Towards a Multimodal Wireless Video Capsule for Detection of Colonic Polyps as Prevention of Colorectal Cancer

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***Abstract*— Wireless capsule endoscopy (WCE) is commonly used for noninvasive gastrointestinal tract evaluation, including the identification of polyps. In this paper, a new multimodal embeddable method for polyp detection and classification in wireless capsule endoscopic images was developed and tested. The multimodal wireless capsule used both 2D and 3D data to identify possible polyps and to deliver cancerous information of the polyps based on 3D geometric features. Possible polyps within the image (2D) were extracted using simple geometric shape features and, in a second step, the candidate regions of interest (ROI) were evaluated with a boosting-based method using textural features. Once the 2D identification of polyps has been performed, the two-class ("malignant" or "begnin") classification of the polyps is achieved using the 3D parameters computed from the preselected ROI using an active stereo vision system. At this stage, a Support Vector Machine (SVM) classifier is used to proceed to the final classification and to make possible a pre diagnosis. The new proposed multimodal approach based on 2D - 3D feature extraction improves WCE capabilities to identify and classify polyps: The boosting-based polyp classification demonstrated a sensitivity of 91%, a specificity of 95% and a false detection rate of 4.8% on a database composed of 300 hundred positive examples and 1200 negative ones; Considering the 3D performance, a large scale demonstrator was evaluated and tested to perform in vitro experiments on an ad hoc polyp database. The performance of the 3D approach achieved a correct classification rate (malignant or benin) of approximately 95%.**

I. 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. The risk of transformation of an adenoma into cancer depends on various features such as size and tissue architecture (villous type, degree of dysplasia). Thus, it is considered that adenoma represents a critical risk of degeneration when at least one of three features appears: its size exceeds ten millimeters, villous occupies over 25% of its surface and / or it contains an area of high-grade dysplasia.

Currently, colonoscopy is the "gold standard" technique for diagnosis of colorectal adenoma and cancer. Because, videocolonoscopy is performed under general anesthesia, mini-invasive techniques such as computed-tomography-based colonography and wireless capsule endoscopy (WCE) have been developed for patients with contra-indication or low compliance to sedation drugs. 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 of course 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 with the same clinical workflow: After ingestion of the capsule, more than 50,000 images are captured along the digestive tract, each of them are wirelessly transmitted to a wearable receiver and finally, 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 tract. In the context of early diagnosis of colorectal adenoma and cancer, the challenge of "Cyclope" project is to propose a new generation of WCE (the so-called Cyclope-WCE) 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 this article, we propose a new multimodal approach based on 2D and 3D feature extractions from images acquired by a new generation of WCE. While the 2D allows to identify possible polyps, the 3D information extracted on the 2D ROI produces a classification based on some geometrical parameters usually used in clinical routine. The remainder of this paper is as follows: After a general presentation of the proposed hardware structure of the multimodal WCE, a focus is given on the automatic detection of the polyps considering first characteristics extracted only from the 2D images provided by the camera within the WCE. Thus, we presented the method used to classify the polyps into two categories (malignant or not) by exploiting the 3D characteristics from the active stereovision within the capsule itself.

II. Problem statement and related work

Several previous references have considered the detection of intestinal polyps in videocolonoscopy images in the last few years ([4], [5], [6], [7], [8] among recent ones). They are mainly divided into two categories: those based on geometric features of the polyps (size and shape) and those based on textural features.

We focused here on four of the aforementionned contributions: In [5], Bernal *et al.* authors propose a study made on videoendoscopy images. They developed a region descriptor based on the depth of valleys (SA-DOVA). Resulting algorithm, divided into several steps, including region segmentation, region description and region classification, is characterized by promising detection performance (see Tab. I).

In [6], 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. The main drawback of the proposed approach is the strong dependance on the protrusion measure of the polyp to identify potential candidates. The consequence is that if

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a polyp is not protruding "enough" from the surrounding mucosal folds, it may be missed.

In [7], 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 the taking into account of texture or color-based features within the detection/classification scheme would significantly increase related performance.

