UNIVERSIDAD NACIONAL DE COLOMBIA

Estimation of gastrointestinal polyp size in video endoscopy

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Bogota, Colombia
2013

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Tesis presentada como requisito parcial para optar al título de:
Magister en Ingeniería Biomédica

Director:
Ph.D. MD. Eduardo Romero Castro

Línea de Investigación:
Procesamiento de Imágenes
Grupo de Investigación:
Cim@Lab

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"Me gusta andar ... pero no sigo el camino pues lo seguro ya no tiene misterio"
Facundo Cabral

Abstract

Worldwide the colorectal cancer is one of the most common public health problems, constituting in 2010 the seventh cause of death. This aggressive cancer is firstly identified during an endoscopy routine examination by characterizing a set of polyps that appear along the digestive tract, mainly in the colon and rectum. The polyp size is one of the most important features that determines the surgical endoscopy management and even can be used to predict the level of aggressiveness. For instance, the gastroenterologists only send a polyp sample to the pathology examination if the polyp diameter is larger than 10 mm, a measure that is achieved typically by examining the lesion with a calibrated endoscopy tool. However, the polyp size measure is very challenging because it must be performed during a procedure subjected to a complex mix of noise sources, such as: the distorted optical characteristics of the endoscopy, the exacerbated physiological conditions and abrupt motion. The main goal of this thesis was estimated the polyp size during an endoscopy video sequence using a spatio-temporal characterization. Firstly, the method estimated the region with more motion within which the polyp shape is approximated by those pixels with the largest temporal variance. On the above, an initial manual polyp delineation in the first frame captures the main features to be follow in posterior frames by a cross correlation procedure. Afterwards, a bayesian tracking strategy is used to refine the polyp segmentation. Finally a defocus strategy allows to estimate on the clear cut frame at a certain depth as a reference to determine the polyp size obtaining reliable results. In the segmentation task, the approach achieved a Dice Score of 0.7 in real endoscopy video-sequences, when comparing with an expert. In addition, the results polyp size estimation obtained a Root Mean Square Error (RMSE) of 0.87 mm with spheres of known size that simulated the polyps, and in real endoscopy sequences obtaining a RMSE of 4.7 mm compared with measures obtained by a group of four experts with similar experience.

Keywords: Polyp size estimation, Endoscopy, Colorectal cancer, Polyp shape segmentation, Spatio-temporal characterization.

Resumen

El cáncer colorectal es uno de los problemas de salud pública más comunes a nivel mundial, ocupando la séptima causa de muerte en el 2010. Este tipo de cáncer tan agresivo es identificado prematuramente por un conjunto de pólipos que crecen a lo largo del tracto digestivo, principalmente en el colon y el recto. El tamaño de los pólipos es una de las características mas importantes, con la cual se determina el manejo quirúrgico de la lesíon e incluso puede ser usado para predecir el grado de malignidad. Acorde a esto, el experto solo envía una muestra del pólipo para un examen patológico, sí el diámetro del pólipo es más largo que 10 mm. Típicamente, esta medida es tomada examinando la lesión con una herramienta endoscópica calibrada. Sin embargo, la medición del tamaño del pólipo es realmente difícil debido a que el procedimiento está sujeto a fuentes de ruido bastante complejas, tales como: la distorsión óptica que es característica del endoscopio, las condiciones fisiológicas del tracto digestivo y los movimientos abruptos con el dispositivo. La contribución principal de este trabajo fue la estimación del tamaño de los pólipos, sobre una secuencia de video de un procedimiento de endoscopia usando una caracterización espacio-temporal. En primera parte, el método estima la región con mayor movimiento que corresponde aproximadamente a la region del pólipo, tomando aquellos pixeles con mayor varianza temporal. Sobre lo anterior, una delineación manual de la lesión es realizada en el primer cuadro para establecer las principales características, para ser seguidas en los cuadros posteriores usando un método de correlación cruzada. Después, se usó una estrategia de seguimiento bayesiana para refinar la segmentación del pólipo. Finalmente, una estrategia basada en la correspondencia del desenfoque de las imagenes de una secuencia a una profundidad o distancia determinada, se pudo obtener una referencia para determinar el tamaño de los pólipos, obteniendo resultados fiables. En la etapa de segmentación, la estrategia logra un Dice score de $0,7$ al comparar con un experto en secuencias de endoscopia reales. Y en la estimación del tamaño de los pólipo se obtuvo un error cuadrático medio (RMSE) de 0.87 mm, comparando con esferas de tamaño conocido que simulaban los pólipos, y en secuencias de endoscopia reales se obtuvo un RMSE de 4.7 mm comparando con las medidas obtenidas por un grupo de cuatro expertos con experiencia similar.

