clear liquids is allowed after 2 hours and a light meal after4 hours. The reusable data-recording system can be disconnected from the patient after the lifespan of the battery has expired. The capsule is disposable and designed to be excreted. The data recorder is subsequently connected to a work- station for transfer of the acquired images it may cause reduction in productivity. Generally through the naked eyes the observations taken by the Experts ancient time for the detection and identification of crop diseases. But for this the continuous monitoring is required by the Experts and It is too expensive in large fields. So in many under developed countries in agricultural area, farmer needs to take lots of efforts .Simultaneously it will be so expensive and time consuming also for both experts and farmers. This work will described that how can we do the automatic detection of Crop diseases as this can gives much benefits in monitoring large fields of crops and detect the symptoms of diseases. Again we can tell the future preventions and treatment for the infested crop. Here in this way want to look for the Fast, Automatic, Less Exclusive and Accurate method to detect , classify, identify the crop diseases. Many research works have been published regarding the advancements of image processing for feature extraction and classification..

A. CT COLONOGRAPHY:

CT colonography (CTC) was accessible in 1994 as a technique with which a 3Dimage of a patient‘s stomach is recorded by a CT scanner. Unlike optical colonoscopy, the technique is non-invasive1 and does not require sedation. CTC has been studied extensively over the last years Traditionally, the images are visually inspected by a combination of slice by slice inspection and volume interpretations. Two factors hamper the inspection. Segments of the colon may be collapsed and stool may be present in the colon. Stool typically has an attenuation similar to tissue and thus may yields false interpretation of the colon surface location. In order to reduce the sensitivity to these artifacts, it is clinical practice to scan patients twice (in prone and supine position). Typical inspection times per patient is about 20-30 minutes. An important aspect that is used in deciding on a patient‘s treatment is the polyp size. It is measured from the largest object diameter in cross sectional views or in volume renderings . A role of CT colonography in selection is to pre-select patients with polyps such that only patients with polyps are sent to colonoscopy. Another advantage of CT colonography that it aids colonoscopy by localizing the lesion and hence increasing the overall sensitivity.

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B.AUTOMATED DETECTION

A number of key issues are associated with the automation of polyp detection. Similarly to manual assessment, patient preparation is important. The use of extensive laxative preparation may remove most fecal remains, however, the ones that remain are often difficult to distinguish from polyps. This may be resolved by the use of tagging. Tagging has the advantage that fecal remains and fluid are easily discriminated from tissue by means of their intensity (which is increased). However, for automated detection, the use of a contrast agents introduces the risk that polyps are fully or partially covered by (bright) fluid, which hampers its detection. In such situations, digital techniques are required to remove the labelling from the images before

applying detection algorithms. The techniques presented in this theory are intended to be applied to data that have been digitally cleansed first. The multicentre validation , includes results obtained from data without applying digital cleansing. Another issue, specific to automated detection, is false detections on either the ileocecal valve, or the rectal tube, which both have characteristics similar to polyps. This thesis has ignored the issue of detections on ileocecaln valveIt is addressed in a number of other studies the issue of false detections on the rectal tube is discussed Currently, there is an ingoing argument on the prevalence and clinical significance of so called 'flat' polyps. The term ‗flat' usually defines elevations less than 1 cm in diameter with a polyp height that is less than half of its width and which have a plague like morphology. Because these lesions are generally less conspicuous than polypoid lesions, they can be more difficult to detect both in optical colonoscopy as well as CTC. In it is argued that, although flat lesions remain a diagnostic challenge they do not represent a major drawback to widespread CTC screening. it is argued that "completely flat lesions are exceedingly rare". This thesis does not specifically address the detection of flat polyps, but, the techniques developed are designed to detect any elevations from surrounding surfaces before ordering them based on size and intensity measures. As such flat polyps may be detected by techniques proposed in this work. In this context, two distinct roles for Computer Aided Detection (CAD) area acknowledged. In situations where CAD is 2nd reader, after human expert, the sites are to be presented in an orderly fashion, such that the most prominent ones missed by the expert are shown first. In the other case, where CAD is to be first reader, an absolute measure of 'polypness' is required, instead of a relative ranking. Additionally, as a first reader, information is required, which allows performing a diagnosis. That is, information which relates to the chance to develop cancer, such as a measure for the polyp size. The polyp detection pipeline consists of three steps (segmentation of the colon wall from the CT images; detection (and segmentation) of suspicious sites (polyp candidates); and ranking followed by classification .

