Saliency Maps of Video-colonoscopy Images for the Analysis of Their Content and the Prevention of Colorectal Cancer Risks

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Abstract: The detection and removal of adenomatous polyps via colonoscopy is the gold standard for the prevention of colon cancer. Indeed, polyps are at the origins of colorectal cancer which is one of the deadliest diseases in the world. This article aims to contribute to the wide range of methods already developed for the prevention of colorectal cancer risks. For this, the work is organized around the detection and the localization of polyps in video-colonoscopy images. The aim of this paper is to find the best description of a bowel image in order to classify a patch, that is to say a image fragment, as polyp or not. The classification is achieved thanks to an SVM (Support Vector Machine) using a bag of features. Different types of features extraction will be compared. Thus, the traditional SURF (Speeded-Up Robust Features) extractor will be compared to local features extractors like HOG (Histogram of Oriented Gradient) and LBP (Local Binary Pattern) but also to an original extractor based on the structural entropy.

1 INTRODUCTION

In France, bowel cancer is the second most common cancer in women and the third most common in men. In 2017, 45 000 new cases were reported, and colorectal cancer caused the death of 9294 men and 8390 women in France. Survival rates vary greatly based on the progress of the cancer when it is detected and the beginning of the medical treatment (surgical or drugs). Indeed, the chances of survival are around 90% if the cancer is detected during the first stage whereas they are around only 5% for stage V.

For these reasons, the early detection of polyps is fundamental. However, studies show that 26% of polyps present in the gut remain undetected by doctors during a video-colonoscopy. Some are simply invisible to the camera, others are present in the video stream and therefore detectable. Thus, computer aided diagnosis is a major issue in the diagnosis of colorectal cancer. Many methods have been proposed in recent years to reduce polyp miss rate and improve detection capabilities. These methods can be divided into three groups : ad-hoc, machine learning and hybrid methods.

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The majority of ad-hoc methods are based on exploiting low-level image processing methods to estimate candidate polyp boundaries. For example, (Iwahori et al., 2013) use Hessian filters, (Bernal et al., 2015), intensity valleys and (Silva et al., 2014), the Hough transform. The extracted information is then used to localize polyps using the curvatures analysis in the work of (Zhu et al., 2010), the ellipsoidal shape search according to the (Kang and Doraiswami, 2003) or a combination of both for (Hwang et al., 2007).

For machine learning methods, texture and color information were often used as descriptors such as color wavelets in the work of (Karkanis et al., 2003), coocurrence matrices for (Ameling et al., 2009) or local binary patterns (LBP) which are exploited in the work of (Gross et al., 2009). Some of the most recent methods use deep learning as in the work of (Ribeiro et al., 2016) among many others in the last four years.

Finally, hybrid methods combine both methodologies for polyp detection. For instance, (Tajbakhsh et al., 2014) combine edge detection and feature extraction, (Silva et al., 2014) use hand-crafted features to filter non-informative image regions and (Ševo et al., 2016) mix edge density and convolutional networks.

The performances of these methods can be evaluated on two criteria: accuracy and computation time.

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Indeed, a good polyp detection algorithm must detect most of the polyps without too many false alarms. To be clinically applicable, it also has to meet real-time constraints. For videos acquired at 25 frames per second that corresponds to a maximal processing time of 40 ms per frame. A comparison of recent methods performances is achieved in (Bernal et al., 2017). Ad-hoc method often present good computation time but a weaker accuracy and conversely for machine learning methods. Active learning methodologies have been introduced in the work of (Angermann et al., 2016) to reinforce the compromise between performance and computation time.

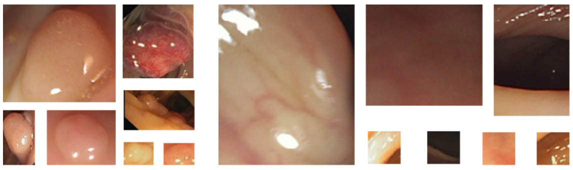
The recent YOLOv3 deep learning architecture (Redmon and Farhadi, 2018) represents a major step further for reliable and real-time polyp detection. Nevertheless, the need for specific computation resources (GPU), can be seen as a limitation for a routine to be used and integrated in standard colonoscope.

