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Active Learning For Real Time Detection Of Polyps In Videocolonoscopy

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Abstract

In this paper a method to perform real-time detection of polyps in videocolonoscopy is introduced. Polyps are at the origins of colorectal cancer which is one of the deadliest disease in the world. Many methods to improve detection of polyps have been proposed so far. But performance of these methods strongly depends on the available computational resources and, until now, are not able to perform real-time detection during a standard exam. The proposed method, based on active learning, is able to solve these issues. Most precisely, this approach allows to detect approximately 90% of polyps on a freely available database introduced to the community in 2012, for a F2 score of 65%, and matches real-time constraint by making possible the analysis of a frame in only 0.039s (average value) on a standard computer not necessarily dedicated to that kind of application.

1. Introduction

Colorectal cancer (CRC) is one of the main cause of death by cancer in the world, with an estimated incidence of 1.370.600 new cases in the world in 2012 and with a fatal outcome in 50% of cases (693.900 estimated deaths)[1]. In developed countries, it is one of the most frequent and killing cancer (with lung and breast cancer) with an incidence of 736.900 estimated new cases. The most efficient way to avoid the spreading of CRC is to perform early screening exams, videocolonoscopy being the "gold standard" in Europe, and to remove as soon as detected preneoplastic lesions or adenomas when detected. During videocolonoscopy the physician looks mainly for polyps (Figure 1) which could be the early state of a cancer development abnormality. Nevertheless, up to 26% of polyps can be missed during videocolonoscopy[2] depending on:

- The endoscopist skills
- The time of the exam (morning or afternoon)
- The quality of colon preparation
- Some polyps are behind folds and difficult to detect
- The size of the polyps (at early stage, some polyps could be flat and difficult to identify from normal intestinal mucosa)

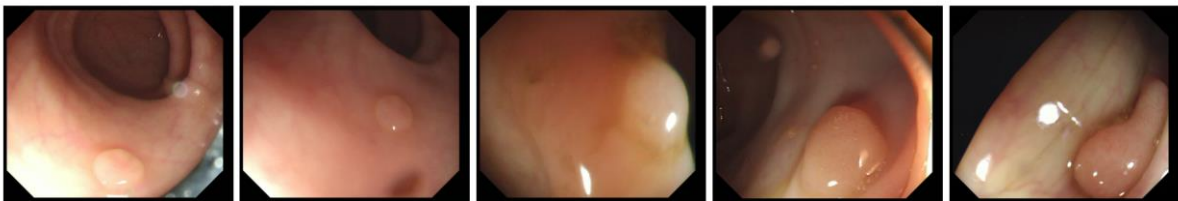


Fig. 1. Examples of several types of polyps that can be seen during a standar videocolonoscopy examination.

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Table 1. Performances of different methods.

Authors	Performances	Database	Real time compatible
Li et al.(2012) ¹²	Accuracy = 92%	100 Capsule Endoscopy Images	Not defined
Tamaki et al.(2013) ¹³	Accuracy = 93%	504 NBI images	No (0.060 seconds per image)
Mamonov et al.(2013) ¹⁴	Sensitivity = 81%, Specificity = 90%	18968 Capsule Endoscopy Images	No
Zhao et al.(2012) ¹¹	Sensitivity = 92%, F ₂ Score = 91%	1200 Capsule Endoscopy Images	Not defined
Bernal et al.(2012) ²⁰	Sensitivity = 89%, F ₂ Score = 89%	CVC-ColonDB	No (19 seconds per image)

To reduce polyp missrate and improve detection capabilities, many methods have been proposed in the recent years :

- Material based methods, like HD Colonoscopy[3], color enhancement colonoscopy (FICE[4], NBI[5]), Autofluorescence Imaging (AFI[6,7]), Full Spectrum Endoscopy[3], Chromoendoscopy[8], Endomicroscopy[8], Virtual Colonoscopy (CT Colonography[9]) and Wireless Capsule Endoscopy[10]. Those methods aim to improve visualisation during the exam. The main drawback of these methods, despite decreasing the polyp miss rate, it still depends on the physician skills.

