Features for the Detection of Flat Polyps in Colonoscopy Video

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Abstract. Colorectal cancer is the second most common cause of cancer death in the United States, with an estimated 140,000 new cases leading to 50,000 deaths this year. The best treatment is to detect and treat the cancer before it becomes invasive and spreads. The most common form of detection is the use of optical colonoscopy in which the clinician visually inspects the surface of the colon through an endoscope to detect the presence of polyps. Studies have shown that even the best clinicians will sometimes miss polyps, especially the more subtle flat polyps, and that many cancers that develop in the years immediately following a colonoscopy likely originate from missed polyps. In this paper we describe techniques for extracting several medically-driven features from colonoscopy video that can be used to detect the presence of flat polyps. Initial quantitative and qualitative results show that each of these features on their own provide some level of discrimination and, when combined, have the potential to support robust detection of flat polyps.

Keywords: colonoscopy, polyp detection

1 Introduction

Colorectal cancer is the second most common cause of cancer death in the United States. The American Cancer Society estimates that there will be 140,000 new cases of colon and rectal cancer this year and that more than 50,000 Americans will likely die from these malignancies [1].

The best treatment for any malignancy is to detect and treat before it becomes deeply invasive and spreads away from its site of origin. To that end more than 11 million colonoscopies are performed each year in the US at an estimated cost of at least $20 billion [2]. The justification for this effort and expense is that colonoscopy screening is effective in detecting and removing polyps that contain, or might develop into, malignancies, and thus this procedure should reduce the rate of subsequent colon cancers.

There are many trials that support the contention that colonoscopy can protect patients against future colorectal malignancies. For example, an extensive review of 88,902 participants followed over a period of 22 years from the Nurses' Health Study and the

Health Professionals Follow-up Study in Boston found that colonoscopy reduced the subsequent colorectal cancer rate by at least a factor of two [3]. A recently published meta-analysis of 11 such trials involving almost 1.5 million patients showed a slightly better result with a 61% reduction of subsequent malignancies [4].

Despite these successes many clinicians feel that a 50-60% reduction in disease can be improved upon, more so because there is evidence to support the assertion that polyps are missed at colonoscopy. Based on a meta-analysis of six studies using immediate, consecutive standard colonoscopies, the pooled miss rate for adenomas was 22% [5]. Although many of these missed polyps were likely small and posed little danger to the patient, in at least one study the miss rate of large polyps (> 1 cm) was 6% [6]. It must be borne in mind that these studies were carried out by highly experienced experts at major universities and thus represent the best that people can do; it is likely that less experienced endoscopists do less well. Finally, there is mounting evidence that even experienced endoscopists may routinely miss flat polyps (including the predominately right-sided serrated sessile polyps) which means that the missed polyp rate of 22% should be considered a minimum; the real value is likely much higher [7].

Why are polyps missed? In the broadest sense there can be only two reasons. First, perhaps they were not seen at all because the colonic surface that contained them was never visualized. Second, the polyps may have been seen but not recognized as such for a variety of reasons including the subtlety of their appearance, especially in the case of flat neoplasms, inadequate lighting, a view that was too fleeting, or human error. Our goal is to ameliorate this second problem, improving the detection of subtle polyps which are seen but not initially recognized.

Due to evidence that many of the colon cancers that occur within a few years of a negative colonoscopy originate from missed polyps, there have been many attempts to improve colonoscopy including increased physician training [8], the use of specific procedural measures (protocols) to increase the quality and effectiveness of the colonoscopy [9], at least eleven technical improvements to the colonoscope itself [10], the use of lesion staining during the procedure [12,13], having a second trained observer during the colonoscopy procedure, and the use of alternative bowel preparation regimens [14]. Most endoscopists agree that these approaches have not resulted in significant improvements.

Most recently there has been interest and a growing literature on using computer vision methods to identify colonic polyps, but most of this effort uses CT colonography as its starting point rather than optical colonoscopy which for several medical reasons is the predominant and preferred screening method at most medical centers.