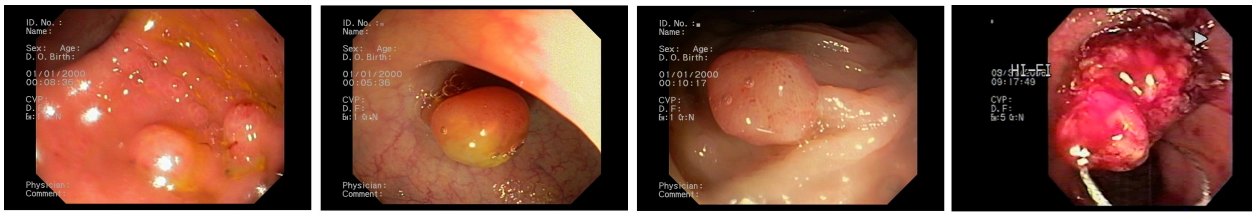
Palabras claves: Estimación del tamaño de los pólipos, Endoscopía, Cancer colorectal, Segmentación de la forma de los pólipos, Caracterización espacio-temporal.

Contents

1 Theoretical Framework

1.1 Introduction

Digestive diseases prevail as one of the most critical public health issues, reporting in 2010 more than 70 million affected people [11]. The colorectal cancer is the seventh cause of death in the world [37], with 1.2 million new cases reported and 5000 cases reported in Colombia, during the 2009 [23, 36, 42]. Particularly, the cancer is characterized by asymptomatic illness characteristic, being the first evidence, a set of abnormal mucosa growth out along the digestive tract, typically named polyps [1, 38].



a b c d

Figure 1-1: The progression from polyp to cancer, that usually begin as set of benign polyps that grow from the mucosa. Firstly in (a), show the stage 0 and stage I of early colorectal cancer, that usually begin as set of benign polyps that grow from the mucosal (hyper cell proliferation). In (b), it is a stage II is consider as high grade of dysplasia. In (c), the stage III the lesion is consider as adenocarcinoma and in (d), the stage IV is a cancer tumor which invade through the submucosa producing metastasis.

During the first cancer stages, the polyps look sessile with smooth and glassy appearance, as illustrated in Figure. Currently, the main diagnosis mechanism to evaluate and follow the aggressiveness of the diseases is the observational analysis through a endoscopic clinical examination. In this case, characteristics as the irregular morphology and the size are the main indicators of the lesion. Particularly, the speed up growing is the most important factor to determine the disease evolution, i.e., if the lesion grows in average 3 mm per year it is recommended a deeply histological examinations and surgical management is strongly recommended [19, 33]. This factor is supported by different statistical analysis, for instance, a study developed with 345 removed polyps with size larger than 10 mm were also pathologically analyzed found that the 83% of lesions were carcinogenic [41]. Hence, polyp size

estimation during a routine endoscopy result fundamental to determine the surgical management, i.e., if the polyp is smaller than 10 mm [34, 40], it is removed, otherwise a sample is sent to pathology and the procedure is re-programmed for an extirpation [38, 1, 40]. Histologically, the polyps evolution can be classified as hyperplastic, inflammatory, fundic and adenomatous, being these two last the most probable lesions that evolve in cancer [40]. In fundic and adenomatous cases the genetic alterations disrupt the cellular proliferation, differentiation, senescence and programmed cell death [13, 35].

