Integration of Valley Orientation Distribution for Polyp Region Identification in Colonoscopy

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Abstract. This work presents a region descriptor based on the integration of the information that the depth of valleys image provides. The depth of valleys image is based on the presence of intensity valleys around polyps due to the image acquisition. Our proposed description method consists of defining, for each point, a series of radial sectors around it and then accumulate the maxima of the depth of valleys image only if the orientation of the intensity valley coincides with the orientation of the sector above. We apply our descriptor to a prior segmentation of the images and we present promising results on polyp detection, outperforming another approach that also integrate depth of valleys information.

Keywords: Colonoscopy, Polyp Detection, VO-DOVA descriptor.

1 Introduction

Colon cancer's survival rate depends on the stage in which it is detected, decreasing from rates higher than 95% in the first stages to rates lower than 35% in stages IV and V [9]; hence the importance of detecting it early by using screening techniques, such as colonoscopy [4].

Intensity valleys appear to surround polyps as the light of the colonoscope and the camera are in the same direction, and for this reason, they are proposed as a cue to detect polyps by means of computer vision techniques [2]. In this paper we present a novel region descriptor built on the concept of the depth of valleys image (DoV image), which combines valley localization given by a valleys detector with the intensity information provided by morphological gradient.

We present in this paper the Valley Orientation-Depth of Valleys Accumulation descriptor (VO-DOVA) which consists of accumulating, by using a series of radial sectors, the maxima of the DoV image. This descriptor will be incorporated into a polyp detection scheme in order to classify previously segmented regions into polyp containing or not. In this case, if a point is surrounded by a boundary constituted by points with high value in the DoV image, the accumulation value for this point will be high. We also consider the orientation of the valleys that were used to build the DoV image in a way such if the orientation of a maxima of the depth of valleys image is not similar to the orientation of the sector that would accumulate it, this value would not be considered.

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The structure of the paper is as it follows: in Section 2 we introduce previous approaches on polyp detection in colonoscopy videos. In Section 3 we present our polyp detection method. In Section 4 we show our experimental setup along with polyp detection results. Finally we finish this paper in Section 5 with the main conclusions extracted from our work and our proposals for future work.

2 Related Work

Polyp detection in colonoscopy videos has been an active field of research during the last 20 years and it has gained the interest of several research groups, although the lack of a public database makes it difficult to make a proper comparison between different approaches. If we had to divide the different approaches, we would do it into shape-based (which normally approximate polyps as elliptical shapes) and texture-based approaches.

Shape-based approaches aim to fit the shapes which polyps commonly have on the test images. Many of them start with a basic segmentation such as watershed and try to fit polyp shapes in the segmented regions. Belonging to this group we have the work of [5], which consists of fitting ellipses into the frontiers obtained after a first segmentation, and then classifying candidate regions by considering curvature, distance to edges and intensity value. The work presented in [6], relies on a first watershed segmentation and then performs an edge detection in each of the R, G and B channels after applying a contrast enhancement algorithm. In order to classify the several regions (connected by closed edges) this method uses area, color and elliptical shape.

Texture-based approaches aim at selecting an adequate texture descriptor and apply it to the image. In the work shown in [7], polyps are detected by combining wavelets coefficients extraction and co-ocurrence matrices and then learning via neural networks. A method which combines the use of local binary patterns and grey-level co-ocurrence matrices is presented in [1].

3 Valley Orientation-Depth of Valleys Accumulation Descriptor

Before explaining the VO-DOVA descriptor, we will introduce the DoV image. This DoV image [2] combines the information obtained from the ridges and valleys detector [8] with the one that the morphological gradient provides (see equation 1), to define valleys in both localization and intensity:

$$\forall i, j \in \mathbf{I} \quad DoV(i,j) = V(i,j) \cdot MG(i,j) \tag{1}$$

where DoV stands for the DoV image, V for the output of the ridges and valleys detector and MG for the morphological gradient image, being their corresponding values normalized to unit (although this does not mean they are binarized) and their corresponding scale parameters equal. Under the assumption that polyps generally present elliptical shapes with soft boundaries (that

