

TOWARDS REAL-TIME IN SITU POLYP DETECTION IN WCE IMAGES USING A BOOSTING-BASED APPROACH

J. SILVA¹, A. HISTACE¹, O. ROMAIN¹, X. DRAY², B. GRANADO³, A. PINNA³

¹ ETIS Lab, ENSEA, University of Cergy-Pontoise, CNRS, France

²iTEC/CRB3 lab, Paris Diderot, Paris 7 University, France

³LIP6 Lab, University Pierre et Marie Curie, CNRS, Paris, France

aymeric.histace@u-cergy.fr, olivier.romain@u-cergy.fr

ABSTRACT

This paper presents a new embeddable method for polyp detections in Wireless Capsule Endoscopic - WCE images. this approach consists first of extracting candidate polyps within the image using geometric considerations about related shape, and second, in classifying (polyp/non-polyp) obtained candidates by a boosting-based method using texture features. The proposed approach has been designed in accordance with the hardware constraints related to FPGA implementation for integration within WCE imaging device. The classification performance of the method have been evaluated on a large dataset of 300 polyps, and 1200 non-polyps images. Experiments show interesting and promising performance: the boosting-based classification is characterized by a sensitivity of 91%, a specificity of 95% and a false detection rate of 4.8%, the detection rate of the overall processing chain being of 68%. The performance of the boosting-based classification are in accordance with the most recent reference on this particular topic using the same dataset. Building of a dedicated WCE image database should permit the improvement of the global detection rate.

Index Terms— Colorectal cancer, polyp, WCE, videoendoscopy, boosting, co-occurrence matrix.

1. INTRODUCTION

Colorectal cancer (CRC) is the first cause of death by cancer in developed countries, with an estimated incidence of 728.550 cases worldwide in 2008, with fatal outcome in 43% of cases. Overall, CRC is the third more frequent cancer after lung cancer and breast cancer [1]. Prevention of CRC by detection and removal of pre-neoplastic lesions (colorectal adenomas) is therefore of paramount importance and has become a worldwide public health priority. Currently, colonoscopy is the “gold standard” technique for diagnosis of colorectal adenoma and cancer. Colonoscopy is performed under general anesthesia, mini-invasive techniques such as computed-tomography-based colonography and wireless capsule endoscopy (WCE) have been developed. Both techniques are currently considered valid alternative options to videocolonoscopy in patients with contra-indication or low compliance to general anesthesia. WCE takes form of a pill equipped with a camera, two batteries, and a RF (radiofrequency) transmitter, that enables the off-line identification of gastrointestinal abnormalities such as ulcers, blood and polyps [2]. Many fabricants such as Given Imaging, IntroMedic, and Olympus [3] have developed a variety of capsules for the complete examination of the gastrointestinal tract. After ingestion of the capsule, about 50,000 images are captured along the digestive tract and

each of them are wirelessly transmitted to a wearable receiver and saved for a postponed physician’s reading. The off-line image processing enables the identification of gastrointestinal abnormalities like the aforementioned polyps and adenoma.

However, the complete analysis of the 50,000+ images is time-consuming for physicians, and even for experienced ones, WCE diagnoses are sometimes challenging. Finally, the transmission of the 50,000+ images, that represents 80% of the overall energy consumption of the embedded batteries, limits to 8 hours the autonomy of the classic WCE, whereas 12 hours are necessary to scan the complete intestinal track.

In the context of early diagnosis of colorectal adenoma and cancer, main aim of the “Cyclope” project is to propose a new generation of WCE (see Fig. 1 for illustration) that will permit an in situ detection of the polyps and, consequently, to only emit the images which are important for the final diagnosis. In [4] and [5], a first prototype demonstrator was proposed with a particular focus on the recognition of three-dimensional colon polyps captured by an active stereo vision sensor. The proposed detection algorithm used a SVM classifier trained on robust 3D feature descriptors. The overall detection performance were very promising with a global classification rate of 97% on an in vitro dataset consisting of 111 polyps (40 adenomas and 81 hyperplasias) made in silicon. Nevertheless, it appears that for real case examination, 3D features are not sufficient to detect the large variety of polyp shapes that can be very flat at an early evolution stage.