Alternatively to "fast" deep learning approach like Yolo, an improved polyp detector, in terms of sensitivity and specificity, can be designed by defining a saliency detection approach than can be both used for direct detection or for the reduction of false alarms using classic shallow methods. In this paper, as an alternative to deep learning approaches, we propose a saliency-based strategy which aim is to compare different types of classic but also original feature extractors in order to find the more relevant for polyp detection and localization tasks.

Our method is based on the previous work of (Raynaud et al., 2019) about localization of angiodysplasias in videocapsule images. They developed an active contour segmentation approach for small bowel lesions characterization using saliency maps as extractors. These saliency maps are generated using a dictionary learning strategy (bag of words) associated with a binary SVM classifier. More precisely, the classifier allows for a given input image to create a probability map of angiodisplasia presence using a sliding window of predefined size all over the image for which center-pixel is associated to the probability given by the SVM classifier. We propose here to investigate this method for polyp detection and localization.

In this paper, we propose to test and estimate performance of different features extractors that will be used for the dictionary learning step, including classic ones from the literature, such as SIFT (Scale-Invariant Features Transform) but also an original one based on approximate entropy (Histace et al., 2014).

The paper is organized as follows: in section 2 we introduce our methodology and present the different features extractor used. Then section 3 presents the experiments and the results for each extractor. Finally, section 4 concludes the paper.



(a) (b)

Figure 1: Examples of patches used for training: (a) Polyp patches. (b) Non-polyp patches.

2 METHODOLOGY

Our method can be divided into two parts. First, we have achieved the training and the evaluation of the different bag of features using patches extracted from the classic set of colonoscopic data known as CVC-Clinic and CVC-Colon database (Bernal et al., 2017). This training aims to learn how to classify a patch as a polyp or not from features extracted by the bag of words. The evaluation on patches permits to judge the capacity of a two-class SVM, based on a specific bag of words, to correctly classify a given set of patches. Based on this, for a given image (taken from a different set of the videocolonoscopic images as those used for training), a saliency map is generated and an evaluation of obtained saliency map algorithm is achieved (section 2.2). The aim of this evaluation is to assess how the different descriptors perform on complete images to get a first estimation of the performance related to a given feature extractor.

2.1 Training

In a polyp detection context, we have tested several type of features in order to find the best description of images for colonoscopy. The first step consists in generating all the descriptors for the images, that is to say, finding the interest points and describing interest areas around interest points that will be used for the bag of features dictionary. The next step is to generate the associated optimal dictionary. For this, we classically used the k-means clustering over the descriptors to obtain the representative features of the images which will be the words of the dictionary. These words will be used by the SVM for the classification.

The training is done on patches (see examples Figure 1). All images considered in this paper are from the CVC Colon and CVC Clinic databases. Our specific patches database was composed of 4412

Table 1: Confusion matrix for the SURF descriptor.

KNOWN	PREDICTED Negative	PREDICTED Positive
Negative	0.98	0.02
Positive	0.06	0.94

Table 2: Confusion matrix for the SURF + LBP descriptor.

KNOWN	PREDICTED Negative	PREDICTED Positive
Negative	0.98	0.02
Positive	0.11	0.89

negative patches and 942 positive patches from the two databases. 80% of them were used for training and 20% for the evaluation, first made on a patches classification task. Negative patches were randomly selected from the negative images whereas positive patches were generated from the pixel-wise polyp ground truth. Three images and there associated patches were kept out of these databases to generate the saliency map and evaluate the method on complete images.

The training and the evaluation are repeated three times on different set of patches for each of these parameters combinations: the extraction of patches being random, the training and the evaluation database were different for each test.

The patch classification is evaluated using the confusion matrix which gives the percentage of true positives, false negatives, true negatives and false positives. For the second step, that is the saliency map detection approach, a psychovisual metric is proposed.

In the following section, short descriptions of the considered feature descriptors are given along with obtained results for the patch classification tasks.

