COMPUTER-AIDED PREDICTION OF POLYP HISTOLOGY ON WHITE-LIGHT COLONOSCOPY USING SURFACE PATTERN ANALYSIS

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ABSTRACT

Background and study aims: To evaluate a new computational histology prediction system based on colorectal polyp textural surface patterns using high definition white light images.

Patients and methods: Textural elements (textons) were characterized according to their contrast with respect to the surface, shape and number of bifurcations, assuming that dysplastic polyps are associated with highly contrasted, large tubular patterns with some degree of bifurcation. Computer-aided diagnosis (CAD) was compared with pathological diagnosis and the diagnosis by the endoscopists using Kudo and NICE classification.

Results: Images of 225 polyps were evaluated (142 dysplastic and 83 non-dysplastic). CAD system correctly classified 205 (91.1%) polyps, 131/142 (92.3%) dysplastic and 74/83 (89.2%) non-dysplastic. For the subgroup of 100 diminutive (\leq 5 mm) polyps, CAD correctly classified 87 (87%) polyps, 43/50 (86%) dysplastic and 44/50 (88%) non-dysplastic. There were not statistically significant differences in polyp histology prediction based on CAD system and on endoscopist assessment.

Conclusion: A computer vision system based on the characterization of the polyp surface in the white light accurately predicts colorectal polyp histology.

INTRODUCTION

Screening colonoscopies reduce the risk of colorectal cancer (CRC) and CRCassociated mortality [1, 2] due to the possibility to detect and resect the precursor lesions.

To improve the diagnostic efficiency of colonoscopy, several authors have proposed the strategy of "resect and discard" [3] or "leave in-situ" [4] based on an invivo histology prediction. This strategy applies to diminutive (≤5 mm) polyps with a high-confidence optical diagnosis of adenoma and those located in the rectum or sigmoid colon with a high-confidence optical diagnosis of hyperplastic polyp. In this context, several paradigms have been proposed to guide clinicians to predict histology such as Kudo [5] and Narrow Band Imaging (NBI)-International Colorectal Endoscopic (NICE) [6] classifications, but none of them are directly applied to white light (WL) colonoscopy images and are manufacturer-dependent.

Computer-aided diagnosis (CAD) has emerged as an alternative for histology and several CAD systems have been proposed. However, they are based on advanced imaging modalities such as magnifying NBI, endocytoscopy or laser-induced fluorescence spectroscopy [7,8].

The objective of this study was the development and assessment of a CAD system for in-vivo histology diagnosis using the information provided by WL colonoscopy images.

PATIENTS AND METHODS

Images of polyps from routine colonoscopies performed at Hospital Clínic of Barcelona with high definition (HD) WL videocolonoscope (CF-H190 and CF-H180; Olympus Europe, Hamburg, Germany) were prospectively collected using an external computer with a frame grabber to ensure image acquisition with the highest quality. Polyps were first detected by HD-WL colonoscopy without magnification or chromoendoscopy and then by NBI. The study was approved by the Institutional Review Board and patients gave written informed consent.

During colonoscopy, 9 endoscopists with a mean adenoma detection rate of 29.8% in primary colonoscopy screening and 47.1% in FIT-based screening classified the lesions into non-dysplastic or dysplastic polyp using HD-WL and NBI. Subsequently, the stored images were retrospectively classified by an endoscopist experienced in advanced imaging techniques blinded to the histologic findings.

The final diagnosis was based on the histological report and lesions were classified into dysplastic (LGD adenoma, HGD adenoma, intramucosal carcinoma, invasive carcinoma) and non-dysplastic (hyperplastic polyps and sessile serrated polyps [SSP] without dysplasia). [9].

Computer-aided diagnosis system for polyp classification

We created a database with 225 different polyp images and manually identified the regions of interest. Images that were considered unsuitable for evaluation (out-offocus images or poor bowel preparation) were excluded.

Our WL-CAD system was developed at the Computer Science Department of Universitat Autònoma de Barcelona and Computer Vision Center [10]. It is inspired by pit patterns used in Kudo classification and identifies surface textural patterns (textons) which can guide the identification of dysplastic lesions. The system involves 3 stages (Figure 1): 1) Image preprocessing; 2) Extraction of textons (bright regions) and 3) Characterization using three metrics (contrast of the texton with respect to surface, tubularity and branching), following the assumption that highly contrasted, tubular and bifurcated patterns are associated to a dysplastic lesion. We used Support Vector Machines with K-fold cross-validation to train and validate our model [11] (Figure 2).