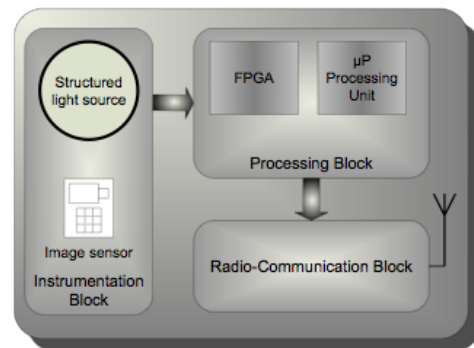


Fig. 1. Block Diagram of the “Cyclope WCE”

In this article, we give a particular focus on the 2D analysis of the videoendoscopy images in order to investigate other possibilities than 3D shape characterization of polyps to improve capabilities of

WCE. As in [4], a particular attention will be given to propose a global detection/classification scheme that can be integrated within the “Cyclope”-WCE architecture shown in Fig. 1.

The remainder of this article organized as it follows: a state-of-the-art on detection of polyps in videocolonoscopy using 2D features is proposed in Section 2. In Section 3, the proposed approach is detailed. Experimental results are given in Section 4. Discussion and conclusion are given in the last Section.

2. RELATED WORKS

Several previous works have considered the detection of intestinal polyps in videocolonoscopy images. They are mainly divided into two categories: those based on geometric features of the polyps (size and shape) and those based on textural features. Bernal *et al.* [6] propose a study made on videoendoscopies images. They developed a region descriptor based on the depth of valleys (SA-DOVA). Resulting algorithm, constituted of several steps (region segmentation, region description and region classification), is characterized by promising detection and classification performances.

In [7], Figueiredo *et al.* assume that polyps show up as protrusions that can be detected using the local curvature of the image. Consequently, a method based on the mean and geometric curvature of the WCE image is proposed, differentiating the polyps from non protruding images. The main drawback of the proposed approach is the reliance only on the protrusion measure of the polyp to identify potential candidates. The consequence is that if a polyp is not protruding enough from the surrounding mucosal folds it may be missed.

Kodogioannis and Boulougoura [8] propose an approach based on the texture of the WCE images. Authors introduce new texture features in the texture spectra of chromatic and achromatic Region of Interest (ROI). For classification, a neurofuzzy scheme is proposed. Main result is that the textural information is of first importance for the discrimination between polyps and non-polyps.

Finally, in [9], Karargyris and Bourbakis propose an algorithm for WCE images mainly based on Log Gabor filters and Susan edge detector. Based on the geometric information of the resulting detected ROI, a level-set segmentation is then initialized for an accurate delineation of the polyps. On the considered WCE image database (10 polyps and 40 non-polyps), the method gives satisfying results but authors highlight that inclusion of textural or color features within the detection/classification scheme would significantly increase related performance.

Table 1 summarizes the obtained performance of these four main contributions. All four presented approaches for polyp detection and classification are definitely of primary interest, but does not compel to the hardware constraints of Cyclope architecture since the detection algorithm is to be embedded in the FPGA block of Fig. 1 of limited resources. This can be explained by the fact that all developed approaches were designed for an off-line use mainly. It also appears that image databases used for performance estimation are size-limited or not freely available for possible comparison, except [6]), more particularly when considering WCE images. Taking benefits of the aforementioned reference, and taking into account the heavy hardware constraints of “Cyclope” WCE, we propose in this article a learning-based polyp detection approach using texture descriptors. In order to compare related performance to the most recent literature, we will use for illustration the database freely provided by [6].

Authors	Classification performance	Database
[6]	Sensitivity 89% Specificity 98%	300 videocolonoscopy images containing a polyp (freely available)
[7]	No indicated performance	17 WCE videos of 100 images each, containing example of polyps (10), flat lesions, diverticula, bubbles, and trash liquids
[8]	Sensitivity 97% Specificity 94%	140 WCE images (70 polyps and 70 non-polyps)
[9]	Sensitivity 100% Specificity 67.5%	50 WCE images (10 polyps and 40 non-polyps)