2.1.1 SURF Descriptor

The SURF descriptor is considered for its improved performances in terms of robustness and speed compared to the SIFT descriptor. For the purpose of having the best bag of features, we have tested several combination of parameters namely the dictionary size (from 500 to 4000 visuals words) and the detector (SURF and square grid with a size varying from 4 x 4 to 12 x 12 pixels). The SVM kernel has also been chosen in accordance with the best obtained performance. We have tested the Gaussian, the linear and the polynomial (order 2 and 4) kernel. Finally, we have tested different types of input images: classical RGB image, but also each component taken separately (red, green and blue channels).

For this descriptor the best classifier used a dictionary with 800 words, a square grid (4 x 4 pixels) detector, a multi-scale SURF descriptor, a polynomial kernel (order 2) and the blue channel as input. The performance results for this classifier are presented in the confusion matrix of Table 1.

The blue channel is often used in polyp detection because it is the most representative of the polyp information, as shown by (Bernal et al., 2015). Indeed, they prove that the blue channel permits to mitigate useless information like blood vessels in a context of valley detection. But it can be generalized for all polyp detection approaches. The size of the dictionary, the detector and the kernel will be the same for all the bags of words tested.

2.1.2 LBP Descriptor

We have decided to use a LBP descriptor in addition to the SURF descriptor. Indeed, this type of descriptor adds another local information. Moreover, it has given satisfying results in the study of (Angermann et al., 2016). This can be explained by the fact that LBP descriptors code texture information and it has been proven that polyps have a typical texture as shown in (Ameling et al., 2009).

This is evaluated on the blue channel, as used in (Angermann et al., 2016) and because it was the most relevant channel for the SURF descriptor. The SURF descriptor is the same as in the previous experience.

Using the same evaluation protocol, we obtain the confusion matrix presented in Table 2. With an unchanged True-Negative detection rate, the True-Positive detection rate is slightly lower than for the SURF descriptor alone.

2.1.3 HOG Descriptor

Another classic local descriptor is the HOG descriptor. This type of descriptor is especially efficient for edge detection. (Iwahori et al., 2013) use this type of descriptor in their polyp detection method with Hessian filters because polyp and non-polyp regions have approximately the same color which is not taken into account by the HOG descriptor.

The HOG features are extracted from the same multi-scale grid as the SURF descriptor. Because HOG features are very dense, we have decided to use it alone, without SURF features. This descriptor was tested on both grayscale and blue channel images. Always with the same validation conditions, we have obtained the confusion matrices given in Tables 3 and 4. In this case there is a slight better True-Positive detection rate on the grayscale images compared to the blue channel.

Table 3: Confusion matrix for the HOG descriptor with blue channel.

KNOWN	PREDICTED Negative	PREDICTED Positive
Negative	0.97	0.03
Positive	0.19	0.81

Table 4: Confusion matrix for the HOG descriptor with grayscale images.

KNOWN	PREDICTED Negative	PREDICTED Positive
Negative	0.97	0.03
Positive	0.17	0.83

2.1.4 Classic Descriptors Applied on Approximate Entropy Maps

In this section, we propose to consider an original approach for indirect feature extraction, based on Approximate Entropy (ApEn) formerly introduced for active contour image segmentation by (Histace et al., 2014). The ApEn, also called structured entropy, is a statistical metric which measures the regularity in a sequence of numerical data. It measures the probability for two segments, which are extracted from the same sequence, to stay close if their length is incremented by one.

The parameters are the length of the sequence N, the length of the extracted segments m and the filtering level r which imposes the necessary similarity between two sequence to be considered as close. For instance, if we consider the following sequence of numbers:

$$u = [u(1), u(2) \dots u(k), u(k+1) \dots u(k+m) \dots u(N)] \quad (1)$$

We can now construct a series $x(i)$ with $N-m+1$ segments from u and where $x(i) = [u(i), \dots u(i+m)]$ is a segment of length m.