Finally, Kodogioannis and Boulougoura [8] propose a texture-based approach. Authors introduce new texture-based features computed from the chromatic and achromatic spectra of the Region of Interest (ROI) that may contain a polyp. 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.

Table I summarizes the main principle and the obtained performance of these four main contributions.

All these methods are designed for an offline 2D image processing and does not integrate malignant or benin classification capabilities. Nevertheless, during a usual exam, the movement of the WCE can be heratic and the images are acquired at a constant sampling frequencies (0.25HZ, 4Hz and 32Hz) depending on the localization of the WCE (esophagus, small bowel or colon) and are then transmitted to an external recorder via wireless communication. Consequently, several thousands of photos are transmitted without specially pertinent informations which on the one hand, is time consuming for the physician when he analyzes the overall video and, on the other hand, reduces the autonomy of the WCE.

III. Multimodal WCE

The approach presented in this paper suggests a new approach to overcome some of WCE drawbacks by moving towards an intelligent multimodal wireless capsule endoscopy (the Cyclope-WCE). The strategy used here is based on multispectral acquisition and machine learning techniques to perform real-time identification and classification. Cyclope-WCE has the ability to acquire both 3D data and color texture of the scene (2D) using two spectral bands (visible and infrared). To take advantage of these imaging capabilities, we proposed here, firstly to identify the polyps (ROI) using extraction of the features from the texture (2D) that are then fed to a boosting-based learning algorithm and secondly, to retrieve the 3D information of the preclassified ROI to make a classification of the polyps using a two-classes-SVM strategy (malignant (adenoma) or benin (hyperplasia)).

Our enhanced strategy is based on a pre-diagnosis performed in situ: Only identified polyps are then transmitted to the recorder. This strategy should increase the autonomy of the capsule by reducing energy consumption during transmission, which represents the largest portion of the energy consumed by a wireless sensor [9].

The detailed technical description of the 3D imaging capabilities of Cyclope-WCE is beyond the scope of this article, although the reader can refer to [10], [11] and [12] for a more detailed description of the calibration technique and reconstruction process based on triangulation and matching. The scope of this paper is to introduce the strategy we propose to identify and classify a polyp. This classification ability would moreover reduce the number of images the clinician had to analyze from thousands to only few hundreds.

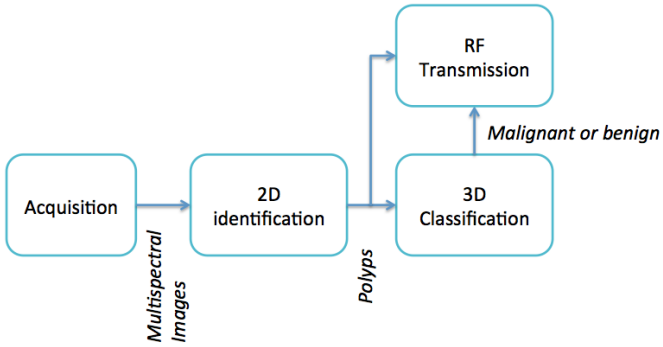

Fig. 1. Global scheme of the strategy proposed for the detection of polyps within WCE with two objectives: (i) to improve WCE with an "in situ diagosis" capabilty and (ii) to reduce the RF power consumption and consequently improve the life duration of the embedded-battery

IV. 2D identification of polyps

A. Method

The proposed approach is inspired from the psychovisual methodology used by the physician when doing an endoscopic examination: First, a detection of the Regions of Interests (ROI) that may contain a polyp is performed using shape and size features extracted from the image. This first pre-selection allows a first fast scanning of the image. Once the ROI are detected, a second analysis, based on texture (homogeneity, granularity, coarseness...) is achieved. Practically speaking, we propose a global scheme for the detection/classification of possible polyps divided into two steps:

1) Considering the geometric step of the proposed approach, simple image processing tools make possible the detection of circular/elliptical shape like the Hough transform for instance.
2) The texture-based classification is the main key-point of the global scheme since the rejection of most of the false positive preselected ROI have to be performed at this stage before going for the 3D feature extraction step. To achieve this, we propose to design an ad hoc classifier based on a boosting-based learning process using textural features.