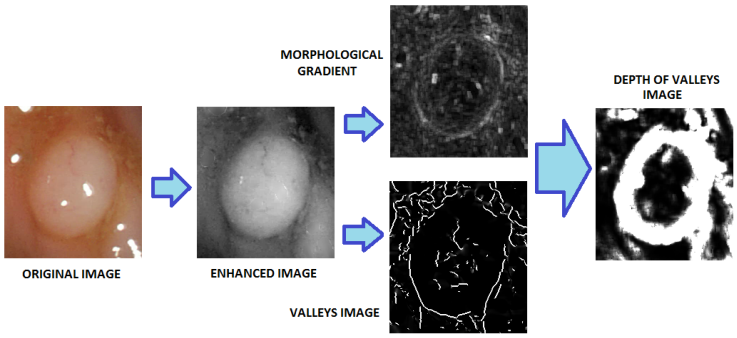


Fig. 1. Definition of the depth of valleys image

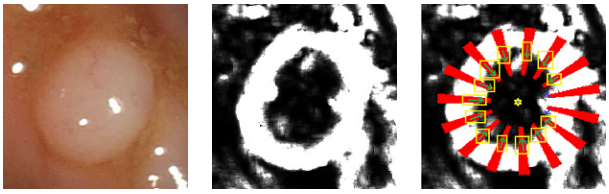
show extremal values in the valleys image), our aim is to define a descriptor that is able to to accurately find those image regions that are inside either completely or even partially closed boundaries in the DoV image (see Figure 1).

One first approach could be to fit elliptical shapes inside the boundaries that appear on the DoV image, following the basis of some of the methods depicted in Section 2. The Ellipse Fitting-Depth of Valleys Accumulation algorithm (EF-DOVA) presented in [3] is also built on this idea, although in this case the method does not fit ellipses to boundaries but aims at approximating ellipses using accumulative information from the entire region.

In our case, we will integrate the information from the DoV image by using a series of radial sectors to accumulate the maxima of the DoV image. The VO-DOVA algorithm has the following steps:

- *Obtaining the enhanced DoV image:* The first step will consist of calculating the DoV image. As specular highlights have an impact in the valleys detection [2] we mitigate their effect by approximating what should really should be under them, by substituting the affected pixels by a linear combination of the values around them. The valley detector used to obtain the DV image needs of two parameters, differentiation and integration sigma [8]. The latter should be equal to the size of the structural element used in the calculation of the morphological gradient in order to work in the same scale.
- *Depth of Valleys accumulation:* We denote a point as interior to a structure if it is surrounded by boundaries constituted by pixels with high value in the DoV image (up to a threshold value). We define a series of radial sectors centred in each point and we accumulate, for each sector, the maxima of the portion of the DoV image that falls under it. We use the orientation of the valleys provided by the valleys detector in order to filter which maxima points should be accumulated. As each sector will comprise a series of angles, we will only accumulate maxima of the DoV image whose orientation is within a range of angles defined from those that the sector covers. The accumulation algorithm needs three parameters: 1) Minimum radius of the sector; 2) Maximum radius of the sector, and 3) number of sectors.

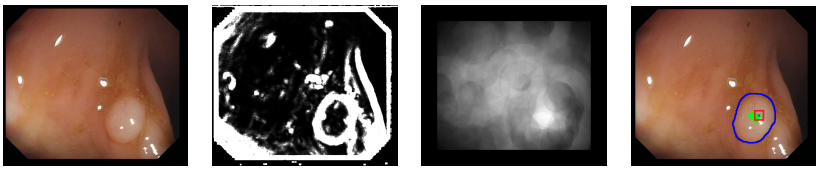
We can see how VO-DOVA works by observing Figure 2. For each point we define a series of sectors, shown in red, and we only accumulate those maxima points with similar orientation to the particular sector. In this case we will only accumulate those maxima whose orientation coincides with the range of angles covered by the sector (depicted as green arrows surrounded by yellow boxes) and not those whose orientation is very different (depicted as blue arrows).



(a) (b) (c)

Fig. 2. VO-DOVA descriptor: (a) Original image; (b) Depth of valleys image. (c) VO-DOVA descriptor, where points with suitable orientation are marked with green arrows and surrounded by a yellow box, points with wrong orientation are marked with blue arrows and sectors are shown in red.