Technically, a routine endoscopy examination uses a monocular video-camera equipped with specialized wide angle lens to a wide visualization of the digestive tract [40]. During this procedure can be used special micro-rules and biopsy forceps that allows to compare a lesion width with known dimensions [15, 40]. This routine size estimation procedure is however highly subjective and prone to errors because the observational expert dependency, the handling of the measure tools, the distorted optical characteristics of the endoscopy and the exacerbated physiological conditions. All of this facts make necessary that gastroenterologist needed a specialized intense training to achieve reliable polyp measures [25].

1.1.1 Dealing with observational polyp size variability

The diagnosis of gastric cancer has been established in around of 94% of the patients by using typical endoscopy clinical [47]. Following diagnosis, preoperative evaluation allows to establish and classify the polyp malignancy based on the shape, size, color and location characteristics according to the Borrmann classification[3]. Additionally, the morphological characteristics of the polyps are fundamental to correlate the diagnosis with histological analysis. However, features such as the polyp size are lost once they are excised because the loss of blood pressure and the formalin fixation procedure [32, 43]. In spite of the importance of the quantification of morphological polyp features, the evaluation of the polyps vary according to the gastroenterologist experience, the techniques that support the evaluation and the endoscopy video characteristics [3, 12].

In clinical routine, the polyps sizes are can be estimated: 1) by using an exhaustive expert observation, 2) by associating the polyp size with open biopsy forceps or 3) with probe tools. The most common methodology is a simple observational analysis fully based on the doctor expertise. However, this technique is highly variable and prone to errors since there not exist a known reference to compare the lesion. This absence of ground truth result in inaccurate estimation, reporting around of 6.4% of error between the real and estimated sizes [15]. Interestingly enough, the expert support the polyp size estimation by using a direct comparison with biopsy forceps that are open near to lesion. Nevertheless, this method has reported a 12.3% of error w.r.t real measures because the variability of the localization of the biopsy forceps, the perspective of observation from the endoscopy and the limited range of aperture of the device. Currently, the best polyp size estimation is obtained by supporting the observational evaluation with probe tools. This device is a flexible grid of measure that is

introduced by a channel of the endoscopy and allows a direct comparison with the lesion. In a study with 100 polyps of wide range of size, a comparison of real measures with the probe tools obtained a 3.4% the mean difference [15]. Despite of probe tools estimate the polyp size with less error that the other classical approaches, these methodologies remain limited because are highly dependent of the expert observation, they are in most of the cases invasives and they are dependent of the appropriate localization of the supporting tools. Additional techniques and devices are used during the endoscopic examination to complement or search more specific characteristics of the pathology. For instance, in some cases are used the echo-endoscopy device to identify extramural polyps [40]. A more sophisticated endoscopy allows to the magnification zooms out the lesion as to show the histological characteristics in vivo [21, 5]. Also, there exist stereo-endoscopy devices that allows to reconstruct three dimensional surfaces, to a complete evaluation of the digestive tract [24]. Other strategies include the virtual endoscopy from CT images to obtain three dimensional reconstruction but with the main problem of long exposition periods to ionizing irradiation [45, 10, 8, 48].

Computational video- strategies to characterize polyps

Currently, image and video processing strategies have been adapted over endoscopy video-sequences to characterize polyps that are non invasive, reduce the subjectivity and allows more repeatable estimations to better predict and follow the pathology [5, 24, 10]. In general, these strategies search predominant primitives such as the appearance, contrast, motion among other, which are correlated with the lesion and allows to solve classification, tracking and recognition tasks to support the diagnosis. In spite of the advantages of these computational strategies, currently there exist many limitations and challenges to characterize properly the polyps, mainly because: 1) certain zones of the image look completely saturated due to specular highlights [1] [4, 25], 2) the fuzzy boundary between the polyp and the tract [2] [25] and 3) abrupt movements of the endoscope device while carried out the navigation.