The global scheme of this approach is summarized in figure 2.

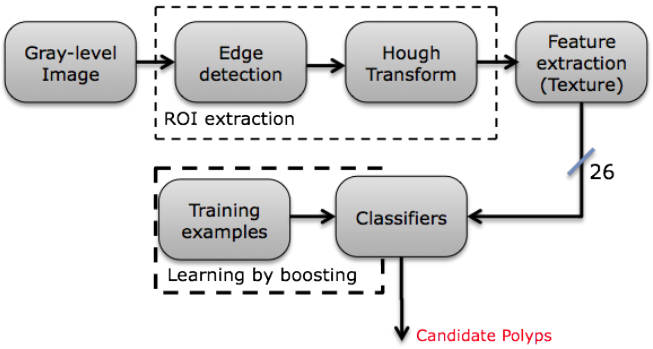

Fig. 2. Proposed diagram for the detection of polyps within videoendoscopy images.

"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 (a little

Authors	Main principle	Classification performance	Database
Bernal [5]	Geometry	Sensitivity 89% Specificity 98%	300 videocolonoscopy images containing a polyp (**freely available**)
Figueiredo [6]	Geometry	No indicated performance	17 WCE videos of 100 images each, containing example of polyps (10), flat lesions, diverticula, bubbles, and trash liquids
Karkargyris [7]	Geometry	Sensitivity 100% Specificity 67.5%	50 WCE images (10 polyps and 40 non-polyps)
Kodogiannis [8]	Texture	Sensitivity 97% Specificity 94%	140 WCE images (70 polyps and 70 non-polyps)

TABLE I
MAIN CHARACTERISTICS OF THE MOST RELEVANT REFERENCES.

better than chance) with the true classification), that once combined together generate a strong classifier, well-correlated with the ground truth provided by the expert. In the framework of our proposed approach, we use the boosting-based method of [14] set-up in attentional cascade (Cascade Adaboost). This configuration allows us to create a strong classifier which performance can be priorly set-up in order to optimize the sensibility of the classification along with the specificity.

B. Results

Tests were performed on the database proposed by J. Bernal from the Universitat Autonoma de Barcelona [5], which consists of 300 videoendoscopy images presenting with one single polyp each, identified and segmented by a specialist. The data are courtesy made available by authors. To our knowledge, in the particular framework of colorectal polyp detections, this is currently the only existing online database with a sufficient amount of examples to be statistically meaningful. Figure 3 shows some example of polyps extracted from the database.

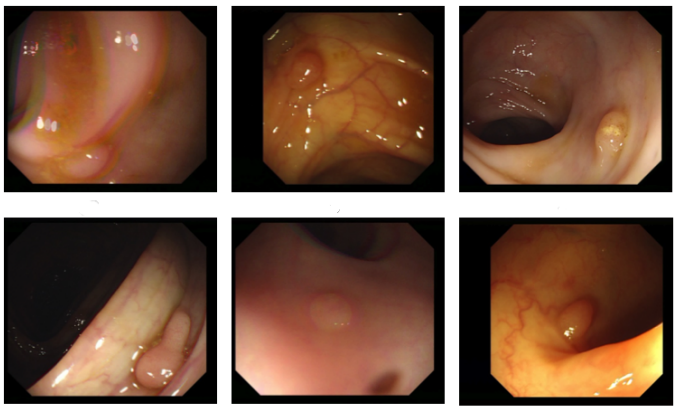

Fig. 3. Example of polyps extracted from the database of [5]

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To build the learning database each image of the main dataset was sub-divided into five thumbnails by the gastroenterologist: A first ROI corresponds to the polyp, and the other four to non-polyps (b-e). The resulting learning/testing database is then composed of a total of 1500 images, with 300 images of polyps and 1200 images of non-polyps, the labeling being performed,once again, by a specialist.

