3D Stable Spatio-temporal Polyp Localization in Colonoscopy Videos

Debora Gil *, F. Javier Sánchez *, Gloria Fernández-Esparrach **, and Jorge Bernal *

* Computer Vision Center and Computer Science Department, Campus Universitat Autònoma de Barcelona, 08193 Bellaterra, Barcelona, Spain
** Endoscopy Unit, Gastroenterology Service, CIBERHED, IDIBAPS Hospital Clinic, Universidad de Barcelona, Barcelona, Spain
{debora, javier, jbernal}@cvc.uab.es
mgfernan@clinic.ub.es
http://ivendis.cvc.uab.es/

Abstract. Computational intelligent systems could reduce polyp miss rate in colonoscopy for colon cancer diagnosis and, thus, increase the efficiency of the procedure. One of the main problems of existing polyp localization methods is a lack of spatio-temporal stability in their response. We propose to explore the response of a given polyp localization across temporal windows in order to select those image regions presenting the highest stable spatio-temporal response. Spatio-temporal stability is achieved by extracting 3D watershed regions on the temporal window. Stability in localization response is statistically determined by analysis of the variance of the output of the localization method inside each 3D region. We have explored the benefits of considering spatio-temporal stability in two different tasks: polyp localization and polyp detection. Experimental results indicate an average improvement of 21.5% in polyp localization and 43.78% in polyp detection.

Keywords: Colonoscopy, Polyp Detection, Polyp Localization, Region Extraction, Watersheds

1 Introduction

1.1 Intelligent systems for colonoscopy

Colorectal cancer (CRC) is a serious health problem that affects the general population and is considered the fourth cause of cancer death worldwide with around 750.000 new cases diagnosed in 2012. Out of all found lesions, it is considered that at least two thirds of CRC develop through adenoma-carcinoma pathway [1]. Considering this, early screening with colonoscopy to search for CRC and its precursor lesion has become a generalized practice [2] and it is shown as crucial to patients' survival. Although colonoscopy has become the gold standard for colon screening, it still presents some drawbacks being polyp miss-rate -reported to be as high as 22%- the most relevant affecting its effectiveness [3].

Several actions have been proposed to reduce polyp miss rate, such as optimal patient preparation and novel methodologies to carry out a complete examination of the

mucosa. However, sometimes these new methodologies have impact in other quality metrics such as withdrawal time, as exposed in [4]. Regarding the technology itself, during the last years most of the developments in endoscopy have been focused on improving the quality of the images. This improvement in image quality has attracted the interest of computer scientists and has resulted in the creation of a new research field referred as intelligent systems for colonoscopy [5]. Among the different applications a given intelligent system can have, the one that has attracted higher research interest is the development of automatic polyp characterization methods.

Existing computational methods can be divided into those devoted to obtain an accurate localization of the polyp in the image -polyp localization- and those focus on providing as output an indicator of the presence or absence of polyps in the image -polyp detection-. The majority of these works rely on the extraction of shape, texture and color features to characterize polyps. The former includes methods which explore shape features of the different structures in the image to search for cues that discriminate polyps from other elements in the scene. Examples of methods belonging to this group can be found at [6, 7, 8, 9, 10]. Concerning texture-based approaches, we can find in the literature works that explore intensity patterns in the image to aid in polyp characterization, such as the works of [11, 9]. Other approaches involve the use of state-of-the-art feature extraction methods such as local binary patterns [12] or MPEG-7 [13].

Although there is a great variety of methods, it is very difficult to compare them as they are commonly tested in private databases, hindering their actual performance in general cases of study that can appear in routinely procedures, therefore limiting their potential clinical deployment. In order to cope with this, efforts have been made to create and publish annotated databases of both still frames (CVC-ClinicDB database [7]) and videos (ASU-Mayo Clinic database [14]). Moreover, in order to gather researchers on the field, two different challenges on automatic polyp detection have been organized in 2015, at ISBI conference and as part of MICCAI Endoscopic Vision Challenge.