We have identified several features which are germane to flat polyps and which clinicians use to locate them in optical colonoscopy images, including disruption of the local innominate groove pattern, color difference, neoplasm-specific texture, disruption of vessel patterns, darkness under narrow-band imaging, and elevation. In this paper, we develop techniques for detecting several of these features with the eventual goal of using deep learning methods to detect the presence of a polyp.

2 Related Work

There are two main types of analysis done to detect colon polyps: optical colonoscopy, performed with an endoscope, and virtual colonoscopy or colonography, performed using a CT image of the colon. As compared to colonography, colonoscopy video provides up to 10 times better spatial resolution of the colonic surface than does CT and additionally provides both mucosal color and texture, both of which are lacking on CT. CT does provide geometric information — even flat polyps are slightly raised compared to their surroundings — but we have now shown that this information can be extracted from colonoscopy videos at least as well as from CT. In this work, we focus on images from optical colonoscopy videos.

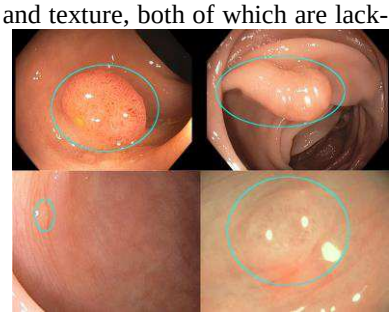

Figure 1: Typical raised (top) and flat (bottom) polyps. The flat polyps are more subtle geometrically.

Most [15-17] of the work done on analyzing optical colonoscopy images focus on raised polyps either explicitly or implicitly by using features which do not perform well on flat polyps. As shown in figure 1, raised polyps are much more obvious geometrically, and creating a system which can detect them and also detect flat polyps using the same features would be difficult if not impossible. For this reason, we focus specifically on features designed to detect the presence of flat polyps.

3 Methodology

In this section we present our current methodology for detecting polyps based on three of the previously mentioned features: disruption to local groove patterns, difference in color distribution from surrounding areas, and depth changes.

3.1 Specular Reflection Removal

Before analyzing the texture of the image we must deal with the ubiquitous presence of specular reflections caused by the light source attached to the colonoscope reflecting off of shiny parts of the colon surface. To do this, we have trained a neural network to remove specular reflections from images taken from colonoscopy videos.

To create a set of training images, we processed 256 frames of colonoscopy video containing specular reflections with the acne removal features of the Meitu [18] image processing app to remove specular reflections. These formed a set of before and after images used to train a specularity-removing neural network using the DispNet architecture [19]. Figure 2 shows example results of the trained neural network.

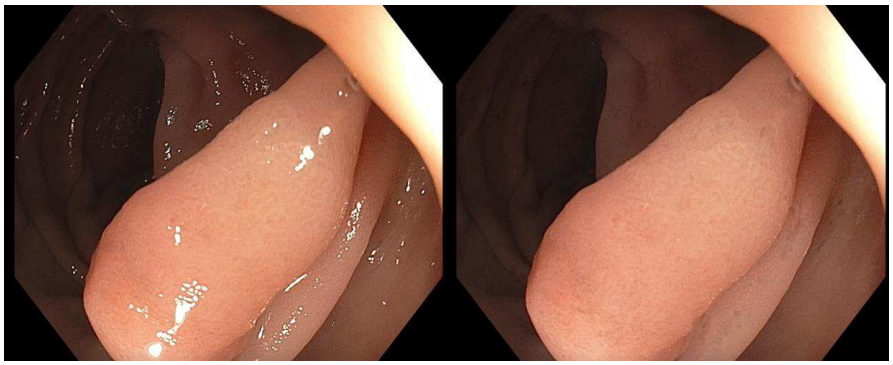

Figure 2: Polyp image from a colonoscopy video before (left) and after (right) specular reflection removal.

3.2 Polyp Detection

After removing specular reflections, we can focus on detecting the local changes in colon appearance resulting from the presence of flat polyps.