Sample size and statistical analysis

In a previous study, endoscopists' prediction with NBI reached an accuracy of 87% [12]. On the assumption that a computational method with an accuracy of 95% would be clinically relevant, a normal corrected sample size calculation method for one single proportion requires a minimum of 163 images to achieve a two-sided significance level of 5% and statistical power of 90%.

Sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV) and accuracy with 95% CI were calculated and differences were compared by applying the two-sided McNemar test. A value of two-sided P<0.05 was considered statistically significant.

All calculations were performed with Stata software pack version 12 (StataCorp LLC, USA).

RESULTS

142 out of 225 (63.1%) evaluated polyps were dysplastic and 83 (36.9%) were non-dysplastic (Table 1). Polyp mean size was 10.4 mm \pm 10.5 mm (1-50 mm). One hundred polyps (44.4%) were diminutive (\leq 5 mm); 54 of them were located in the rectosigmoid colon.

WL-CAD correctly classified 205 polyps, 131/142 (92.3%) dysplastic and 74/83 (89.2%) non-dysplastic. For the subgroup of 100 diminutive polyps, WL-CAD correctly classified 87 polyps: 43/50 (86%) dysplastic and 44/50 (88%) non-dysplastic. There were not statistically significant differences in polyp histology prediction based on WL-CAD and on endoscopist assessment using Kudo and NICE classification (Table 2).

DISCUSSION

To the best of our knowledge, this is the first report of a CAD system using HD-WL endoscopy images to predict histology of colorectal polyps. The overall diagnostic performance of the system was comparable to that achieved by the endoscopists who used Kudo and NICE classifications during colonoscopy and an expert endoscopist who evaluated polyp images off-site, after colonoscopy. Considering this, our system can offer an accurate prediction on polyp histology working only with already widespread available equipment.

The use of textons to automatically predict polyp histology has been explored in only one previous study that used magnification endoscopes with chromoendoscopy and did not compare the results with final histology [13].

The overall accuracy of our WL-CAD was 91.1%, approaching the accuracy of real-time endoscopic assessment and off-site assessment by an expert endoscopists. In this context, our WL-CAD could be used to reinforce the decision taken by the endoscopist to remove or not to remove a polyp. The goal of any computational classification should not be to replace the endoscopist or pathologist decision but to assist them in their diagnosis. This may be especially important for inexperienced endoscopists.

Our method did fulfill the 90% threshold for NPV established by the Preservation and Incorporation of Valuable Endoscopic Innovations (PIVI) document of the American Society for Gastrointestinal Endoscopy [14]. Other CAD endoscopic systems tested up to now have also reached this threshold, but they use advanced endoscopic imaging techniques that require intensive training [7] whereas our method is solely based on WL endoscopy.

WL-CAD incorrecity predicted histology of 20 polyps (11 dysplastic and 9 nondysplastic). The main sources of errors in case of dysplastic polyps were: excessive distance from the camera to the polyp and the presence of big specular highlights occluding textural patterns. To solve them we propose using transparent caps to stabilize and normalize image acquisition. Concerning the non-dysplastic polyps, isolated lacy vessels in polyp surface were misidentified as tubular structures. However, four of these non-dysplastic polyps were SSP. Although SSP usually do not harbor dysplasia, their removal is recommended because they have the potential for cancer progression through the serrated pathway, which is one of the possible causes of interval cancer. Therefore, there is a real need to improve their diagnosis [15].

The main strength of this study is that the WL-CAD was tested on a large database containing only one image per polyp and this confirms the robustness of the method against variations in polyp appearance. The main limitation is that SSP were not included as a separate group because they are not considered as a different group in the Kudo and NICE classifications and it can be challenging to distinguish them from hyperplastic polyps. Though the results are promising, the inclusion of other polyp characteristics (i.e. shape, color, vessels), a comparison with the performance provided by endoscopists with different level of expertise as well as enlarging the validation database in order to have more SSP and be able to analyze them separately could benefit the robustness of our methodology.