We show in Figure 3 how VO-DOVA algorithm would perform in the whole frame. We can see in Figure 3 (c) VO-DOVA accumulation results. Brighter areas in the image correspond to pixels whose accumulation value is high, conversely to dark areas which correspond to pixels with low accumulation value. In order to make the results more understandable, we shown in Figure 3 (d) how VO-DOVA descriptor places points with high accumulation value inside the polyp region, placing also the maxima of the accumulation inside the polyp region.

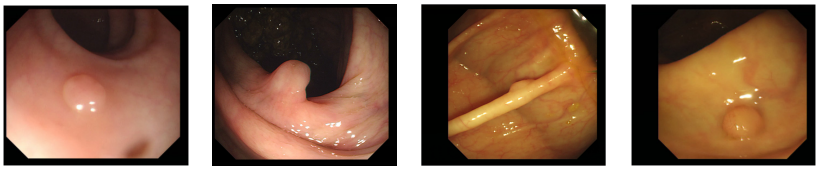


(a) (b) (c) (d)

Fig. 3. Example of VO-DOVA (a) Original image; (b) Depth of Valleys image, and (c) Accumulation image. (d) Result image, where the polyp is surrounded by a blue line, the points with high accumulation value are shown in green and the maxima of the VO-DOVA descriptor is marked as an orange square surrounded by a red frame.

4 Experimental Results

To test the performance of our novel VO-DOVA descriptor, we have created a database with different studies of polyp appearance. We were provided 15 random cases, in which the experts (physicians) annotated all the sequences showing polyps, and a random sample of 20 frames per sequence was obtained. The experts guaranteed that all these 20 frames showed a significantly different point of view (as it can be seen in Figure 4 (c) and (d)) which resulted in the rejection of similar frames. This allows us to maximize the variability of the images used, while not jeopardizing any bias at all. As we are interested in the performance of our descriptor when detecting polyps, our database will contain only frames with polyps, up to 300 different images.



(a) (b) (c) (d)

Fig. 4. Polyp examples (a) flat (b) peduncular (c) lateral view (d) overhead view

Our whole polyp detection scheme consists of 3 stages, namely: region segmentation, region description and region classification. As we mentioned in Section 1, we will use as the region segmentation stage the results provided in [2], which provides, for each image, a reduced number of regions one of them containing a polyp. In the case of region description, we will use both EF-DOVA [3] and the novel VO-DOVA. In the case of EF-DOVA we will use the combination of parameters values that gave better detection results whereas for VO-DOVA we have used the following set of parameters values: 1) Minimum radius ($[30, 40, 50]$); 2) Maximum radius ($[80, 100, 120]$), and 3) Number of sectors ($[60, 120, 180]$).

We will classify the final segmented regions according to their maxima of the DOVA descriptor. In this case we have considered two possible classification scenarios, namely region-based and frame based. In the former we will classify for each frame each one of the final segmented regions according to their descriptor value whereas in the latter we will only consider two regions in each frame: the one that we predict the polyp is inside (according to the value of the DOVA descriptor) and the one where we predict there is no polyp inside. In order to evaluate the performance of both descriptors we calculate, for each image, the number of True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN). We will also present precision, recall, accuracy,

and specificity results for the best combination of parameters in terms of highest additive value for the cited measures, along with providing ROC and PR curves.

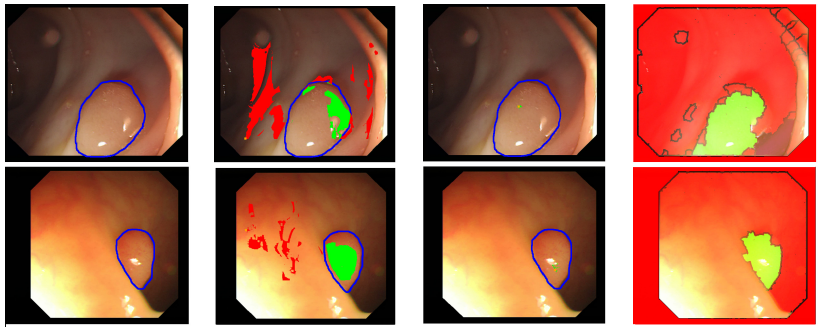
As it can be seen in Table 1, there is a difference between the performance of both descriptors for both mentioned criteria (frame-based criteria only affects the number of FP and TN, which improves EF-DOVA results, damaged by the high number of FP). EF-DOVA outperforms VO-DOVA in terms of TP and FN, that is, it detects polyps better but we can also observe that it performs worse in terms of FP and TN. Therefore, the difference between EF-DOVA and VO-DOVA is that the former places more maxima of accumulation in the image whereas the latter, where it places a maxima, it is more likely to be a polyp. We can observe this in the precision, accuracy or specificity results, where VO-DOVA outperforms EF-DOVA, which is only better in terms of recall.