1.2 Motivation and objectives of research

After an analysis of the results of the different available methods, we have come to the conclusion that the majority of them present the following problem. Although they are able to locate/detect accurately the polyp in some frames, when this method is tested in a whole sequence performance scores decrease. We attribute this decrease in the performance to the lack of spatio-temporal stability in the response of the given methods, which can produce situations such as the one shown in Figure 1. We can observe in this figure how a given polyp localization method (in this case, an implementation of Window-Median Depth of Valley Accumulation (WM-DOVA energy maps [7]) can provide a good localization output for isolated frames but, when analyzing its performance during a sequence of frames, we can observe how the polyp localization (in this case marked as a blue square) is not stable even for the two last images where the movement between them is small.

We propose in this paper a novel methodology to add spatial and temporal coherence to the response of a given polyp localization method. The use of temporal windows for increasing polyp detection capabilities has been explored in other works such as [15], although in this case the authors propose the use of Conditional Random Fields for

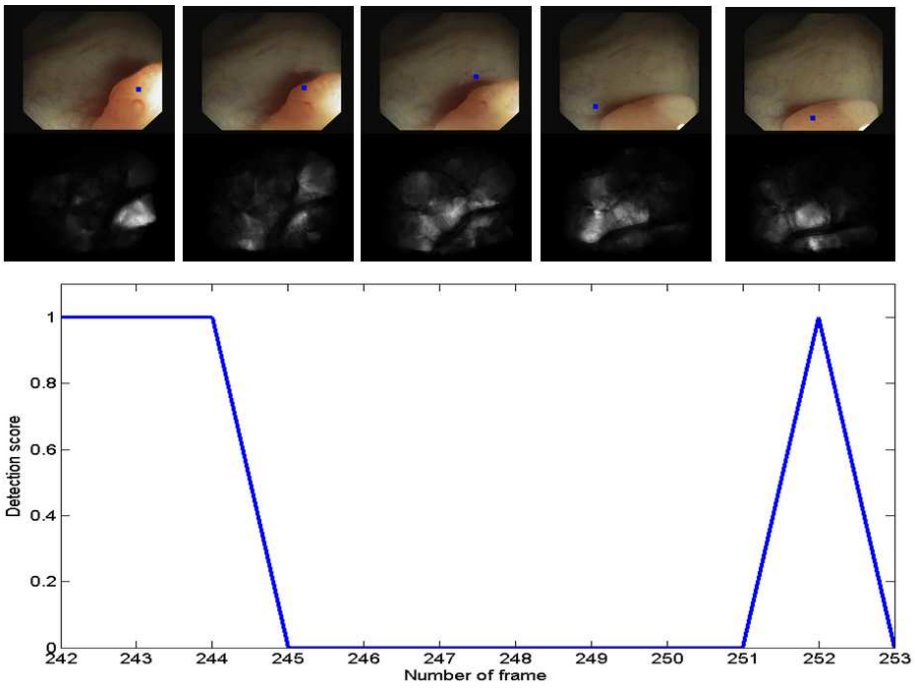


Fig. 1: Example of lack of spatio-temporal stability in the response of state-of-the-art polyp localization methods

adding spatio-temporal coherence to a texture-based polyp detection method. As WM-DOVA maps are the only ones tested on a public annotated frame-based database, we will take as base localization method these maps for this preliminary study, although our methodology could be used for any given energy-map based polyp localization method. Our methodology explores the consistency of the response by considering the displacement of the structures that appear in the image in a way such if a given polyp is localized in a region of the area with a high response, it is expected that a similar response will be given in a consecutive frame where the movement between frames is minimal. Moreover, we assess the potential of a given localization method as a polyp detection method by exploring if the response given by a polyp in a given frame loses stability when the polyp disappears from the scene. We validate our methodology in terms of polyp localization, by comparing the performance of state-of-the-art method with and without applying spatio-temporal stability and, in terms of polyp detection, in a sequence with frames with presence and absence of the polyp.

The structure of the paper is as follows: we present our methodology in Section 2. Experimental results on both polyp localization and detection are discussed in Section 3 and we close this paper by exposing the main conclusions along with guidelines for future work in Section 4.