Table 1. Features of the polyp’s detection methods

3. PROPOSED APPROACH

In this section, we present an empirical methodology for detecting polyps in the colon that could be implemented in hardware. The method is composed by the abstraction of the methodology used by the physician when doing an endoscopic examination: To make a pre-selection of images that may contain a polyp, the physician looks for structures with a specific size and a circular shape. This first pre-selection allows the physician to scan the image in a glance detecting some possible abnormal regions of interest (ROI). Once the ROI is detected, a second visual analysis, based on texture (homogeneity, granularity, coarseness...) is achieved. Taking benefits of this physician’s approach, we propose a global scheme for the detection/classification of possible polyps which is summarized in figure 2. Considering the geometric step of the proposed approach,

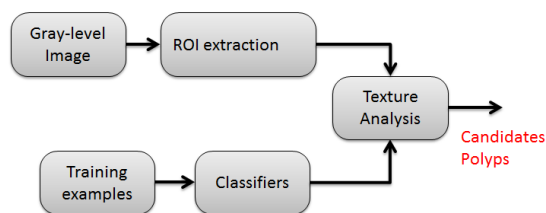


Fig. 2. Global scheme for the detection of polyps

simple image processing tools make possible the detection of circular/elliptical shape like the Hough transform for instance. The textural classification is the main keypoint of the global scheme since the rejection of most of the false positive preselected ROI have to be performed at this stage. To achieve this, we propose to design an ad hoc classifier based on a boosting-based learning process using textural features.

3.1. Geometric features

As mentioned before, the first useful characteristics for preclassification are size and shape of candidate structures. To obtain the mistrustful ROI (Region Of Interest), an algorithm based on the circular

form of the polyps is implemented. Instead of using the curvature or the Log-Gabor filtering, as suggested in [9], the circular Hough transform is used for three reasons; firstly, processing remains simple and efficient; secondly, all polyps must be detected even if numerous false positive ROI are also considered; thirdly, the Hough transform can be embedded in FPGA like shown in [10] for an *in situ* and real-time detection.

3.2. Textural features

For the textural analysis of pre-detected ROI, the co-occurrence matrix [11] is used to discriminate textural patterns of polyps and non-polyps. Mainly, these matrices calculate how often a pixel with grey-level value i occurs either horizontally, vertically, or diagonally to adjacent pixels with the value j . One main advantage of those matrices is that their computation has recently been implemented on FPGA [12].

Twenty-six features (known as the Haralick's features) are then extracted from each of the computed matrices (Energy, Entropy, Homogeneity, etc.). Since the textural classification will be performed by using a boosting based algorithm, no limitation about the number of parameters is considered: the main idea is to let the learning process converge to the best choice without any prior information.

3.3. Classification

The boosting is a machine learning algorithm for supervised learning (see [13] among other publications of the same authors). It consists of the accumulation and constant learning of weak classifiers (a weak classifier is considered slightly correlated (just little better than chance) with the true classification), that once combined together generate a strong classifier, well-correlated with the true classification. Considering the proposed approach, we used the boosting method of [14] set-up in attentional cascade. This configuration makes possible the computation of a strong classifier with a greater value of true positives (TP) whereas the value of false positives (FP) is reduced drastically. As for Hough transform and cooccurrence matrices, Attentional Cascade has been recently implemented in FPGA [15]. For our purpose, the considered weak classifiers are based on a truncated binary decision tree built from the 26 textural parameters computed for each example of the related learning database.

4. EXPERIMENTS

Tests were performed on the database proposed by J. Bernal from the Universitat Autònoma de Barcelona [6], which consists of 300 images from videoendoscopies in which polyps were identified and segmented by a specialist. The data have been courtesy made available by authors. To our knowledge, in the particular framework of colorectal polyp detections, this is currently the only existing on-line database with a sufficient amount of examples to be statistically meaningful. To create an exploitable learning database each image of the main dataset was sub-divided into five thumbnails, as shown in figure 3. A first ROI corresponds to the polyp (a), and the other four to non-polyps (b-e). The resulting database is composed of a total of 1500 images, with 300 images of polyps and 1200 images of non-polyps. To evaluate the performances of the proposed learning method, three measures are usually considered meaningful and complementary. Those are, the sensitivity, the specificity and the false positive rate (FPR) defined as: $Sensitivity = \frac{TP}{TP+FN}$, $Specificity = \frac{TN}{TN+FP}$, $FPR = \frac{FP}{FP+TN}$ with TP , FN , TN ,