The first step is relatively simple due to the high contrast between tissue outside and air inside the colon which allows for a segmentation of the colon from the 3D CT volume by a stationary threshold. The threshold is roughly set to halfway the value for tissue and air. User interaction is sometimes used to discard air in the small intestines, lungs or other air containing tissues Proper patient preparation is important to avoid two main causes for waning segmentation. First of all, remaining stool has very little contrast with tissue and, if present in the colon.

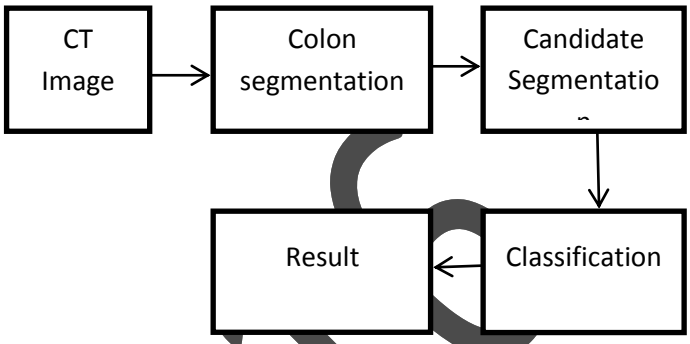


Fig 1 Three steps of a typical detection scheme.

The first step is relatively simple due to the high difference between tissue outside and air inside the colon which allows for a segmentation of the colon from the 3D CT volume by a fixed threshold. The threshold is roughly set to midway the value for tissue and air. User interaction is sometimes used to reject air in the small intestines, lungs or other air containing organs Proper patient preparation is important to avoid two main causes for failing segmentation. First of all, remaining stool has very little contrast with tissue and, if present in the colon, may lead to false positive detections or polyps inundated in stool may be missed. The use of contrast agent to tag stool present in the colon is common practice nowadays. Advanced segmentation techniques were proposed to sustain 3D viewing . Secondly, proper distinction is vital to avoid collapsed segments. This thesis does not further address the issue of colon segmentation. The student is referred to The second step, the detection of doubtful sites on the colon wall, is performed to discard large parts of colon wall, which are 'obviously' nonpolypoid. The aim of this step is to retain a high sensitivity. The specificity may be rather low, as it is to be improved in a subsequent supervised pattern recognition step. A large number of methods have been proposed for entrant detection. The most common approach is to focus on the characteristic protruding shape of polyps. It involves measures that describes the local shape of the colon wall and they are often compared to values expected for polypoidshapes .

BINARY CLASSIFIER WITH PRESELECTION:

The recommended algorithm of polyp detection is based on extracting certain geometric information from the frames captured by the capsule endoscope's