2 Methodology

The basis of our methodology is to improve the response of a given localization method in a given frame by incorporating information of neighboring frames in a temporal window centered at the frame (Figure 2). Our method assumes that the response to the localization method keeps stable in such a window centered in a frame containing a polyp, in contrast to responses due to other structures (such as folds or specular highlights) which should be more spatially erratic. It is true that lumen region can also be considered as an stable structure that appears during consecutive frames and, in this case, we have used our methodology regarding non-informative region identification [16] to mitigate its impact in our approach. In order to explore such spatio-temporal response stability, we first need to obtain and track the different regions that appear in the given set of frames for a later classification of the regions in terms of polyp presence by performing a 3D statistical analysis of the output of the given localization methods for the extracted regions. By this, the output of the polyp localization in a given frame will depend on the output of polyp localization in a window of frames centered on it in a way such the output of a polyp localization method in a region of the image will rely on statistics over the output of the localization method for this specific region in a window of frames.

Before starting with the explanation of our 3D spatio-temporal stabilization of the output of polyp localization method, we will make a brief review of the localization method we will use as base, WM-DOVA energy maps.

Window Median Depth of Valley Accumulation (WM-DOVA) energy maps are based on a model of appearance for polyps which characterize polyp boundaries in terms of valley information [7]. This model is designed to foster those features characteristic of polyp boundaries (continuity, concavity, completeness and robustness to noisy structures) and it is specially designed to favor polyps from other structures on the image which also convey valley information such as folds, blood vessels or image artifacts such as specular highlights. The method is based on the accumulation on the output of a valley detector -in this case completed with information from morphological gradient to achieve a sense of the depth of the valleys- by using a ring of radial sectors. The final accumulation value for each pixel is calculated from the contribution of the different sectors centred on it but, in this case, the behaviour of a neighborhood of sectors is observed before calculating sectors' contribution to the final accumulation value. More details on WM-DOVA energy maps creation can be found at [7]. WM-DOVA maps are proven to perform well for a wide range of images, appearing specially useful when having zenithal views of the polyps, regardless of their morphology and size.

2.1 Spatio-Temporal Region Extraction using Watersheds

The first stage in our processing scheme aims at extracting a set of connected regions over a temporal window centered on each sequence frame. Each region represents an element which presence is kept in some consecutive frames from the temporal window. The question is to decide whether this element is a polyp or not and in order to take this decision we propose to perform a statistical study regarding characteristics of WM-DOVA maps during the temporal window where it appears. Considering this, region

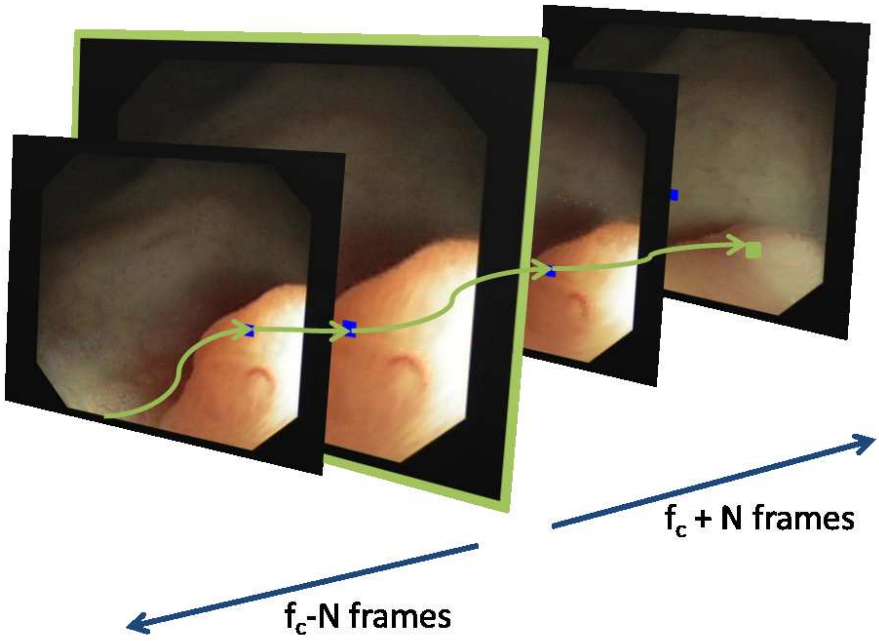


Fig. 2: Graphical scheme of the use of neighbor information to stabilize the output of a polyp localization method

extraction should not be performed in a single-frame basis, but on a temporal window centered on the specific frame we are working with. In order to achieve this, we will perform watersheds in 3D over this window of greyscale images. In this context, the first two dimensions represent the image in 2D and the third dimension represents the time -understood as the temporal sequence of frames-.