Our present method processes an individual frame to detect the presence of areas with large disruption of the typical appearance of the colon's surface. In particular, the wall of the colon has many small grooves, called *innominate grooves*, which are roughly parallel to each other. The presence of polyps causes an interruption in this regular pattern. In addition, the polyps themselves show high-frequency, randomly-oriented texture patterns. Figure 3 shows a close-up example of typical polyp appearance.

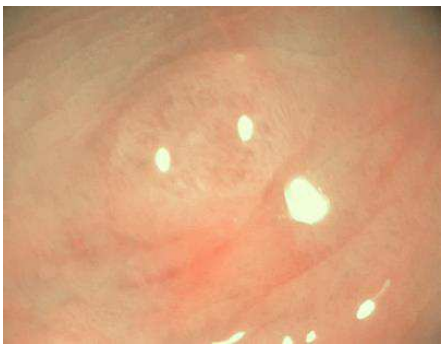

Figure 3: A close-up view of a polyp and the resulting disruption of the local innominate groove pattern.

3.2.1 Groove Features

We use oriented 2D Gabor filters to detect the presence of innominate grooves on the surface of the colon. We compute Gabor filter responses at 36 orientations (every 10 degrees) and at 19 scales. To combine these features into a single response, we first take the maximum response over scale at each orientation and then compute the mean square of these 36 values as the final value for the response image. Example response

images are shown in figure 4. From these responses we want to classify the resulting edges into three categories: edges from large ridges, from small, parallel innominate grooves, and from small, randomly-oriented edges characteristic of polyps.

First, we separate out the large ridges from the smaller grooves. We do this by applying thresholds on both intensity and edge length to the response images, as these large grooves are typically much brighter and longer than the smaller grooves.

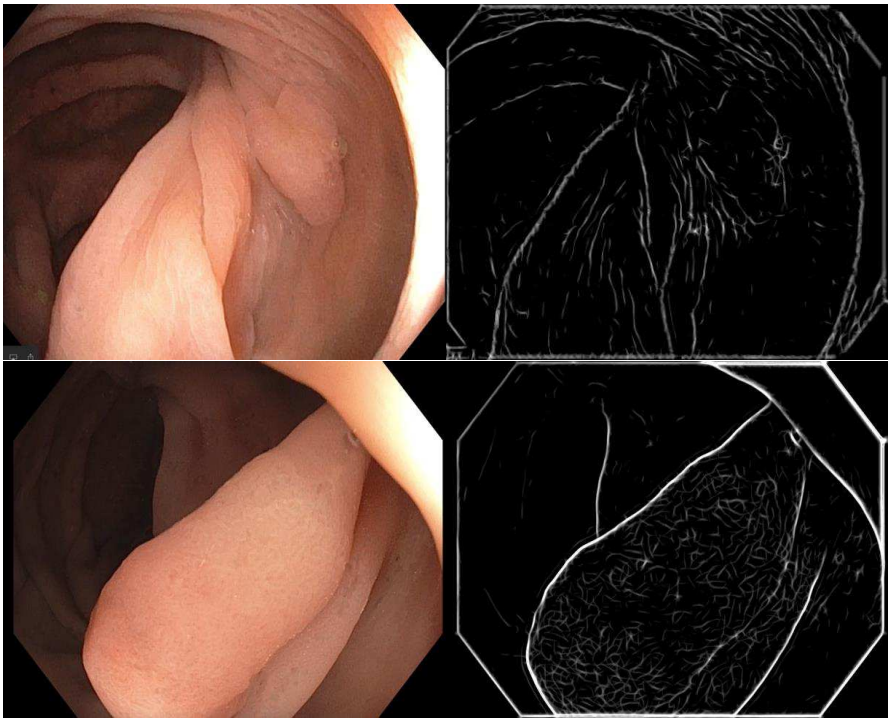

Figure 4: Colonoscopy images (left) and resulting Gabor feature maps (right).