Then, we can calculate the coefficient :

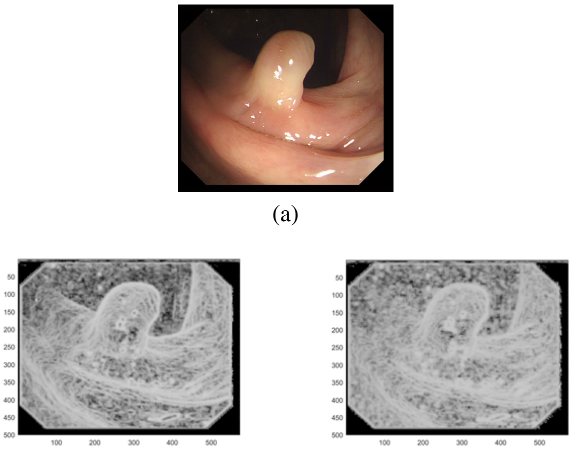
$$C_m^i(r) = \frac{\text{Number of } x(j) \text{ such that } d(x(i),x(j)) \leq r}{N-m+1} \quad (2)$$

where:

$$d(x(i),x(j)) = \frac{1}{m} \sum_{k=1}^{m} |x_k(i) - x_k(j)| \quad (3)$$

The average of the coefficients is :

$$C_m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} C_i^m(r) \quad (4)$$



(a) (b) (c)

Figure 2: Approximate entropy images: (a) Original image. (b) ApEn on grayscale image. (c) ApEn on blue channel image.

All of this permits to define the approximate entropy as :

$$ApEn = \ln \frac{C_m(r)}{C_{m+1}(r)} \quad (5)$$

Because it measures the regularity in a sequence, it is efficient to determine homogeneity changes as Pincus has proven in 1901. For this reason, the metric can be used to detect edges and in our case, polyps. (Nagy et al., 2019) use this entropy in order to detect polyps thanks to their specific curves. However, this entropy has never been used in a machine learning context. We propose to use it in polyp detection with this approach.

For this, we have chosen a filtering level $r = 1.75$, a sequence length $N = 9 \times 9$ corresponding to a vectorised thumbnail (9×9 pixels) and a segment length $m = 2$ as (Histace et al., 2014) chose. For illustration, we have computed the distance map in term of approximate entropy for video-colonoscopy images. We have applied this on grayscale and blue channel images. The results are presented on Figure 2.

We show that approximate entropy is a good edge detector especially when it is applied on grayscale images. We propose to use this type of image as input image for our classification thanks to a SURF descriptor which is the most used in features extraction and a HOG descriptor. Indeed, the HOG descriptor is particularly appropriate for edges and the approximate entropy map emphasizes them. The confusion matrices are given in Tables 5 and 6.

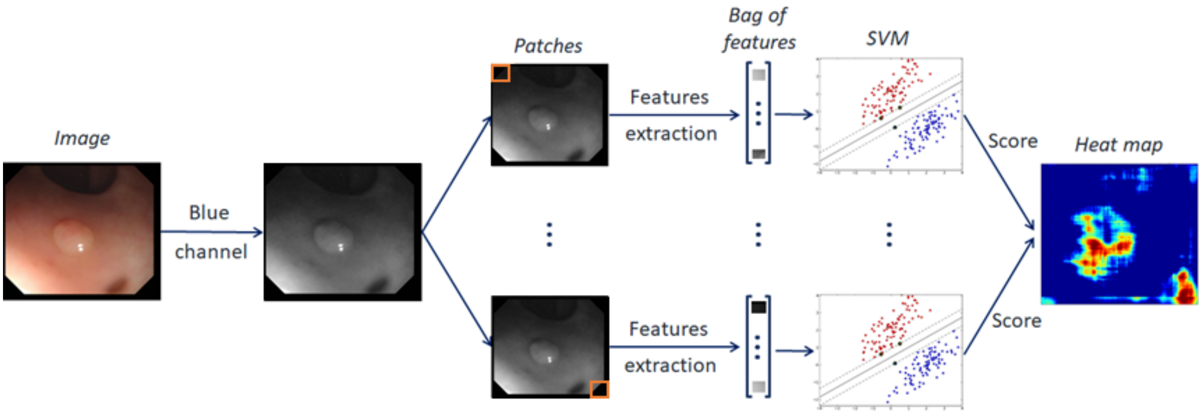


Figure 3: Proposed method. A variant consists in replacing the blue channel by a grayscale image or a distance map.