Table 1. EF-DOVA and VO-DOVA performance results

	EF-DOVA		VO-DOVA	
	Region-based	Frame-based	Region-based	Frame-based
TP	291	293	267	265
FP	655	147	31	31
TN	1638	153	2262	269
FN	9	7	33	35
Precision	30.76%	66.59%	89.59%	89.52%
Recall	97%	97.66%	89%	88.33%
Accuracy	74.61%	74.33%	97.53%	89%
Specificity	71.43%	51%	98.64%	89.66%
AUC ROC	0.85	0.63	0.96	0.77
AUC PR	0.3	0.38	0.67	0.46

We show in Figure 5 a graphical comparison in polyp detection between EF-DOVA and VO-DOVA. We can observe how EF-DOVA places more maxima inside the polyp region (shown in yellow) but also places maxima outside the polyp region (shown in red). We can also see how EF-DOVA places the maxima of accumulation (marked as an orange square) outside the polyp for the two examples, whereas VO-DOVA places them inside the polyp region.

We can also observe the superior performance that VO-DOVA provides by observing the ROC and PR curves in Figure 6. In terms of area under curve values, we outperform EF-DOVA, for our best combination of parameter values, for ROC and PR curves, as it can be seen in Table 1. The curves for EF-DOVA present more abrupt changes because we only consider 33 possible accumulation values from 0 to 8, therefore we can only have 33 threshold values. In the case of VO-DOVA the accumulation value and threshold values can go from 0 to 255.



(a) (b) (c) (d)

Fig. 5. Comparative results (a) Original images (b) Polyp detection via EF-DOVA (c) Polyp detection via VO-DOVA. (d) Classified image (yellowish part denote polyp regions, reddish part non-polyp regions.

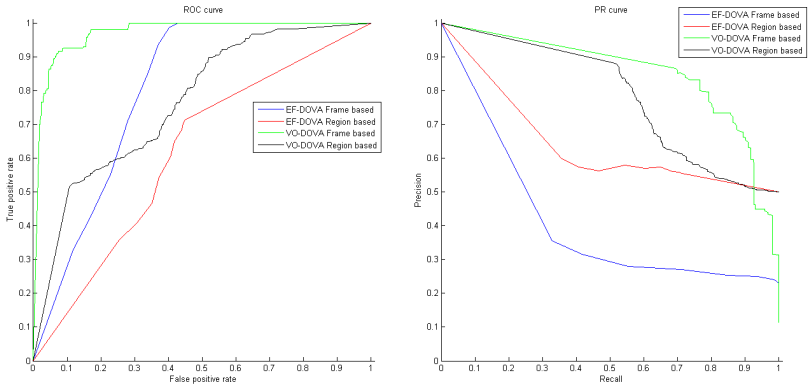


Fig. 6. ROC and PR curves for both EF-DOVA and VO-DOVA

5 Conclusions

In this paper a novel approach to polyp detection in colonoscopy images has been presented by using valley information of the image. The combination of the output of a ridges and valleys detector and the morphological gradient image give us information about valleys' location and intensity. We introduce our novel VO-DOVA descriptor that defines when a pixel is interior to a depth of valleys boundary (complete or incomplete) and when it is not. The direct application of VO-DOVA descriptor into a detection scheme provides promising results on polyp detection, specially when detecting what is not a polyp in the image, letting discard most of the image with no risk of losing polyp information.

The future work may consist of introducing VO-DOVA results earlier in the detection process to help segmentation by, for instance, developing marker-based segmentation using the maxima of the VO-DOVA descriptor. Another possible research line could be to study which description cues (such as color or texture) can be added to improve results. Finally, VO-DOVA's could probably benefit from a multi-scale approach that may also lead to have less parameters.

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