camera.. Such approach is not new, as it has been noticed before that the polyps can be characterized as protrusions from the surrounding mucosal tissue, which was used in CT colonography and in the analysis of conventional colonoscopy videos . Thus, it is natural to compute some measure of protrusion and try to detect the frames containing polyps as the ones for which such measure is high. However, this leads to an issue that was also observed in the above mentioned works. The issue is distinguishing between the protrusions that are polyps and the numerous folds of healthy mucosal tissue. This problem can be alleviated by some form of image segmentation that takes place prior to the computation of the measure of protrusion, which is what we do in this work as well. A particular choice of a measure of protrusion is of crucial importance. Many authors have proposed the use of principal curvatures and the related quantities, such as the shape index and curvedness , or the Gaussian and mean curvatures .The main disadvantage of such approaches is that the computation of the curvatures is based on differentiation of the image, which must be approximated by finite differences. In the presence of noise these computations are rather unstable, which requires some form of smoothing to be applied to the image first. However, even if the image is smoothed before computing the finite differences, the curvatures are still sensitive to small highly curved protrusions that are unlikely to correspond to polyps. Thus, in this work we use a more globalized measure of protrusion, the radius of the best fit ball. A similar sphere fitting approach was used in the CT colonography setting in .In our approach, we do not do the fitting to the image itself, but we first apply a certain type of a mid-pass filter to it. This allow us to isolate the protrusions within certain size limits .We use the radius of the best fit ball as the decision parameter in a binary classifier. If the decision parameter is larger than the discrimination threshold, then the frame is classified as containing a polyp. Another feature that distinguishes our approach from the ones mentioned above is the use of texture information. The surface of polyps is often highly textured, so it makes sense to discard the frames with too little texture content in them. On the other hand, too much texture implies the presence of bubbles and/or trash liquids in the frame. These unwanted features may lead a geometry-based classifier to classify the frame as containing a polyp when no polyp is present, i.e., they lead to an increased number of false positives. Thus, in order to avoid both of the situations mentioned above, we apply a pre-selection procedure that discards the frames with too much or too little texture content. Combined with the binary classifier this gives the algorithm that we refer to as binary classification with pre-selection.

DETAILS OF THE ALGORITHAM & RESULTS:

In the section below we present the detailed step-by-step description of the algorithm of processing of single frames from a capsule endoscope video sequence. The algorithm

makes a decision for every frame whether to classify it either as containing polyps (—polyp‖ frame) or as containing normal tissue only (—normal‖ frame).Besides the frame to be processed, the algorithm accepts as the inputs a number of numerical parameters that have to be chosen in advance. The choice of these parameters and the robustness of the algorithm with respect to the changes in them is addressed in Section IV-C. For the purpose of numerical experiments, the values of these parameters were chosen manually.

Ideally, we would like to have a systematic way to *calibrate* our algorithm, i.e., to assign the optimal values tothe parameters based on the algorithm‘s performance for some calibration dataset.. In this work we convert the captured color frames to gray scale before processing. This choice provides good polyp detection results, as we observe from the numerical experiments in Section V. However, we believe that certain improvements in this area are possible. For example, the polyps are often highly vascularised, so one would expect them to have a stronger red color component. Thus, one may use a measure of red color content in the frame, like the component of the color space in polyp detection. Here we rely mostly on the geometrical information for polyp detection, but our algorithm could still be supplemented by the use of color information.

A.PREPROCESSING:

Since the capsule endoscope operates in an absence of ambient light, an on-board light source is used to capture the images. Because of the directional nature of the light source and the optical properties of the camera‘s lens, the captured frames are often subject to an. artifact known as vignetting, which refers to the fall-off of intensity of the captured frame away from its centre. As a first step of frame pre-processing we perform the normalization of intensity using the vignetting correction algorithm of Zheng*et al.* Performance of the intensity normalization procedure is illustrated in Fig .The images acquired by the endoscope are of circular shape .The area of the rectangular frame outside the circular mask is typically filled with a solid

color. This creates a discontinuityalong the edge of the circular mask, which may cause problems in the subsequent steps of the algorithm. To remove this discontinuity we use a simple linear extrapolation to extend the values from the interior of a circular mask to the rest of the rectangular frame.

B.TEXTURE COMPUTATION AND CONVOLUTION:

Computation of the texture content in the frame is an important first step of the algorithm. We use the thresholding on the texture content as a pre-selection criterion, i.e., some frames are discarded from the consideration (and labelled as—normal‖) based on the texture content alone. To separate the pre-processed frame into the texture and cartoon components F=t+c The use of texture in pre-selection is motivated by two considerations. First, the surface of polyps is often textured, so discarding the frames with low texture content helps to distinguish the polyp frames from the frames with flat mucosa. Second when trash liquids or bubbles are present in the frame, most of ends up in , so we expect the texture content to be abnormally high in this case. Since detecting polyps in the frames polluted with trash or bubbles is not feasible anyway, we may as well discard the frames with very high texture content. Another reason to discard such frames is that the mid-pass filtering that we use in polyp detection is sensitive to the presence of large areas covered with trash and bubbles. If such frames are not discarded, this may result in an increased number of false positives.