To proceed to performance evaluation of the proposed boosting-based method, three measures are usually considered meaningful and complementary: the sensitivity, the specificity and the false positive rate.

For these experiments, the ad hoc generated polyp/non-polyp database was 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. In order to obtain classification performance statistically meaningful, the drawing of the elements of both learning and testing databases were randomly made, and presented quantitative results correspond to the average value obtained on 100 different configurations.

In a first experiment, different kinds of methods for classification were compared: Learning Vector Quantization technic (LVQ) [15], classic Adaboost and finally Attentional Boosting (cascade adaboost). In terms of performance, as long as, contrary to cascade adaboost, it is not possible to set the obtained performance for LVQ or classic Adaboost, we privileged the balance between "Sensibility" and "Specificity". The results of this experimentation are shown in Table II: the most efficient approach was the Attentional Boosting.

Type Adaboost	Sensitivity	Specificity	FPR
Real Adaboost	77%	92.5%	7.5%
Attentional	91%	95.2%	4.8%
LVQ classification	92%	86%	14%
[5]	89%	98%	2%

TABLE II
PERFORMANCE COMPARISONS AMONG DIFFERENT TYPES OF CLASSIFICATION APPROACHES.

As it can be noticed, among the different classification technics used, Cascade Adaboost provides the best compromise between "Sensibility" and "Specificity". If LVQ leads to a good classification of True Positive examples, the total amount of FPR remains too important considering the fact that 10% of the polyps are misclassified.

In a second experiment, only Cascade Adaboost is considered with a setting of the performance parameters chosen in order to have a "Sensibility" the closer to 100%, whatever "Specificity" will be. This scenario fits better the expectations of radiologists who do not wish to miss possible polyps. Performance are shown in Table III.

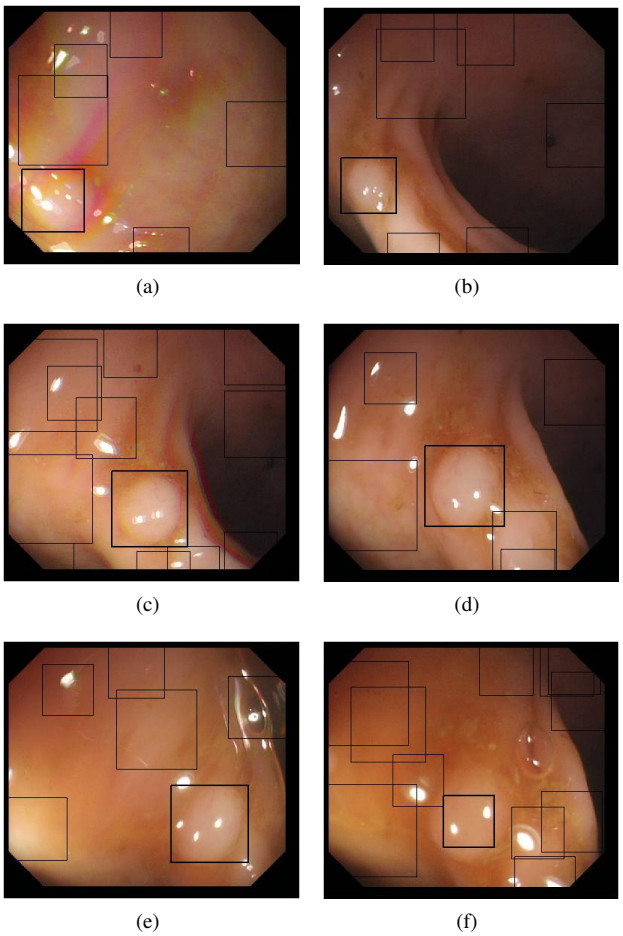
Tab. III shows that a high"Sensibility" is an objective that can be reached with a cascade adaboost setting of the learning process. Of course the "FPR" rate increases, but finally not that much considering the fact that for 100 polyps detected, only 14 more will be showed as possible candidates to the radiologist.