In the current state-of-the-art some computational strategies have been proposed to characterize lesions along the digestive tract, most of them based on intensity, geometrical, appearance observations at each frame which commonly and require manual intervention [20]. Liu et al. [29] reconstructs a 3D intestinal tract based on flow deformation maps computed during an endoscopy sequence. In this strategy also a set of salient point were matched and propagated[15]. Despite of probe tools estimate the polyp size with less error that the other classical approaches, these methodologies rem from a manual initialization to identify the presence/absence of polyps. However, these salient points are hardly correlated in homogeneous textures as intestinal tract and the apparent motion estimation is noise sensible in scenes with abrupt motion. In contrast, Bernal et al. [4] and Condessa [7] approximate the polyp shape by using per-frame static features such local binary maps and a set of local

[1] caused by reflection and refraction of non-static light source in the mucosa of the digestive tract
[2] due to homogeneous texture and surrounding liquid

derivatives which are mapped to a typical support vector machined to obtain the polyp segmentation. The [4] use the intensity and edges that must follow a polyp appearance model and [7] using a set of classical geometrical and color descriptors. Nevertheless these kind of characterizations are sensible to strong intensity polyp changes occurred during the sequence and fuzzy edges that can overflow the segmentation by the high illumination variation.

Other strategies have been proposed to highlight 3D polyp shape characteristics by using geometric and brightness depth assumptions as well as manual interventions. For instance, Hong et al [20] propose a strategy to semi-automatically reconstruct the tract by introducing tubular prior shapes and using a sequence of images as observations. This strategy is however limited to represent the tract as simple geometrical primitives and local deformations are not considered. An additional work was proposed by Kaufman et al. [25] in which a 3D representation was achieved by a local strategy in which the tract is reconstructed by subregions and then partially integrated. In this approach is used shape observations and also is refined the reconstruction with the characterization of the shadows which allows at each frame refine the reconstruction. However this strategy is highly computational cost and the reconstruction may take long time. Additionally, Alcantarilla et al. [2] uses a set of salient points as information to reconstruct the digestive tract. All these strategies may fail because the presence of noise, similar textures pattern and the abrupt changes of the camera during the sequence.

Regarding the polyp size estimation, several computational strategies have been proposed to cope with identification, characterization and measure of polyps. Ganz et al. [14] used a multispectral endoscopic imaging to highlight the region that bounded the polyp, according to certain expected histological properties. Then, the boundary is detected using a prior shape term as regularizer. This method requires a special device to characterize the polyp, that is to say, to define the set of histological characteristics that might be associated to the lesion, additionally this approach results dependent on a very large database that can store the high shape variability. Additionally, Chadebecq et al. [6] proposed a semi-automatic method that started by manually placing a bounding box surrounding the polyp, followed by a conventional affine registration that propagates such initial guess to the whole sequence and estimates the best focused region by a depth learning procedure. However, in real conditions the camera movements may be so rapid that the RoI easily losses the polyp and the break focus is determined on the entire bounding box, with the consequent error coming from calculating the polyp distance as a linear function of the estimated depth within the box.

2 Estimating the size of polyps during actual endoscopy procedures using a spatio-temporal characterization

Presented on the "Journal of Computerized Medical Imaging and Graphics" Journal 2014, July 2014