Once the large ridges are thresholded and removed from the response images, we are left with edges in one of two classes: groups of nearby, parallel edges of the innominate grooves and randomly oriented edges. We first use the Hough transform to detect lines in the Gabor feature map. To separate out the innominate grooves, we consider a window around each pixel with a response in the feature map that contains 3-4 detected lines. For each of these lines, we compare the difference in the minimum and maximum angles from the Hough transform in the window. If this difference is less than 45 degrees, the lines are considered parallel and labeled as innominate grooves. This produces a pixel-by-pixel classification into groove and non-groove classes. Figure 5 shows results of this initial classification.

This pixelwise labeling produces a mostly reasonable classification but is not accurate enough to be useful on its own. We refine these results by exploiting the inherent connectedness of the lines in the image. Using a larger window than in the

previous step around each pixel, we count the number of neighboring pixels that were classified as parallel. Non-parallel-labeled pixels with high numbers of nearby parallel-labeled pixels are then reclassified as parallel, resulting in a more consistent classification. Figure 5 shows the results of this classification.

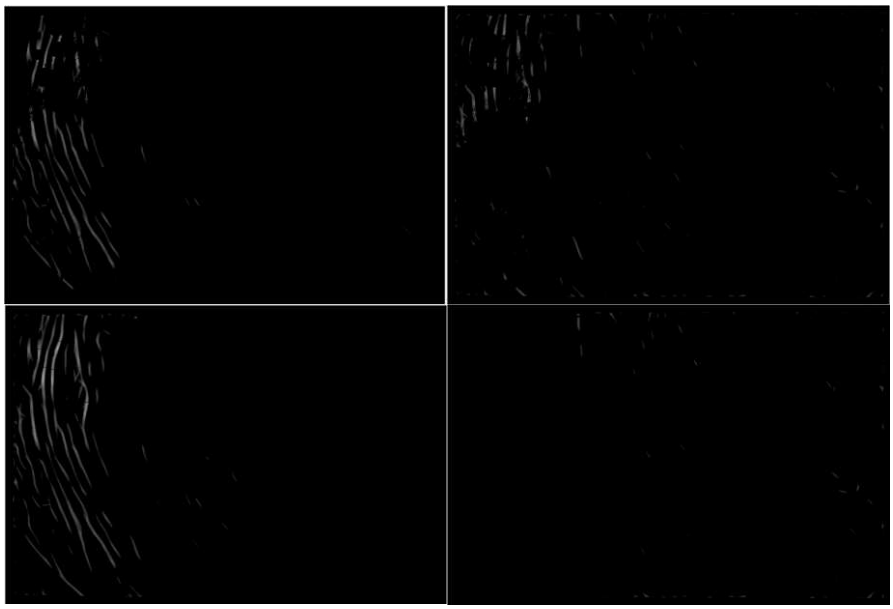

Figure 5: Initial (top) and refined (bottom) classification of lines into parallel (left) and non-parallel (right) groups

3.2.2 Local Color Features

Aside from disruptions to the local groove pattern, polyps may have a different color distribution than the immediately surrounding tissue. In particular, polyps are often either more red or more yellow than normal tissue. Figure 6 shows a polyp image and a red fraction image, computed as $r/\sqrt{r^2+g^2+b^2}$, where r,g, and b are the red, green, and blue values at each pixel. Yellow fraction images can similarly be computed as $1-\ b/\sqrt{r^2+g^2+b^2}$.

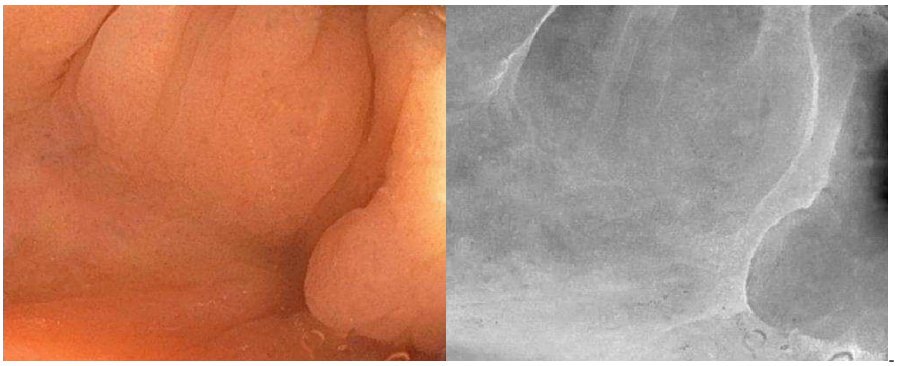

Figure 6: A colonoscopy image (left) and its red fraction image (right). The polyp on the right side has a distinctly different appearance than nearby tissue.