Table 5: Confusion matrix for the SURF descriptor applied on ApEn images.

	PREDICTED	
KNOWN	Negative	Positive
Negative	0.97	0.03
Positive	0.07	0.93

Table 6: Confusion matrix for the HOG descriptor applied on ApEn images.

	PREDICTED	
KNOWN	Negative	Positive
Negative	0.95	0.05
Positive	0.26	0.74

2.2 Saliency Map Generation

In order to evaluate the capacities of our descriptors in a clinical context, that is to say on a complete image, we have used the method introduced in (Raynaud et al., 2019). The saliency map algorithm takes an image as input (see Figure 3). Only the blue channel is used for most of our descriptors but grayscales images and approximate entropy maps are also used. Then the image is divided in patches shifted by one pixel in the two direction of the space, thanks to a moving windows. We have chosen a 100×100 pixels window size, corresponding to the average size of polyps in the database. For each patch, features are extracted according to the bag of features created during the training. These features permit to feed the SVM in order to classify the patch and to obtain a related probability classification. Finally, a heat map is created from the distance to the positive class for each patch associated to its central pixel.

3 EXPERIMENTS AND RESULTS

To evaluate performance of the different feature extractors previously introduced we test the method on three specific images (first row of Figure 4). These images were selected from the CVC-Clinic database for their characteristics, making them representative of the different types of polyps that can be found in a clinical context: a flat polyp seen from above, a pedunculated polyp seen from the side and a polyp which is slightly hidden by bowel folds. Then we can create the probability maps with the different descriptors, through the SVM local response as described in previous section. These results are shown in Figure 4.

We first notice that all the descriptors predict the specular highlight as a polyp. Indeed, the third image presents very clearly a specular light spot at the bottom left and the polyp presence probability is high in this area for all the descriptors. It is due to the typical form of a polyp, called blob, which predisposes light reflection. The only exception is the SURF descriptor using the approximated entropy (Figure 4(r)). It is not sensitive to this type of reflection which is a major advantage since specular light is a problem in many polyp detection methods of the literature.

Additionally, results show that the LBP feature in addition of the SURF descriptor (Figure 4(g, h, i)), permit to reinforce the decision taken with the SURF descriptor only (Figure 4(d, e, f)).

The HOG descriptor with grayscale images (Figure 4(m, n, o)) is not at all specific as almost the entire image is considered as a polyp. On the other hand, the HOG descriptor applied on the blue channel (Figure 4(j, k, l)) of the images is very specific. Indeed, the polyp presence probability higher than 0,5 only on the polyp, especially for the flat polyp (Figure 4(j)). The HOG descriptor using the approximate entropy