- Software based methods, or computer aided detection system that combine computer vision and machine learning to automatically detect polyps in colonoscopy video. Different methods of machine learning have been used (including SVM[11,12,13], Binary Classification[14], kNN[11] or AdaBoost[11,15]).

In this article, we propose to tackle the improvement of polyp detection considering the Computer Aided Detection point of view. The main drawback of existing approaches is that, to our knowledge (Table 1), the detection has to be performed offline and does not compel with real time [11,12,14] processing or only tends to approach real time (15 images per second)[13]. Also, we can notice these methods were tested on different databases and CVC-ColonDB is the only available freely. That's why we aim at developing a system that is able to automatically detect polyps in real time during videocolonoscopy. This system is designed to assist the endoscopist and has the objective to decrease the polyp miss-rate by providing real-time alarms to the physician. A particular focus will be given to propose a resource efficient algorithm that can operate on different kind of machines such as GPUs, FPGAs or even small computer (RaspberryPi). To reach this goal, we have developed a machine learning based algorithm using OpenCV with a reduced computational complexity to detect a maximum of polyps and minimize the false detection rate.

2. Methodology

2.1. Detection process overview



Fig. 2. Detection process.

Figure 2 shows the polyp detection process we developed. First, the original image containing a polyp is considered and particularly, the blue channel of the image (see section 2.1.1. for details). Secondly, we pass it through a classifier obtained through an active learning process that aims to minimize the false detection rate without decreasing the overall performance in terms of polyp detection. Finally, the algorithm output is a set of regions of interest containing polyp candidates.

2.1.1. Blue channel

To reduce the computational complexity, we wanted first to limit the image processing task to a single channel. According to Bernal et al.[18], it seems that the blue channel provide a better enhancement of the polyp area (magnitude of gradients) and that, for this reason, can be used on its own for polyps detection. To quantitatively assess this in the context of this work, we decided to test it by comparing different classifiers: one learned on grayscale images (composed of 7.22% of blue, 71.52% of green and 21.26% of red), one using only the blue channel, one using only the green channel and finally one using only the red channel. In each case, performance metrics will be computed (see following section) and the average computational time per image provided.

2.1.2. Performance estimation

To compare the different obtained results, the following usual metrics have been used:

- True Positive (TP): A true positive detection is the result when a polyp is properly detected by the algorithm.
- False Positive (FP): A false positive detection is the result when a polyp is found positive while it was not.
- False Negative (FN): A false negative detection is the result when a polyp said negative while it was positive.
- Recall: It represents the percentage of true detections provided by the algorithm.
- Precision: Also known as Sensitivity or True Positive Rate (TPR), is used to indicate the number of lesions that have been detected out of total of present lesions.
- F2 Score: It combines Precision and Recall giving more weight to recall. This is used to make a balance between the number of false alarm and the number of missed lesions.

2.2. Learning process overview

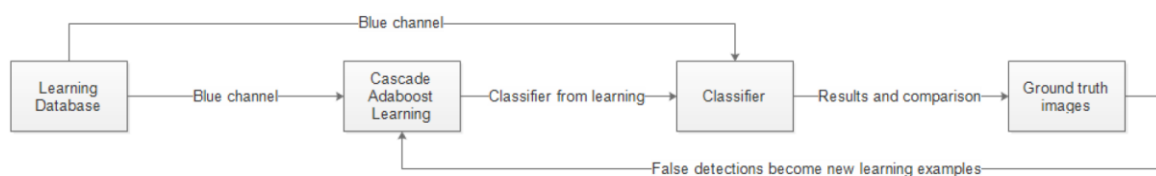


Fig. 3. Learning process.

Figure 3 shows the learning process we used to build our classifiers. As one can notice, we propose to use a boosting based approach and an active learning step is introduced to minimize the false detection rate without decreasing the polyp detection score.

2.2.1. Learning and classification

Among the existing boosting-based methods, we focus our attention on AdaBoost[16] algorithm for two main reason, according to Zhao et al.[11], AdaBoost gives the best results to detect polyp (Recall = 91.1%, F 2 = 90.7%)[11]. Secondly, this boosting-technic as proved to compel with real-time detection when considering face-detection application, above all when considering the Cascade AdaBoost algorithm[17]. Cascade AdaBoost has also the advantage of reducing drastically the number of false detection (for example on face detection, Viola and Jones obtained a 88.8% detection rate with only 50 false alarms (for 130 images with 507 faces)).