3.2.3 Depth Features

In addition to these texture features, we are able to obtain single-frame depth maps and 3D reconstructions using an adaptation of the method of Wang et al [20] originally developed for endoscopy of the throat. Even "flat" polyps have a subtle raising of the colon surface at the polyp, and by analyzing local curvature and shape features we can distinguish the polyp from neighboring tissue. In particular, we use the estimated depth maps to compute Koenderink's shape type measure [21], a higher-order geometric feature which takes values from -1 (convex) to +1 (concave). We can compute the gradient of this measure to find the changes to local geometry around the edges of the polyp. Figure 7 shows an example frame with its 3D reconstruction and computed shape type gradient image.

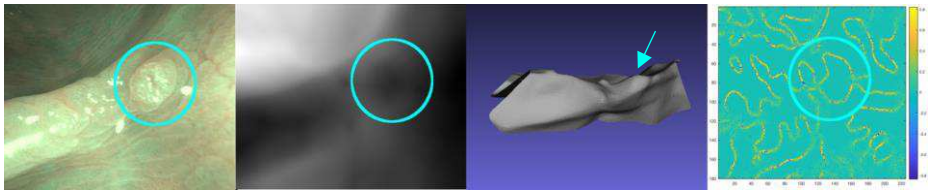

Figure 7: From left to right: A frame containing a polyp, a depth map estimated for that frame, a 3D reconstruction of that frame, and a shape type gradient image showing an edge around the polyp. The polyp is indicated by circles/arrow.

4 Experiments & Results

We have conducted several tests of the methodology in Section 3 on a dataset of 20 frames with identified flat polyps and 20 frames with no flat polyps.

4.1 Groove Classification

As described in section 3.2.1, we classify grooves detected by Gabor feature analysis into one of three groups: large grooves, small parallel innominate grooves, and randomly oriented grooves. We remove grooves from the first two categories from the image and consider only the randomly oriented grooves for polyp detection. In particular, we look for density of random grooves in a window to determine how likely it is to contain a polyp.

We compute random groove maps for 20 images with flat polyps and 20 images without. In these images we look at windows of size 158×175 (on images of size 540×675). For the images with polyps, we choose a window containing the polyp as well as the window not containing the polyp that contains the most randomly oriented grooves. For each of these windows, we then count the ratio of pixels labeled as grooves to those that are not so labeled. In *every* case in which there were random grooves detected, there were more pixels detected as grooves for the polyp window compared to the non-polyp window with a mean difference of 0.13. We can reject with very low p value the hypothesis that there is no difference between the fraction of randomly-oriented grooves in polyp and non-polyp windows.

For the 20 images without polyps, we only consider the window containing the most randomly oriented grooves and compare its ratios to the ratios from images with polyps. Table 1 summarizes the results of this experiment. While the non-polyp images have a notably smaller fraction of pixels with random edges, a conclusion as to the ability to avoid false positives needs further study since the histogram of random edge ratios in non-polyp images is far from symmetric.

	Polyp	No polyp, polyp image	No polyp, non-polyp image
Mean	0.18	0.062	0.070
Std. Dev.	0.13	0.055	0.10

Table 1: Mean and standard deviation of fraction of pixels labeled as grooves in different window types. Non-polyp windows in both polyp and non-polyp images appear very similar while the results for polyp windows are much higher.

4.2 Local Color Distribution

We have examined the color distributions of many slides both with and without polyps. In general, as shown in figure 8, polyps have a different color distribution than the immediately surrounding tissue; however, these differences are not consistent across all cases nor do they always differentiate the polyp from other tissue in the frame. These features can be useful for detecting the boundary between polyps and their surrounding tissue but are not individually useful for detecting the presence of polyps. Figure 8 shows original frames and their red and yellow fraction images.