In figure 4 some examples of detection/classification are shown. ROI that are skirted by a non-bolded plain rectangle are the ROI

Cascade Adaboost	Sensibility	Specificity	FPR
Mean	99,5%	86.1%	13.9%
Standard deviation	0.00	0.07	0.07

TABLE III
AVERAGE PERFORMANCE OF THE CASCADE ADABOOST LEARNING PROCESS WITH A "SENSIBILITY" SET TO A MINIMUM OF 99%.

candidate 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 texture-based classification.



(a) (b) (c) (d) (e) (f)

Fig. 4. Detection examples

C. Discussion

The overall performance of the proposed 2D approach is in accordance with the most recent literature [5] for instance). Therefore, the complete developed detection/classification scheme is in accordance with a hardware implementation (Hough transform [16], boosting classification [17] and co-occurence matrices [18], [19]). Reader could refer to [20] in which a complete discussion is proposed on this particular aspect.

V. 3D CHARACTERIZATION OF POLYPS

A. Method

The method consists in the acquisition of 3D information of the pre classified ROI that contain a polyp and then, to compute eight parameters characterizing the shape of the overall 3D scene. A SVM based strategy is used to classify the 3D objects from this parameter. As usual WCE have not yet 3D imaging capabilities, a large scale demonstrator was created on purpose. The image sequences are captured by an active stereovision sensor created by a 1/4 color CMOS imager with digital output (356292 array size), and a structured light generator constituted by an array of 361 laser beams. The Processing block is constituted by a XUP Virtex-II Pro Development System Board, and a RF module is used for remote communication.

B. Dataset

To carry out the set of experiments, we designed and manufactured an experimental prototype made of silicone to be used for the in vitro learning and validation phases of our recognition system (see 5. The bowel polyps are made of silicone with a scale factor of 2. Polyps are fixed on the internal wall of the intestine, which is simulated by a tube in silicone with also a scale factor of 2 compared to classic size. The database consists of 185 models, 67 classified as adenomas (malignant), and others as hyperplasias (benin). Note that the classification was performed under supervision of a gastroenterologist and adhered to the well-known Milan criteria. Each resulting dataset element consisted of a cloud of N points in space defined by their Cartesian coordinates (X, Y, Z) in the real world. We have separated the dataset into two parts: 60% (111 models) of data is considered to be unknown and is reserved for testing, whereas the rest of the data is used for training.

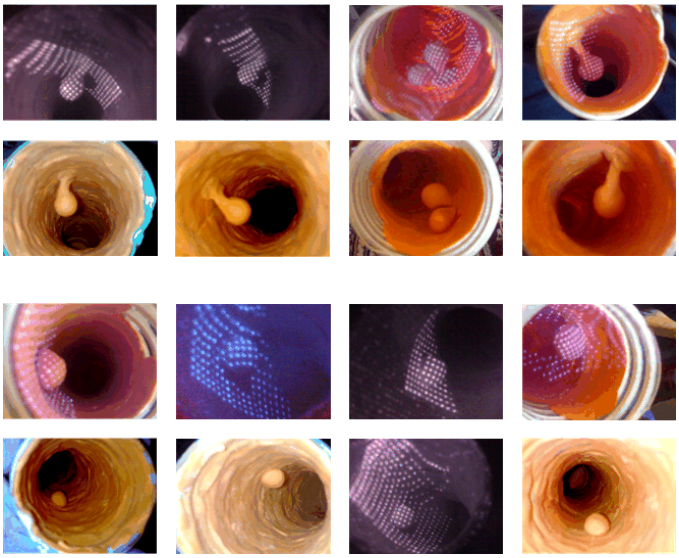


Fig. 5. Silicone model of hyperplasias (above) adenomas (below)