2.2.2. Active learning

Generally, active learning is a special case of machine learning in which the process is able to interact with the user to reach the desired aim. In our case, which is more specific, active learning is used to reinforce the classification, which is not assumed to be as performant as first wished. More precisely, the process that we used is the following one:

- A first classifier is computed using a given percentage of a training dataset and tested on the remaining data.
- The classifier will return regions of interest with an object labeled as a polyp.
- All regions of interest containing false alarms become new negative training examples for the learning process.
- So, we create a new Cascade AdaBoost classifier from the learning database and the new negative examples.
- This process is repeated several times to get new strengthened classifiers with better performance (up to 3 in this article).

3. Experiments & Results

3.1. Experiments

3.1.1. Data

In Table 2 are detailed the databases used to first, train our classifier and second, to test it. For the test database, we did not use the entire set of images to evaluate performance of our algorithm since some images are not exploitable due to poor image quality. Finally, only 273 images were used for performance evaluation purpose.

Table 2. Misc informations on the learning and test databases.

Database	Database Name	Content	Resolution	Availability
Learning database	CVC-ClinicDB ¹⁹	612 images	384 x 288	Free
Test database	CVC-ColonDB ²⁰	300 images	574 x 500	Free

3.1.2. Training

OpenCV offers the possibility to use either Local Binary Pattern (LBP) features or Haar-like features to train our classifier. We chose LBP features for their fast computational time to train the classifier. Indeed, computational time was 30 minutes (respectively 1 hour, 2 hours and 6 hours) for the non reinforced classifier (respectively 1st, 2nd and 3rd reinforced classifier) compared to Haar-like features computational time which was of 7 days for the non reinforced classifier. These classifications were created with the same computer (a 64-bits Windows with 32Go of RAM and Intel Xeon E5 (2.80 GHz)). For each image of the training database, we marked the position of the polyp and we created 5 negative examples. To test the blue component, classifiers were built with 550 positive examples and 3000 negative examples. Then, for the active learning, the three different classifiers were built as described in Table 3.

Table 3. Training configuration.

Classifier	Number of positives examples used	Number of negatives examples used	Computational time
Non Reinforced Classifier	550	3000	30 minutes
1 st Reinforced Classifier	550	6000	1 hour
2 nd Reinforced Classifier	550	7500	2 hours
3 rd Reinforced Classifier	550	8500	6 hours

3.2. Results

3.2.1. Blue Channel

Table 4. Results of the classification on test database according to image component.

Local Binary Pattern Classifier	Grayscale Image	Red Channel Image	Green Channel Image	Blue Channel Image
True Positive Detections	155	238	241	254
False Positive Detections	117	867	898	1067
False Negative Detections	118	35	32	19
Recall (%)	56.78	87.18	88.24	93.04
Precision (%)	56.99	21.54	21.16	19.23
F ₂ Score (%)	56.82	54.16	54.01	52.63
Average Detection Time for 1 Image (s)	0.221	0.092	0.066	0.051

Table 4 shows that the blue channel is the one that can detect more polyps as it was accepted, but also, which allows an average detection time that is the lowest. Moreover, it shows that is definitely imperative to reduce number of false detections if blue channel is used.

3.2.2. Active Learning

Table 5 shows the results of the classification on the test database and for sake of clarity, a graphic illustration is showed in Figure 4 for the different considered classifiers. We found that the recall is still almost high, which shows that our algorithm detects most of the polyps. The precision and the different scores only increase as we strengthen our classification. This shows that we reduce the number of false positives. However, the number of false positives does not decrease linearly with each improved classifier and seems to tend towards a limit. Moreover, with the second and third reinforced classifiers, we match real time constraint and we are able to detect polyp in video with a frame rate of 25 images per second (only an average time of 0.039s for detection per image). Figure 4 shows results of the detection on images containing polyps. Our detection algorithm was tested on a computer running 64 bits Windows 10 with Intel Core i5 (1.60Ghz) and 4 Go of RAM.