In conclusion, a computer vision system based on the extraction and characterization of surface patterns in the image, using only WL colonoscopy images,

can be used to obtain an accurate prediction of polyp histology during colonoscopy. This method offers comparable diagnostic performance to that of endoscopists using additional techniques.

REFERENCE LIST

Quintero E, Castells A, Bujanda L, et al; COLONPREV Study Investigators.
Colonoscopy versus fecal immunochemical testing in colorectal-cancer screening. N
Engl J Med 2012;366:697-706.

2. Corley DA, Jensen CD, Marks AR, et al. Adenoma detection rate and risk of colorectal cancer and death. N Engl J Med 2014;370:1298-306.

3. Rees CJ, Rajasekhar PT, Wilson A, et al. Narrow band imaging optical diagnosis of small colorectal polyps in routine clinical practice: the Detect Inspect Characterise Resect and Discard 2 (DISCARD 2) study. Gut 2017;66:887-895.

4. Ignjatovic A, East JE, Suzuki N, et al. Optical diagnosis of small colorectal polyps at routine colonoscopy (Detect InSpect ChAracteriseResect and Discard; DISCARD trial): a prospective cohort study. Lancet Oncol 2009;10:1171-8.

5. Kudo S, Tamura S, Nakajima T, et al. Diagnosis of colorectal tumorous lesions by magnifying endoscopy. Gastrointest Endosc 1996;44:8-14.

6. Hayashi N, Tanaka S, Hewett DG, et al. Endoscopic prediction of deep submucosal invasive carcinoma: validation of the narrow-band imaging international colorectal endoscopic (NICE) classification. Gastrointest Endosc 2013;78:625-32.

7. Mori Y, Kudo S, Berzin TM, et al. Computer-aided diagnosis for colonoscopy. Endoscopy 2017;49:813-9.

8. Chen P-J, Lin M-C, Lai M-J, et al. Accurate classification of diminutive colorectal polyps using computer-aided analysis. Gastroenterology 2018;154:568-75.

9. East JE, Vieth M, Rex DK. Serrated lesions in colorectal cancer screening: detection, resection, pathology and surveillance. Gut 2015;64:991-1000.

10. Sánchez FJ, Bernal J, Sánchez-Montes C, et al. Bright spot regions segmentation and classification for specular highlights detection in colonoscopy videos. Machine Vision and Applications. 2017 (in press).

11. Cortes C, Vapnik V. Support-vector networks. Machine Learning 1995;20:273-97.

12. Rogart JN, Jain D, Siddiqui UD, et al. Narrow-band imaging without high magnification to differentiate polyps during real-time colonoscopy: improvement with experience. Gastrointest Endosc 2008;68:1136-45.

13. Takemura Y, Yoshida S, Tanaka S, et al. Computer-aided system for predicting the histology of colorectal tumors by using narrow-band imaging magnifying colonoscopy (with video). Gastrointest Endosc 2012;75:179-85.

14. Cohen J, Bosworth BP, Chak A, et al. Preservation and Incorporation of Valuable Endoscopic Innovations (PIVI) on the use of endoscopy simulators for training and assessing skill. Gastrointest Endosc 2012;76:471-5.

15. Carballal S, Rodríguez-Alcalde D, Moreira L, et al. Colorectal cancer risk factors in patients with serrated polyposis syndrome: a large multicenter study. Gut 2016;65:1829-1837.

ACKNOWLEDGEMENTS

This work was supported by the Spanish Government through the funded project iVENDIS (DPI2015-65286-R) and HISINVIA (PI17/00894), by the Foundation of the Spanish Society of Digestive Endoscopy (FSEED), by the Secretaria d'Universitats i Recerca de la Generalitat de Catalunya (2014-SGR-1470, 2014-SGR-135, SGR-2017-1669 and SGR-2017-653) and by CERCA Programme/Generalitat de Catalunya.

FIGURE LEGENDS

Figure 1. Feature vector extraction from input images. We use three texton feature images (contrast, tubularity and branching) generated from textons extracted from the input image. We provide a heat map for each feature image: cold colors represent low values whereas hot colors are associated to high values. Statistical measures are extracted from each feature image to generate image feature vector.

Figure 2. Model building for image classification. Support Vector Machines (SVM) with K-fold cross validation is used to generate the final model used to classify images into dysplastic and non-dysplastic. Distribution of dataset images within folds is done randomly while keeping the same proportion between dysplastic (D) and non-dysplastic (ND) polyps (represented in red and green respectively).