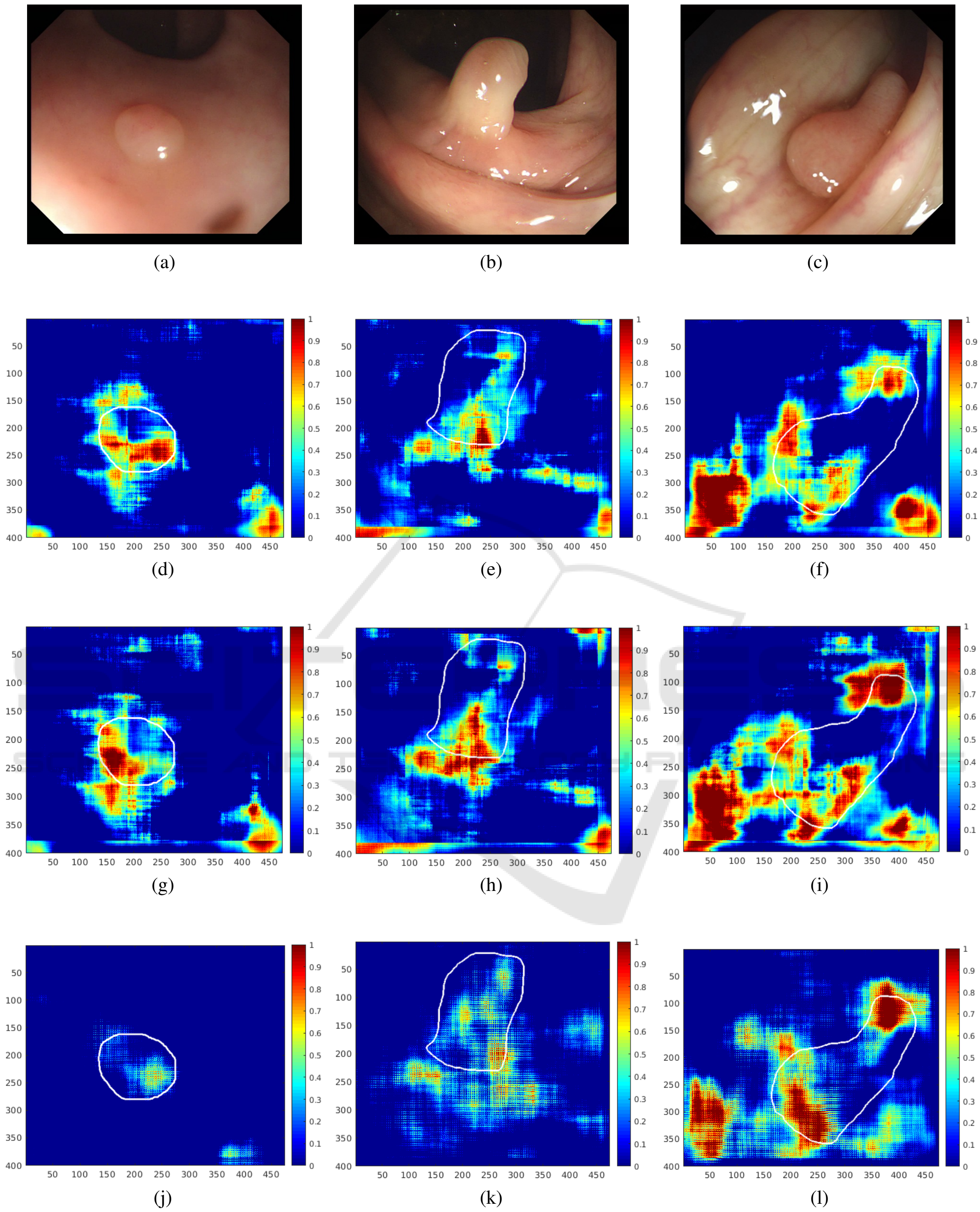


Figure 4: Saliency maps where the ground truth is drawn in white: (a, b, c) Original image. (d, e, f) With SURF descriptor. (g, h, i) With SURF and LBP descriptor. (j, k, l) With HOG descriptor on blue channel. (m, n, o) With HOG descriptor on grayscale images. (p, q, r) With SURF descriptor on ApEn images. (s, t, u) With HOG descriptor on ApEn images.