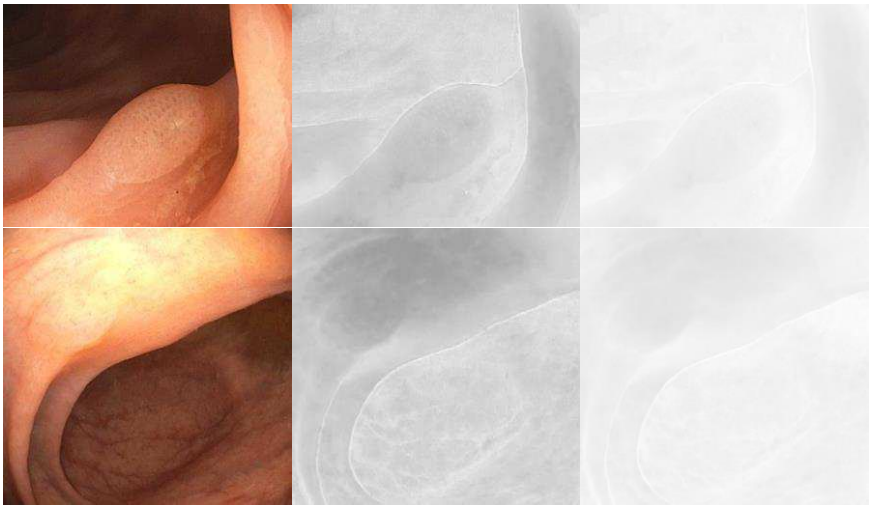

Figure 8: Original (left), red fraction (middle), and yellow fraction (right) images of frames containing a polyp.

4.3 Depth Features

We have shown 3D reconstructions of colon sections to several clinicians who have agreed that adding depth information to these images of flat polyps can make them easier to detect, as even flat polyps are subtly raised above surrounding tissue. This indicates that not only could these visualizations be a useful tool for aiding in visually locating the polyp, but that the addition of depth information could be used to automatically detect the polyp as well. Our gradient of shape type images, as shown in figure 7, show the ability to find edges near the boundary of the polyp based on changes in surface curvature. Figure 9 shows additional examples of 3D reconstructions of frames containing polyps with and without texture mapping.

5 Discussion

In this paper, we describe several features that can be used to detect the presence of flat polyps in frames of optical colonoscopy videos. We have shown that each of these features on their own can indicate the presence of flat polyps. Of the current work, our edge-based features show the strongest ability to be able to detect the presence of a polyp in an image. In images with polyps we notice a clear separation between the number of randomly-oriented edges in the polyp compared with other regions of the image. A way to use this feature alone to distinguish images with polyps from those

without would be to compare the distributions of the fraction of random edges within a window measure across the entire image, as images with polyps should show a more bimodal distribution with a peak at the polyp itself. We currently preprocess the images using Gabor filters to obtain an image with more pronounced edges before using the Hough transform, but this could potentially be replaced by a more simple edge detector. The color-based feature can help to more accurately define the boundary of the polyp but is not suited for detection on its own. Our 3D reconstructions can add important depth information to the image as well as provide for a powerful visualization tool. In future work, we plan to augment these features with others, including texture features such as run-length and co-occurrence, to develop a catalog of features that, while on their own may provide only weak or moderate evidence of polyp presence, but when combined will form the basis of a robust polyp detection method.