3D watersheds extend the calculation of 2D watersheds to 3D volumes or sequences of frames and have already been applied in the context of medical image segmentation [17, 18]. The basic idea of watersheds consists of considering the given input image as a topographic surface. If we start to flood the regions starting by the regional minimums we will get to a point in which the water from one region invades a neighbor region. All the surface points at a given minimum constitute the catchment basin associated with that minimum. Watersheds are the zones which divide adjacent catchment basins. 3D extension aims to keep those regions which can be identified within this window of frames. In our particular case, we apply 3D watershed throughout all the frames belonging to the temporal window centered on the target frame. The methodology to calculate 3D watershed transformation for a given central frame f_c is:

1. Definition of a temporal window $w(f_c)$ of size r centered on f_c as $w(f_c) = \{f_i | i \in [f_c - r, f_c + r]\}$.
2. Calculation of the morphological gradient MG_i for each frame f_i contained in $w(f_c)$.

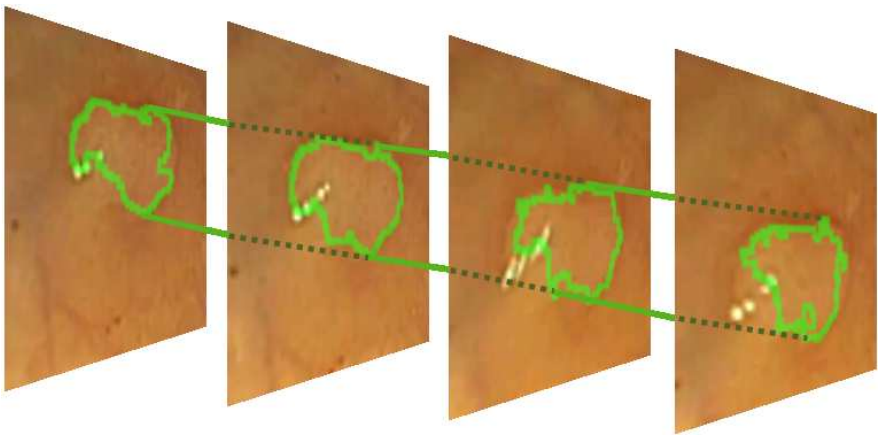


Fig. 3: Graphical explanation of the use of 3D watershed to track a polyp region.

3. Calculation, for the central frame f_c, of the set of markers Mk_c as the local minima of MG_c.
4. Calculation of 3D watershed transform for all the frames in the temporal window, using the set of MG_i for the temporal window $w(f_c)$ as input image and Mk_c as markers .

Although we extend watershed calculation to the temporal window, the puncitual calculation for a given frame uses only as markers the local minima of the morphological gradient information calculated for the central frame. The catchment basin associated with those minima is extended over neighbor frames, following the movement of the image gradients. This behavior causes that each region should only represent one same element of the scene for a series of frames, which allows to perform a statistical study over the time. Unfortunately, this behavior is not common in the analysis of colonoscopy images where watershed fragments image elements in more than a region therefore reducing their statistical representativeness. Moreover, in some residual cases, a given region may cover more than one element of the scene.

For each frame, the output of this processing stage is a 3D representation of the stable regions inside the frame temporal window. By doing this analysis, we can easily observe which regions tend to be stable and which of them disappear, either because they are merged in a larger region or, following our hypothesis, due to the disappearance of the structure that originated them. Figure 3 illustrates the output of the 3D watershed in the case of a stable region corresponding to a polyp.

2.2 3D Region Statistical Analysis for Merging Polyp Region Information

Watershed stable regions provide an over-segmentation of the image in small regions that should be further selected and merged to provide a stable 3D localization of the polyp region. Under the assumption that polyp appearance keeps stable in temporal

windows, those watershed regions inside a polyp should be significantly larger in frame size and DOVA values than regions outside polyps.

Small temporal regions are removed by a threshold, N_{Fr}, on the number of frames, N_{f_c}, contained in the watershed segmentation. To account for sudden scope motions, this threshold should be kept low. Regions with significant larger DOVA values are selected by an statistical analysis of the values obtained inside each watershed region. In order to detect significant differences we use Analysis of Variance (ANOVA) [19]. Given a grouping of a data set and a quantitative variable defined for each group, ANOVA is a statistical test that allows to decide if there are significant differences among the group's quantitative variable average with a given confidence α. The variability analysis is defined as soon as the ANOVA quantitative score and the different factors and methods are determined. In order to applied for polyp region selection, ANOVA groups and variable are defined as follows.