C. Feature extraction

The success of a pattern recognition problem is closely related to the quality of data and variables that characterize the pattern. The presence of redundant or noisy variables makes the learning process more difficult. The set of patterns obtained by our active-stereo matching technique is a cloud of points from the surface of polyp models defined by their 3D coordinates. Until now, these data have been the simplest available features that describe the surface of studied object. We might wish to favor a small number of suitable characteristic features in order to discriminate as thoroughly as possible between different polyps. These extracted features will

be fed into the SVM classifier implemented on the aforementioned FPGA [21] in order to recognize polyps. We took inspiration from previous works on color image statistics and texture modeling [22] and substituted color histogram for third-Dimension histogram to generate a new set of the most effective statistical features [23] based on object dimensions and first order moments (Mean value, Variance, Skewness, Kurtosis, Range, SNR, Area, Width and Volume). In general, the simple model is easier to understand, remember and handle [24], especially if there is a need to reduce resource consumption (storage and computation). This fact leads us to reduce the dimensionality data using feature selection techniques. We used the PCA method (Principal Components Analysis) to carry out the selection phase. However, the complexity of the selection method will not affect the system performance since this phase is carried out off-line when configuring the system. The figure 6 presents the result of applying such a method, and shows the degree of usefulness of each descriptor.

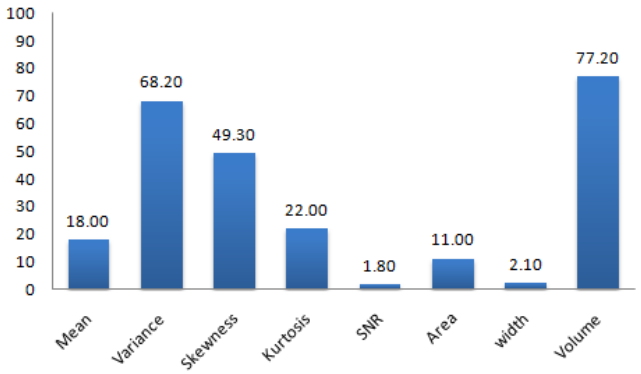


Fig. 6. Degree of usefulness of each descriptor)

D. SVM Classifier

We used a SVM classifier to make the final decision and classify the captured 3D objects. SVM is a robust classification algorithm that is used in many medical applications [25], and which can be used with a small database, as in our case. In this study, we tested the performance of our system with classic colonoscopy, to decide whether the captured image is a benin or malignant polyp. The input of SVM is a set of suitable features extracted from the surface of each polyp, and the output is a soft label denoting the class this object belongs to: Adenoma or Hyperplasia. The recognition system involves several stages of operation to be performed beforehand during an off-line analysis. These activities include calibration of stereovision system, feature selection process to reduce dimensionality of feature space, training of SVM classifier, model selection and cross-validation to find out the best parameters of the classifier.

E. Experimental results

As for the boosting learning scheme, once the learning task is accomplished, it is necessary to evaluate system performance on another set (the "test set"), independently of the data used for learning (the "training" set). This step gives information about the generalizability of the classifier, which is the capacity to correctly classify new data that has not been used to computethe kernel parameters. To improve the predictive accuracy of the classifier in the training stage, we partitioned the set of descriptors into 4 subsets (vectors A, B, C and D) (7). The first vector contains all the descriptors, while the three other vectors comprise a subset of descriptors selected according to their degree of discrimination. We compared the discriminating abilities of different combinations of attributes by examining the three types of kernel functions: linear, polynomial, and RBF (8).

	Average	*Variance*	*Skewness*	*Kurtosis*	*SNR*	*Area*	*Range*	*Volume*	#
Set **A**	✓	✓	✓	✓	✓	✓	✓	✓	8
Set **B**	✓	✓	✓	✓	-	✓	-	✓	6
Set **C**	✓	✓	✓	✓	-	-	-	✓	5
Set **D**	-	✓	✓	-	-	-	-	✓	3

Fig. 7. Degree of usefulness of each of the eight features extracted from the 3D data)