Table 5. Results of the classification on test database.

Local Binary Pattern Classifier	Non Reinforced	1 st Reinforced	2 nd Reinforced	3 rd Reinforced
True Positive Detections	254	256	241	237
False Positive Detections	1067	826	544	485
False Negative Detections	19	17	32	36
Recall (%)	93.04	93.77	88.28	86.21
Precision (%)	19.23	23.66	30.70	32.83
F ₂ Score (%)	52.63	58.88	64.20	65.33
Average Detection Time for 1 Image (s)	0.051	0.044	0.040	0.039

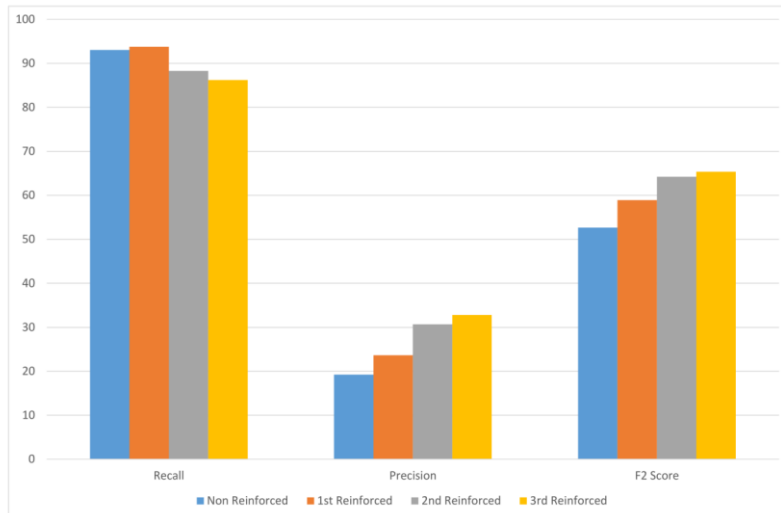


Fig. 4. Results of classification on the test database.

4. Conclusion and discussion

Table 6. Comparisons of performance.

Authors	Performances	Database	Real time compatible
Bernal et al.(2012) ²⁰	Sensitivity = 89%, F ₂ Score = 89%	CVC-ColonDB	No (19 seconds per image)
Proposed Method	Sensitivity = 86%, F ₂ Score = 65%	CVC-ColonDB	Yes (0.039 seconds per image)

In this article a real-time compatible method for polyp detection during videocolonoscopy was introduced. A comparison of the obtained performance with the method of Bernal et al.[20] (using the same data) is shown in Table 6.

It can be noticed that using blue channel of the image in an active learning boosting-based strategy, it was possible to find a satisfying trade-off between performance detection and computing time per image.

Nevertheless, the False Positive Rate could be improved in order to minimize the false alarms that can make difficult the use of this algorithm in a daily clinical practice. A first straightforward option consists in using Haar-like features for classification instead of LBP, despite of the computational time to create the classifier. We also showed in[15] that texture features can bring interesting statistical information to classify a polyp from normal mucosa. The main challenge will be to keep low the processing time even if these texture descriptors could need heavy computational resources.

A second and complementary strategy consists in gathering more images to create a new database that is more representative of the statistical shape and texture appearance of polyps than the one currently used. An effort has already been made in that way by the organization of a MICCAI challenge in 2015 on Polyp Detection from which a new database is currently being built, including HD images.

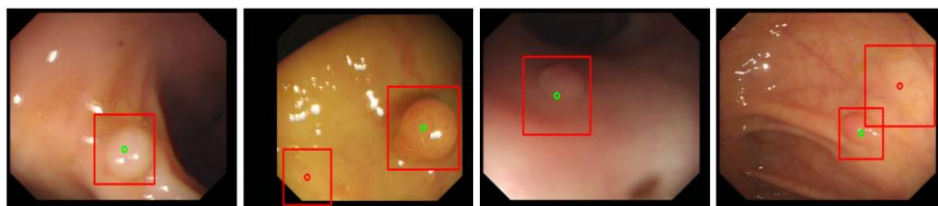


Fig. 5. Results of the detection on images containing polyps.

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