For each frame, f_c, the ANOVA groups are given by watershed labels of regions having more than N_{Fr} frames. For each such a region, the ANOVA variable is given by the median of DOVA values computed for each frame in the temporal window used to compute the 3D watershed. This gives a sampling of size N_{f_c}, being N_{f_c} the number of frames of the watershed region. ANOVA multicomparison is corrected using Tukey [20] to select those regions that have a median DOVA significantly higher.

Finally, the ANOVA selected regions are merged according to spatial connectivity to provide a single response per polyp.

3 Experimental Results

We validate our methodology by performing two separate experiments: the first one aims at assessing the impact of spatio-temporal stabilization of the response of WM-DOVA maps in a sequence of frames, all of them containing a polyp. The second experiment is focused on exploring the potential of this stabilization method in polyp detection tasks when tested in a sequence with polyp and non-polyp frames.

In these experiments, we will note by DOVA the polyp localization given by WM-DOVA global maximum described in [7] and by DOVA3D, our spatio-temporal DOVA response.

3.1 Polyp localization results

In order to explore the benefits of DOVA3D, we have selected five different sequences with a polyp from those which compose CVC-ClinicDB [7]. We use as ground truth those frames from the original sequences that were included in the database. Our experiment consists of checking whether the performance of the localization method for these frames changes if we add spatio-temporal stabilization. To achieve this, we have been kindly granted with permission from the authors in order to analyze all the frames from the full sequences.

We define the following metrics for this experiment:

– Detection Rate (DR) defined as the ratio between the number of polyps in the sequence correctly located and the total number of polyps in the sequence:

$$DR = \frac{\#POk}{\#POk + \#PNOk}$$

where POk represents a polyp correctly located and, conversely, $PNOk$, a polyp which was not located for a given image. In this case we label a polyp as correctly located whenever a polyp region is defined over the ground truth as an output of the statistical analysis.
– False Positive Rate (FPR) defined as the ratio between the total number of regions without polyp content (NPR) and the total number of final regions provided by our system, which also includes regions with polyp content, PR:

$$FPR = \frac{\#NPR}{\#PR + \#NPR}$$

We present DR and FPR results for both original WM-DOVA and spatio-temporal stable WM-DOVA for each sequence in Table 1. As we can observe from the Table, the spatio-temporal stabilization of WM-DOVA maps leads an general improvement of both DR and FPR for all the sequences. It is important to mention that there are some cases, such as sequence 4, where our methodology is able to improve DR in around 65%, which indicates the potential of our approach to recover some mislocalizations by means of spatio-temporal coherence. Another important result is the reduction of FPR for all sequences. This is attributed to the statistical selection of the final regions that discard non-polyp information.

The benefits of our spatio-temporal analysis are assessed using a one-tailed t-test for paired data. For the DR score, we use a right-tailed test with null hypothesis to $H_0 : \mu(DR_{DOVA3D} - DR_{DOVA}) < 0$, so that rejecting the test ($p_{val} < 0.05$) shows that DOVA3D has a significant larger detection rate. For the FPR score, we use a right-tailed test with null hypothesis to $H_0 : \mu(FPR_{DOVA3D} - FPR_{DOVA}) > 0$, so that rejecting the test ($p_{val} < 0.05$) shows that DOVA3D has a significant smaller false positive rate. We have also computed confidence intervals, CI, for the difference in means, $\mu(DR_{DOVA3D} - DR_{DOVA})$, $\mu(FPR_{DOVA3D} - FPR_{DOVA})$ to give the expected difference range. On one hand, the p-value for the DR test is $p_{val} = 3.9593e-005$, which clearly rejects the null hypothesis and, in fact, $CI = [11.3\%, 32.0\%]$, so that differences in average DR are at least 11%. On the other hand, the p-value for the FPR test is $p_{val} = 0.0052$, which also rejects the null hypothesis and, in this case, $CI = [-23.9\%, -3.3\%]$, so that the reduction in average FPR is at least 3%.