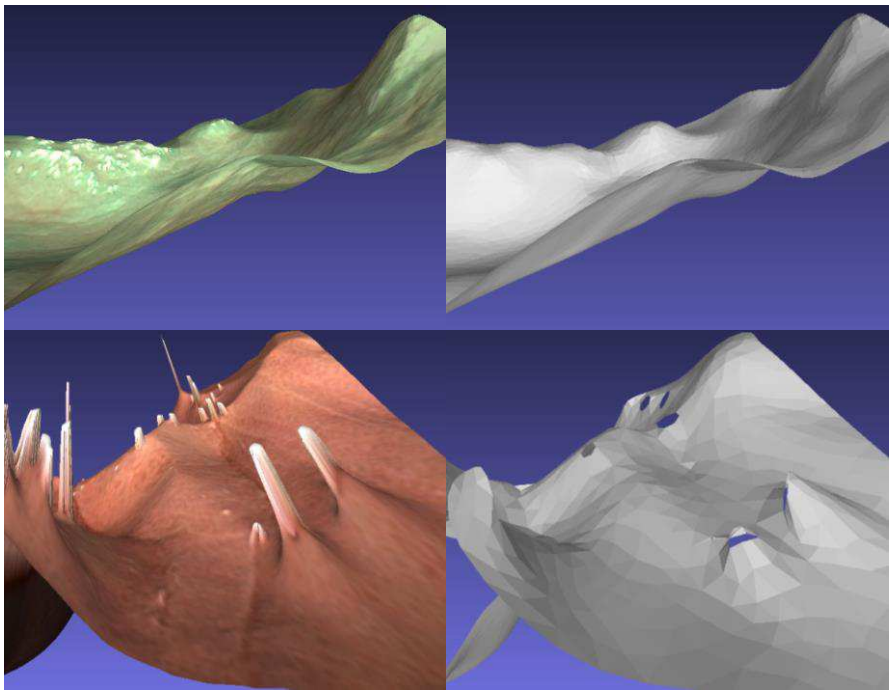

Figure 9: 3D reconstructions of frames containing polyps with (left) and without (right) texture. In both examples, there is a clearly raised polyp in the center of the image.

In addition to the development of new features, for our method to be usable in a clinical setting we must also make these features much faster to compute. In particular, the Gabor-based groove detection presented in section 3.2.1 is implemented in MATLAB and is quite slow. We plan to take advantage of the inherent parallelization of computing each feature as well as parallelizing the computation of the features themselves. Our goal is to have a system that can input a colonoscopy video during

the procedure and detect the possible presence of a missed polyp no more than 30 seconds after it has been seen. If we can detect missed polyps before the clinician has moved too far past them it will be much easier to return to the correct location and remove the polyp.

We have a significant amount of data to be able to test our methods on. We currently have 47 complete colonoscopy videos, many with polyps, and are in the process of collecting more. Having access to this amount of data will help in creating a detection method that will be robust to variations in patient anatomy.

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References

1. Siegel RL, Miller KD, Jemal A. Cancer statistics, 2018. CA Cancer J Clin. 2018 Jan;68(1):7-30. doi: 10.3322/caac.21442.
2. Peery AF, Dellon ES, Lund J, Crockett SD, McGowan CE, Bulsiewicz WJ, Gangarosa LM, Thiny MT, Stizenberg K, Morgan DR, Ringel Y, Kim HP, Dibonaventura MD, Carroll CF, Allen JK, Cook SF, Sandler RS, Kappelman MD, Shaheen NJ. Burden of gastrointestinal disease in the United States: 2012 update. Gastroenterology. 2012 Nov;143(5):1179-87.e1-3
3. Nishihara R, Wu K, Lochhead P, Morikawa T, Liao X, Qian ZR, Inamura K, Kim SA, Kuchiba A, Yamauchi M, Imamura Y, Willett WC, Rosner BA, Fuchs CS, Giovannucci E, Ogino S, Chan AT. Long-term colorectal-cancer incidence and mortality after lower endoscopy. N Engl J Med. 2013 Sep 19;369(12):1095-105.
4. Pan J, Xin L, Ma Y-F, Hu L-H, Li Z-S. Colonoscopy Reduces Colorectal Cancer Incidence and Mortality in Patients With Non-Malignant Findings: A Meta-Analysis. The American Journal of Gastroenterology. 2016;111(3):355-365. doi:10.1038/ajg.2015.418. PMID: 26753884, PMCID: PMC4820666.
5. van Rijn JC, Reitsma JB, Stoker J, Bossuyt PM, van Deventer SJ, Dekker E. Polyp miss rate determined by tandem colonoscopy: a systematic review. Am J Gastroenterol 2006; 101: 343-350.
6. Rex DK, Cutler CS, Lemmel GT, Rahmani EY, Clark DW, Helper DJ, Lehman GA, Mark DG. Colonoscopic miss rates of adenomas determined by back-to-back colonoscopies. Gastroenterology. 1997 Jan;112(1):24-8. PMID: 8978338.
7. O'Connell BM, Crockett SD. The clinical impact of serrated colorectal polyps. Clin Epidemiol. 2017 Feb 22;9:113-125. doi: 10.2147/CLEP.S106257. PMID: 28260946 PMCID: PMC5327852.
8. Brown GJ, Saunders BP. Advances in colonic imaging: technical improvements in colonoscopy. Eur J Gastroenterol Hepatol. 2005 Aug;17(8):785-92.
9. Hancock KS, Mascarenhas R, Lieberman D. What can we do to optimize colonoscopy and how effective can we be? Curr Gastroenterol Rep. 2016 Jun;18(6):27.