Once we have a decomposition (3), we need to define a measure of texture content that would be appropriate for performing the pre-selection. The measure should be more sensitive to the presence of large textured regions and less sensitive to small region even if those are strongly textured, since those typically correspond to occasional trash liquids or bubbles. Thus, we perform the following nonlinear convolution-type transform of the texture.

C.MID PASS FILTERING AND SEGMENTATION:

After the frame passes the pre-selection, we identify certain regions that may correspond to polyps. An essential feature of polyps is that they are protrusions or bumps on a flatter surrounding tissue. The purpose of this step is to detect such geometric features. Note that the polyps have a certain range of characteristic dimensions. Thus, in order to detect possible polyps, the geometrical processing should act as a mid-pass filter that filters out the features that are too small or too large. Here, we use a mid-pass filter of the form.

$$u=H(w).w$$

D.GEOMETRIC ANALYSIS:

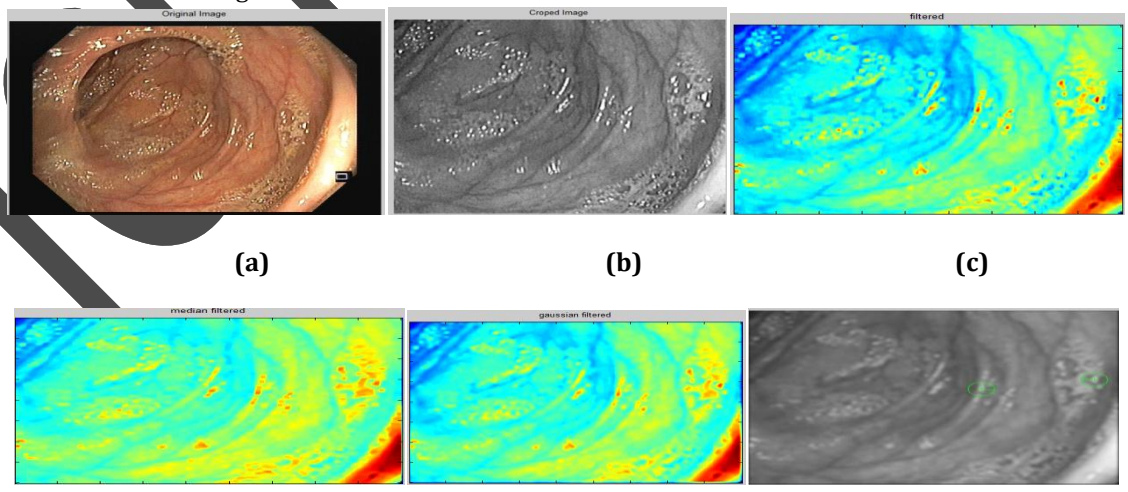
For each N_c of features compute the tensor of inertia $I^{(k)}$via and the eccentricity $E^{(k)}$of the corresponding ellipse of intertia. Apply the eccentricity criterion and the feature $_{KGsize}$ criterion to obtain the features that satisfy both criteria

E..BALL FITTING:

For each $N_c$of features compute the tensor of inertial $^{(k)}$via and the eccentricity $E^{(k)}$of the corresponding ellipse of intertia Apply the eccentricity criterio nand the feature $_{KGsize}$ criterion to obtain the features that satisfy both Criteria.

F.FINAL BINARY CLASSIFIER:

Apply the binary classifier to Rmax to classify the frame as either —normal or —polyp.



(a) **(b)** **(c)**

(d) **(e)** **(f)**

Fig2: a)original image b)cropped image c)Filtered image d) Median filtered image e)Guassian filtered image d)Polyp detection image

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