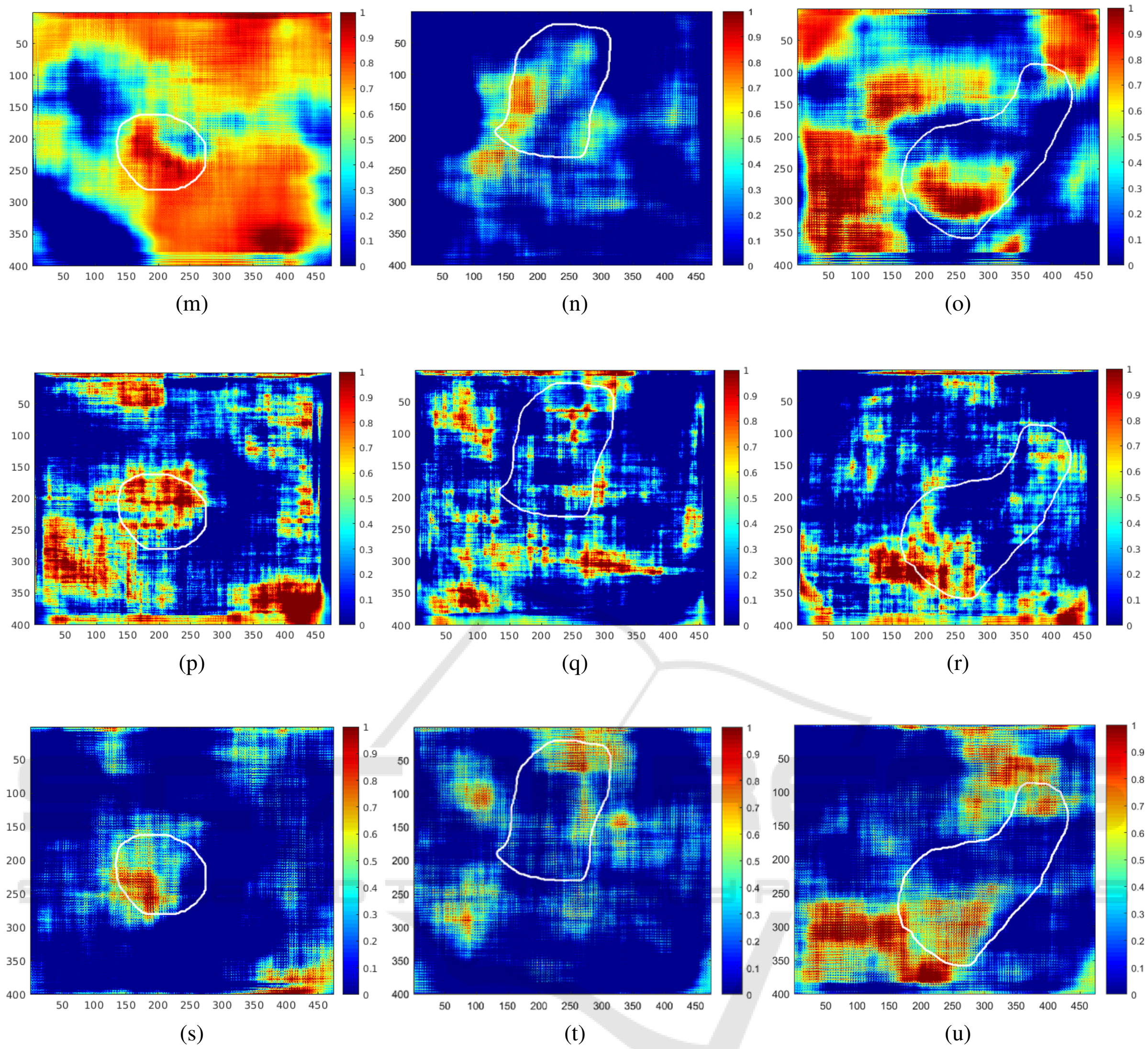


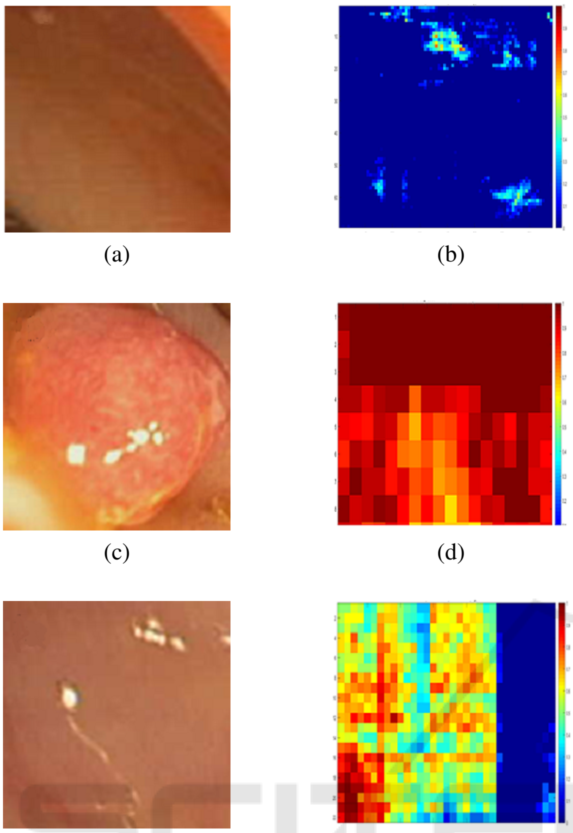
Figure 4: Saliency maps where the ground truth is drawn in white: (a, b, c) Original image. (d, e, f) With SURF descriptor. (g, h, i) With SURF and LBP descriptor. (j, k, l) With HOG descriptor on blue channel. (m, n, o) With HOG descriptor on grayscale images. (p, q, r) With SURF descriptor on ApEn images. (s, t, u) With HOG descriptor on ApEn images (cont.).