TABLES

	N=225	<u><</u> 5 mm	> 5 mm
		N=100	N=125
Histopathology			
Non-dysplastic	83 (36.9%)	50 (50%)	33 (26.4%)
Hyperplastic	43	37	6
SSP without dysplasia	40	13	27
Dysplastic	142 (63.1%)	50 (50%)	92 (73.6%)
LGD adenoma	114	50	64
HGD adenoma	14	0	14
Intramucosal carcinoma	7	0	7
Invasive carcinoma	7	0	7

Table 1. Histopathology of polyps included in the database.

SSP: sessile serrated polyp; LGD: low grade dysplasia; HGD: high grade dysplasia

Table 2. Performance characteristics of the WL-CAD and endoscopists' prediction using Kudo and NICE classifications in the dataset. Results are expressed as percentage plus 95% CI.

	Size	n	Sensitivity	Specificity	PPV	NPV	Accuracy	р
	mm							
WI -	Δ11	225	92.3%	89.2%	93.6%	87.1%	91.1%	
		223	(86.7	(80.7	(88.2	(78.3	(867	
CAD			(80.7-	(30.7-	(86.2 - 06.6)	(70.3-	(80.7-	
			95.0)	94.2)	90.0)	95.0)	94.2)	
	<u><</u> 5	100	86%	88%	87.8%	86.3%	87% (79-	
			(73.8-	(76.2-	(75.8-	(74.3-	92.2)	
			93.1)	94.4)	94.3)	93.2)	,	
	< 5	54	95%	87.9%	82.6%	96.7%	90.6%	
	RS		(76.4-	(72.7-	(62.9-93)	(83.3-	(79.8-	
			99.1)	95.2)	, , ,	99.4)	95.9)	
RTDx	All		95%	95.2%	97.1%	91.9%	95.1%	0.83
(WL)			(90.1-	(88.3-	(92.8-	(84.1-96)	(91.4-	
, ,			97.6)	98.1)	98.9)	, , ,	97.2)	
			, , , , , , , , , , , , , , , , , , ,	,	,		, , , , , , , , , , , , , , , , , , ,	
	<u><</u> 5		92%	96%	95.8%	92.3%	94%	0.80
			(81.2-	(86.5-	(86-98.9)	(81.8-97)	(87.5-	
			96.8)	98.9)			97.2)	
RTDx	All		95% (90-	92.5%	95.7%	91.4%	94.1%	1.00
(NBI)			97.6)	(84.6-	(90.9-98)	(83.2-	(90.2-	
				96.5)		95.8)	96.5)	
			02.00/	01.70/	020/	02.6%	00.00/	0.01
	<u><</u> 5		93.9%	91.7%	92%	93.6%	92.8%	0.81
			(83.5-	(80.5-	(81.2-	(82.8-	(85.9-	
	A 11		97.9)	96.7)	96.9)	97.8)	96.5)	0.00
EXDx	All		97.8%	95.5%	97.8%	95.5%	97.1%	0.23
(WL)			(93.8-	(87.6-	(93.8-	(87.6-	(93.7-	
			99.3)	98.5)	99.3)	98.5)	98.6)	
	< 5		95.8%	97.2%	97.9%	94.6%	96.4%	0.37
			(86-98.9)	(88.8-	(88.9-	(82.3-	(90-	0.57
			(00)0.))	99.5)	99.6)	98.5)	98.8)	
EXDx	A11		98.6%	94.9%	97.2%	97.4%	97.3%	0.35
(NBI)	7 111		(94.9-	(87 7-98)	(93-98.9)	(91-99-3)	(94.2-	0.55
			99.6)	(07.7 90)	()))	()1)).3)	98.7)	
			,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,				20.17	
	<u><</u> 5		98%	95.8%	96%	97.8%	96.9%	0.56
			(89.3-	(85.8-	(86.5-	(88.7-	(91.2-	
			99.6)	98.8)	98.9)	99.6)	98.9)	

WL-CAD: white light computer-aided diagnosis; NBI: Narrow band imaging; RTDx: Real-time diagnosis by the colonoscopist; EXDx: off-site diagnosis by an experienced endoscopist; RS: rectosigmoid colon