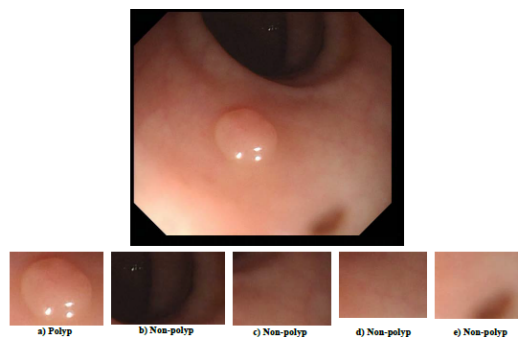


Fig. 3. Example on how the learning/testing database of 1500 images is generated.

FP standing for true positive, false negative, true negative and false positive.

4.1. Geometric performance

In table 2 the detection performance of the Hough transform on the aforementioned database are shown and compared to the Log Gabor filtering of [9].

	Sensitivity	Specificity
Hough transform	94%	15%
Log-Gabor	42%	89%

Table 2. Comparison of the detection sensitivity of the Hough transform and the Log Gabor filtering approach of [9] on the considered polyp/non-polyp database.

At this stage, it can be noticed that the simple Hough transform allows a good detection of ROI containing a polyp. Even if the value of specificity is low, the next classifying step will allow to improve the performances of the overall method.

4.2. Learning-based classification performance using textural features.

For these experiments, the polyp/non-polyp database were divided into two subgroups: A first one composed of 1000 images (200 images of polyps and 800 of non-polyps) for the learning process and a second group for testing composed of the remaining 500 images. Different kinds of methods for classification were compared: Learning Vector Quantization technic (LVQ) [16], classic Adaboost and finally Attentional Boosting (cascade adaboost). The results of this experimentation are shown in Table 3: the most efficient approach was the Attentional Boosting. One can also notice in Tab. 3 that the

Type Adaboost	Sensitivity	Specificity	FPR
Real Adaboost	77%	92.5%	7.5%
Attentional	91%	95.2%	4.8%
LVQ classification	92%	86%	14%
[6]	89%	98%	2%

Table 3. Performance comparisons among different types of classification approaches, including adaboost and attentional boosting.

classification performance resulting from the boosting process are not that far from the classification performance of [6] on the same image database, even if their obtained Specificity remains at a higher level.

4.3. Examples of detection and classification results

In figure 4 some examples of detection/classification are shown. ROI that are skirted by a non-bolded plain rectangle are the candidates issued from the Hough transform step of the proposed approach. ROI skirted by a bold plain rectangle are those which are effectively identified as a polyp after the textural classification. In the two-first

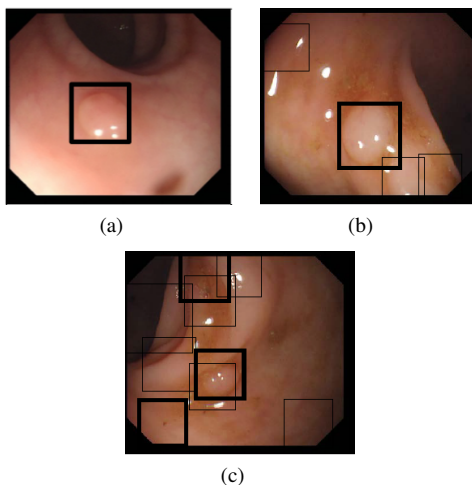


Fig. 4. Three examples of detection/classification of polyps in three different images extracted from the database:

cases, the single polyp is detected and well classified. The third one shows nine detected ROIs from which only three are classified as polyps, including the one containing the real polyp. In figure 4.(c), the misclassifications are errors probably made by the insufficient number of examples in the database used for the learning step. This is the main drawback of the proposed approach, since, because of the insufficient representativity of the generated database, the detection rate of the entire scheme is only of 68%. Nevertheless, classification results remain promising since many FP ROI are discarded after the textural classification step.