(Figure 4(s, t, u)) also presents this feature. The probability is higher on the polyp with the second but it is a little bit less specific. This high specificity could be very interesting in polyp detection.

In fact, all the current methods have a very good sensitivity but weak specificity. It means that almost all the polyps are detected but the method introduces a lot of false alarms. This is a problem because they can distract the doctor during the colonoscopy. Moreover, flat polyps are a major challenge of computer aided diagnosis for colonoscopy because most of the undetected polyps during this exam are flat polyps. Polyps like the second and third images are easily detectable by the clinician. Thereby, our method can be use as a refinement method pre-processed colonoscopy images. The pre-processing could be performed by a method among those proposed in the literature. Our refinement method could then be applied on the parts of the image defined as polyps by the first method. This step would eliminate false alarms, improving the performances of current methods.

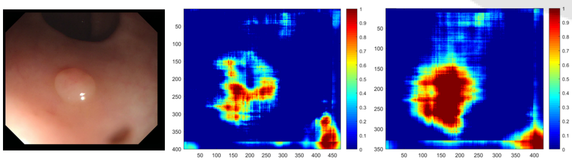
4 CONCLUSION AND DISCUSSION

In this paper, we compared several colonoscopy image descriptors for bag of words. We show that the HOG descriptor applied on the blue channel of the



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

Figure 5: Tests on patches with the SURF descriptor: (a, b) Patch without polyp and corresponding map. (c, d) Patch with a easily detectable polyp and corresponding map. (e, f) Patch with a less visible polyp and corresponding map.



(a) (b) (c)

Figure 6: Patches size test with the SURF descriptor: (a) Original image. (b) Saliency map with a 100 x 100 pixels window. (c) Saliency map with a 150 x 150 pixels window.

image could be use as a confirmation in another polyp detection method. We point also the insensitivity to specular light of the SURF descriptor associated to the approximated entropy. As the specular light is a problem in most of the polyp detection method, it could be useful associated to another method. Another solution is to use images where specular light has been removed by image processing as in (Sánchez et al., 2017).

These results also show that the detection spreads around the ground truth. A solution could be to reinforce our training database adding offset patches. Indeed, our current database only present centered polyps. For more robustness and to train our algorithm to detect cut or decentered polyps, the diversification of the database is necessary.

At last, the confusion matrix and the tests on patches are good as shown in the Figure 5. Nevertheless, the tests on complete images are not totally satisfactory. This could be partly due to the weak robustness of the database but it is also due to the size of the moving window in the segmentation algorithm. This parameter is fundamental for the success of our method. Our work is based on the comparison of images descriptors with stable settings but, in order to use the method for polyp detection, this parameter must be adjusted. Indeed, the results are completely different according when varying the moving window size, as shown in the Figure 6.

The study proposed here shows that our method opens realistic alternative to CNN (Convolutional Neural Network) approaches, even if the parameter settings needs to be improved in order to optimize the saliency map generation. This latter could then become, on its own, a detection map, but also used to reduce the False-Positive rate related to classic machine learning methods such as boosting or SVM for instance.

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