Sub-set	Kernel function	Classification in %	*Specificity*	*Sensibility*
A	Linear	88.29	0.93	0.8
	2^{nd} order polynomial	87.39	0.89	0.85
	RBF	90.09	0.93	0.85
B	Linear	89.19	0.93	0.82
	2^{nd} order polynomial	92.79	0.96	0.87
	RBF	**96.40**	0.97	0.95
C	Linear	88.29	0.89	0.87
	2^{nd} order polynomial	91.89	0.93	0.9
	RBF	**95.50**	0.94	0.97
D	Linear	60.36	0.65	0.52
	2^{nd} order polynomial	63.96	0.68	0.57
	RBF	67.57	0.67	0.70

Fig. 8. Experimental results of the classification of polyps by SVM method

F. Discussion

Figure 9 represents the ROC curves for each kernel function applied to vectors B and C; the ordinate represents the sensitivity and the abscissa represents the quantity 1-specificity. Pairs (1-specificity, sensitivity) for each combination are then placed on the curve. The worst situations are the points closest to the diagonal, obtained with the linear kernel. On the other hand, the more efficient diagnostic test corresponds to the curve near the upper left corner. This situation is achieved with the RBF kernel for two sets. However, vector (B) represents the highest rate and specificity values, whereas vector (C) represents the highest sensitivity. For some applications, the choice of vector (B) is most advantageous. But in our application we chose the vector (C) as a representative vector, for reasons relating to sensitivity, which is the most dominant parameter. That means that some benign polyps will be considered as malignant and, consequently, removed. The removal of these polyps is less critical than mis-classifying an adenoma. In the latter case, the patient would run the risk of developing cancer.

VI. Conclusion

In this paper we investigated a novel strategy for the identification and the classification of polyps for Wireless Capsule Endoscopy that overcomes some of the significant limitations of current WCE. The basic and essential task was to integrate algorithms based on the 2D and 3D information acquired to identify pathologies

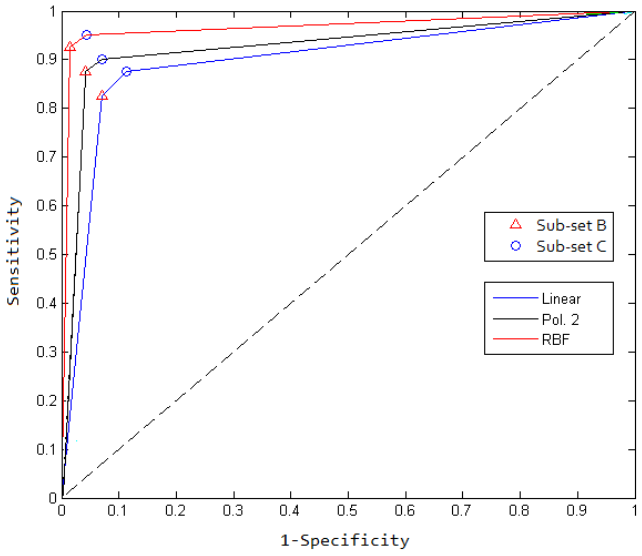


Fig. 9. ROC curves

(begin or malignant polyps). Only this information are transmitted to the data logger in order to (i) increase the autonomy of the WCE and (ii) to make the overall examination of the images by the clinician less time consuming. The detection of the possible polyps is based on texture approach with boosting classifier. The classification of malignant polyps used the parameters computed from the 3D ROI using a SVM classifier. The boosting-based 2D detection/classification step is characterized by very satisfying performance depending on the desired objective as shown in Tabs. II andIII. The following 3D recognition step showed very promising results with a sensibility of 99.5% and a sensibility of 95%.

Technically speaking, we have designed a large scale demonstrator including FPGA hardware capabilities to simulate our multi-stage system for automatic feature extraction and classification of colon polyps using 3D data obtained from an active stereovision system. Implementation of the 2D step is currently on the run.

Further work is required to investigate system performance for a single classifier (boosting) for 2D and 3D information in order to reduce the overall hardware complexity. Another interesting perspective that can improve system performance would be achieved by incorporating an image compression task into the sensor [26]. Such a functionality could increase system precision and autonomy while reducing power consumption via a reduction in transmitted data volume.

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