3.2 Polyp detection results

In order to illustrate the potential benefits of DOVA3D, we were provided by the authors of [7] with an additional sequence from an actual colonoscopy exploration. In this case we asked for a sequence in which the polyp is not present for all the frames, showing special interest in having a sequence in which the polyp is present, then it disappears for a set of frames and, finally, it appears again in the scene. We created a ground truth for all the frames in the sequence, which was validated by clinical personnel.

	Original WM-DOVA		Spatio-temporal Stable WM-DOVA	
Sequence	DR [%]	FPR [%]	DR [%]	FPR [%]
1	84.62	15.38	**91.67**	23.08
2	81.82	18.18	**90.91**	**15.91**
3	50.00	50.00	**66.67**	53.19
4	14.89	72.73	**80.49**	**58.05**
5	84.00	16.00	76.19	**10.29**

Table 1: Comparison of DR and FPR results between original WM-DOVA and spatio-temporal stable WM-DOVA.

Regarding this second experiment, we propose to use FPR and a new metric, Detection Score:

$$DS = \frac{\#DOk}{\#DOk + \#DNOk}$$

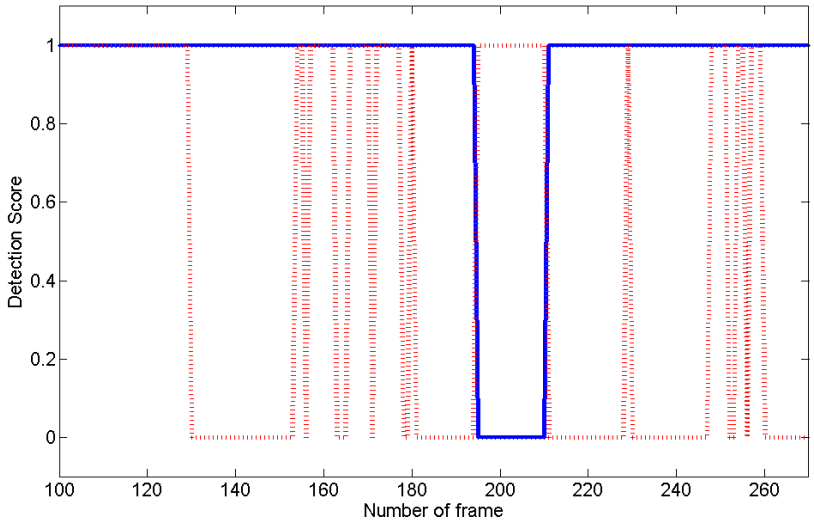
In this case we define a good detection *DOk* as the one whenever our method provides with an actual polyp location in a frame with a polyp or does not provide any kind of output for a frame without a polyp. Conversely, we define a bad detection *DNOk* as our method providing a polyp location in a frame without polyp or not providing a polyp location in a frame with polyp.

We present a graphical comparison of the performance of WM-DOVA maps with and without spatio-temporal stabilization in Figure 4. By observing the plots for the two methods in the comparison, we can observe how spatio-temporal stabilization helps to improve polyp localization results in those frames with a polyp, as for the case of stable spatio-temporal WM-DOVA there is a general coincidence between the output of the method and the ground truth in both presence and absence of the polyp; this can be observed by having coincidence of blue (ground truth) and red (output of the method) lines for the majority of the frames. As can be seen, we can also observe how, in absence of a polyp -frames 190 to 210-, our methodology is able to correct the erroneous localization provided by WM-DOVA maps, which offer a candidate location for every frame analyzed. Overall, DS score improves from 38.71% to a 82.58%, which shows the potential of our approach to obtain good localization results using spatio-temporal coherence of WM-DOVA maps. Aside, we can also observe how the number of false alarms is also reduced, decreasing from 64.77% to 19.87%, indicating the potential of our approach to reduce the impact of noisy structures in overall localization results.