10. Dik VK, Moons LMG, Siersema PD Endoscopic innovations to increase the adenoma detection rate during colonoscopy. World J Gastroenterol. 2014 Mar 7; 20(9): 2200–2211.
11. Huang CS, Farraye FA, Yang S, O'Brien MJ. The clinical significance of serrated polyps. Am J Gastroenterol. 2011 Feb;106(2):229-40.
12. Aslanian HR, Shieh FK, Chan FW, Ciarleglio MM, Deng Y, Rogart JN, Jamidar PA, Siddiqui UD. Nurse observation during colonoscopy increases polyp detection: a randomized prospective study. Am J Gastroenterol. 2013 Feb;108(2):166-72.
13. Lee CK, Park DI, Lee SH, Hwangbo Y, Eun CS, Han DS, Cha JM, Lee BI, Shin JE. Participation by experienced endoscopy nurses increases the detection rate of colon polyps during a screening colonoscopy: a multicenter, prospective, randomized study. Gastrointest Endosc. 2011 Nov;74(5):1094-102.
14. Avalos DJ, Sussman DA, Lara LF, Sarkis FS, Castro FJ. Effect of Diet Liberalization on Bowel Preparation. South Med J. 2017 Jun;110(6):399-407. doi: 10.14423/SMJ.0000000000000662. PMID: 28575897.
15. Tajbakhsh, N., Gurudu, S. R., & Liang, J. (2015). Automatic polyp detection in colonoscopy videos using an ensemble of convolutional neural networks. *2015 IEEE 12th International Symposium on Biomedical Imaging (ISBI)*, 79–83. https://doi.org/10.1109/ISBI.2015.7163821
16. Tajbakhsh, N., Gurudu, S. R., & Liang, J. (2016). Automated polyp detection in colonoscopy videos using shape and context information. *IEEE Transactions on Medical Imaging*, *35*(2), 630–644. https://doi.org/10.1109/TMI.2015.2487997
17. Geetha, K., & Rajan, C. (2016). Automatic Colorectal Polyp Detection in Colonoscopy Video Frames. *Asian Pacific Journal of Cancer Prevention*, *17*(11), 4869–4873.
18. Meitu global website, http://global.meitu.com/en/products
19. Mayer, N., Ilg, E., Häusser, P., Fischer, P., Cremers, D., Dosovitskiy, A., & Brox, T. (2015). A Large Dataset to Train Convolutional Networks for Disparity, Optical Flow, and Scene Flow Estimation. https://doi.org/10.1109/CVPR.2016.438
20. Wang, R., Price, T., Zhao, Q., Frahm, J. M., Rosenman, J., & Pizer, S. (2017, February). Improving 3D surface reconstruction from endoscopic video via fusion and refined reflectance modeling. In *Medical Imaging 2017: Image Processing* (Vol. 10133, p. 101330B). International Society for Optics and Photonics.
21. Koenderink, J. J. (1990). Solid shape. MIT press.