5. CONCLUSION

In this paper, we introduced a new method for detection of polyps in videoendoscopic examinations, based on the physician's approach. The entire detection chain combines geometric and textural features for polyp characterization: if the first geometric step remains simple with the use of the Hough transform, the textural features computed from co-occurrence matrix are integrated within a boosting-based approach making possible to achieve good classification performances similar to those of the most recent state-of-the-art article [6] on the same database. At last, the complete developed detection/classification scheme is in accordance with a hardware implementation (Hough transform [10], boosting classification [15] and co-occurrence matrices [12]). An effort should be made now to improve the overall detection rate of the proposed method and to build a significant database of images taken from WCE videos, which re-

mains a primary objective of "Cyclope" project for a real-time in situ detection of polyps.

6. REFERENCES

- [1] M. C. Parkin F.J. Shin, B.F. Forman, "Globocan 2008 v1.2, cancer incidence and mortality worldwide: Iarc cancerbase no. 10.," *International Agency for Research on Cancer*, 2008.
- [2] A. Moglia, A. Menciassi, A. Dario, and A. Cuschieri, "Capsule endoscopy: progress update and challenges ahead," *Nature reviews. Gastroenterology & hepatology*, no. 6, pp. 352–362, June 2009.
- [3] A. Bergwerk, D. Fleischer, and J. Gerber, "A capsule endoscopy guide for the practising clinician: technology and troubleshooting," *Medline*, pp. 1188–1195, Dec. 2007.
- [4] J. Ayoub, B. Granado, Y. Mhanna, and O. Romain, "SVM based colon polyps classifier in a wireless active stereo endoscope," in *2010 IEEE EMBC*, 2010, pp. 5585–5588.
- [5] A. Kolar, O. Romain, J. Ayoub, S. Viateur, and B. Granado, "Prototype of Video Endoscopic Capsule With 3-D Imaging Capabilities," *Biomedical Circuits and Systems, IEEE Transactions on*, vol. 4, no. 4, pp. 239–249, 2010.
- [6] J. Bernal, J. Sanchez, and F. Vilario, "Towards automatic polyp detection with a polyp appearance model," *Pattern Recognition*, vol. 45, no. 9, pp. 3166–3182, 2012.
- [7] P. N. Figueiredo, I. N. Figueiredo, S. Prasath, and R. Tsai, "Automatic polyp detection in pillcam colon 2 capsule images and videos: Preliminary feasibility report," *Diagnostic and Therapeutic Endoscopy*, 2011.
- [8] V. Kodogiannis and M. Boulougoura, "An adaptive neuro-fuzzy approach for the diagnosis in wireless capsule endoscopy imaging," *Int. J. of Information Technology*, vol. 13, pp. 46–56, 2007.
- [9] A. Karargyris and N. Bourbakis, "Identification of polyps in wireless capsule endoscopy videos using log gabor filters," in *IEEE Workshop LiSSA*, april 2009, pp. 143–147.
- [10] S. Tagzout, K. Achour, and O. Djekoune, "Hough transform algorithm for fpga implementation," *Signal Processing*, vol. 81, no. 6, pp. 1295–1301, 2001.
- [11] R.M. Haralick, "Statistical and structural approaches to texture," *Proceedings of the IEEE*, vol. 67, no. 5, pp. 786–804, 1979.
- [12] L. Siéler, C. Tanougast, and A. Bouridane, "A scalable and embedded FPGA architecture for efficient computation of grey level co-occurrence matrices and haralick textures features," *Microproc. and Microsys.*, vol. 34, no. 1, pp. 14–24, 2010.
- [13] R.E. Schapire and Y. Singer, "Improved boosting algorithms using confidence-rated predictions," *Mach. Learn.*, vol. 37, no. 3, pp. 297–336, Dec. 1999.
- [14] S. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proceedings of the 2001 IEEE CVPR Conference*, pp. 511–518.
- [15] J. Mitran, J. Matas, E. Bourennane, M. Paindavoine, and J. Dubois, "Automatic hardware implementation tool for a discrete adaboost-based decision algorithm," *EURASIP Journal on Applied Signal Processing*, vol. 2005, pp. 1035–1046, 2005.
- [16] T. Kohonen, *The Handbook of Brain Theory and Neural Networks*, chapter Learning vector quantization, MIT Press, Cambridge, MA, 1995.