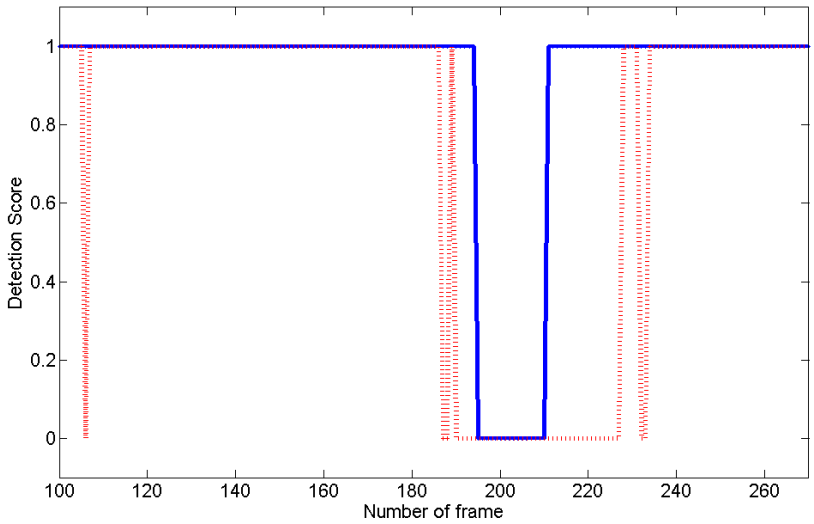
To close this section, we present a qualitative example of the benefits of adding spatio-temporal stability to the output of WM-DOVA in Figure 5. We can observe that, for a same input image, original localization by means of global maximum of WM-DOVA provided a mislocalization outside the polyp (marked as a red square in the first image) whereas the stabilized response over a temporal window centered in this particular frame allows us to correctly localize the polyp (marked as a green square in the third image).

4 Conclusions and Future Work

This paper addresses one of the main drawbacks of frame-based polyp localization algorithms related to the lack of spatio-temporal stability in their output when applied to



(a)



(b)

Fig. 4: Comparison of Detection Score between WM-DOVA maps (a) without and (b) with spatio-temporal stabilization. Blue line in the plots represents the presence (value 1) or absence or polyp in the image (value 0). Red line represents the performance of the method: good localization (value 1) or erroneous localization (value 0).

a sequence of frames. In order to cope with this we propose to incorporate information of a neighborhood of frames. Our methodology is based on the observation of the response of the output of the method over a same region along a temporal window of frames. In order to extract stable regions over time we propose the use of 3D watersheds

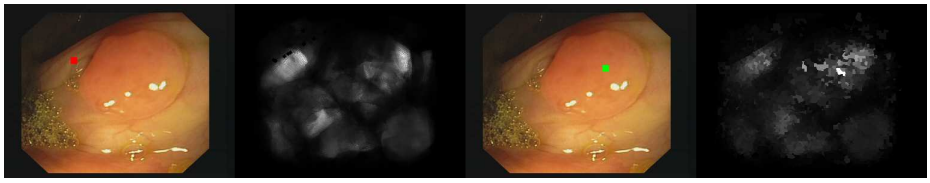


Fig. 5: Qualitative example of the benefits of adding spatio-temporal stabilization the output of WM-DOVA maps over a temporal window: (first image) original image; (second image) corresponding WM-DOVA map; (third image) original image; (fourth image) stabilized WM-DOVA map over 3D watershed regions. Correct localizations are marked as green squares over the original image, false positives as red squares.

and then, in order to integrate the output of the localization method over time, we perform an statistical analysis over the output of the method along all the frames in which the region is present. Experimental results on polyp localization indicate the benefits of adding spatio-temporal stability which is observed by both an increase in Detection Rate (average improvement of 21.50%) and by a strong decrease in the number of false alarms provided by the method (with an average decrease of 13.30% in FPR). Moreover, we have also studied the potential of our methodology in polyp detection tasks: a preliminar study over a full annotated sequence with frames with both presence and absence of polyp shows an improvement over 43% regarding detection score metric.

These preliminary results shows the potential of our methodology but also allows us to sketch future research lines. Although our methodology improves the 3D performance of the localization method, it is clear that an estimation of the movement between frames -using motion descriptors such as optical flow or particle filtering- could also add value to the system as we could complement the output of 3D watershed with this information in order to obtain a more accurate tracking of the regions over the defined temporal window of frames. Additionally, studies about setting the size of the temporal window should be undertaken, which could include definition of automatic systems to assess when the temporal window information should be restarted due to the apparition of a high number of consecutive frames with low quality (blurring, fecal content). Regarding region extraction, region merging strategies may be developed to reduce the number of regions to be tracked, which could ease to reduce the computational cost of the whole methodology, easing the statistical analysis. Finally, this preliminary study should be extended over more sequences in order to account the performance of the whole approach in a wide range of scenarios.

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