Colorectal cancer usually appears in polyps developed from the mucosa. Carcinoma is frequently found in those polyps larger than 10 *mm and therefore only this kind of polyps is sent for pathology examination. In consequence, accurate estimation of a polyp size determines the surveillance interval after polypectomy. The follow up consists in a periodic colonoscopy whose frequency depends on the estimation of the size polyp. Typically, this polyp measure is achieved by examining the lesion with a calibrated endoscopy tool. However, measurement is very challenging because it must be performed during a procedure subjected to a complex mix of noise sources, namely anatomical variability, drastic illumination changes and abrupt camera movements. This work introduces a semi-automatic method that estimates a polyp size by propagating an initial manual delineation in a single frame to the whole video sequence using a spatio-temporal characterization of the lesion, during a routine endoscopic examination. The proposed approach achieved a Dice Score of* 0.7 *in real endoscopy video-sequences, when comparing with an expert. In addition, the method obtained a Root Mean Square Error (RMSE) of* 0.87 *mm in videos artificially captured in a cylindric structure with spheres of known size that simulated the polyps. Finally, in real endoscopy sequences, the diameter estimation was compared with measures obtained by a group of four experts with similar experience, obtaining a RMSE of* 4.7 *mm for a set of polyps measuring from* 5 *to* 20 *mm. An ANOVA test performed for the five groups of measurements (four experts and the method) showed no significant differences (*$p < 0.01$*).*

2.1 Introduction

Colorectal cancer is the seventh most likely cause of death worldwide [37] and frequently asymptomatic illness characterized by a set of malign polyps along the digestive tract [1, 38]. Typically, this disease is discovered during an endoscopy procedure, in which case the polyp size is used as the main endoscopic sign that supports the decision of an immediate resection, i.e., if the polyp is smaller than $10\,mm$ [34, 40], it is removed, otherwise a sample is sent to pathology and the procedure is re-programmed for an extirpation [38, 1, 40]. Usually, the polyp size is estimated by measuring the lesion with a linear colonoscopy probe or by using the aperture of the endoscopy forceps as a repair for comparison [15]. This estimation is a very difficult task, highly subjective and dependent on the expert training [25]. In addition, several technical problems may arise during the procedure, such as: 1) optical distortion (Barrel's effect), 2) difficult handling of the endoscope because of the bowel tone and 3) exacerbated physiological conditions like increased motility or secretion [25]. Current advances on video processing [29, 7, 4] open upactual possibility of identifying polyps during endoscopy, with some potential advantages, namely: 1) real time estimation, 2) less-invasiveness, i.e., no additional tool is needed, 3) low cost procedure, and 4) a lesion characterization that might be used as support to the diagnosis. However, developing automatic approaches for estimation of polyp size is challenging because ofthe high variability of both the endoscopy procedure and the polyp shape [3, 12], interference light patterns due to the bowel motion and blurred captures because of the varying illumination conditions [25].

Current approaches far proposed for segmenting and estimating the polyp size, use features derived from their geometry, appearance and size but difficulties in estimating these parameters limit the accuracy of these methods [20]. Aiming to delineate the polyp, Liu et al. [29] simulate a geometrical 3D intestinal tract, computed from a flow deformation map that matches a set of salient points from consecutive frames. Such method results computationally expensive and prone to errors because the salient points are hardly correlated. This strategy only predicts the presence/absence of the polyp, requiring an initial manual intervention. In [7], a per-frame polyp shape is estimated by using a set of classical geometrical and color descriptors, a strategy that fails under non controlled illumination conditions. In contrast, Bernal et al. [4] approximate the polyp shape by using per-frame static features that must follow a polyp appearance model. This characterization may fail if the polyp is blurred in the endoscopy video, as usually observed in real scenarios. For estimating the polyp size, Chadebecq et al. [25] introduced a prior RoI bounding the polyp and tracked the lesion using a temporal rigid transformation. Afterward, an infocus blur allowed a RoI size estimation. However, in real conditions the camera movements may be so rapid that the RoI easily losses the polyp.

Recent strategies involve the fusion of video-endoscopy with ultrasound images. Nevertheless, such echo-endoscopy device is mainly indicated in case of extramural polyps, i.e., it makes possible to measure advanced stages of the polyp and its use is highly expert depen-

dent [40]. Other strategies include the virtual endoscopy from CT images [45, 10, 8], a 3D reconstruction that requires long exposition to ionizing radiation, report low sensitivity rates [8, 10, 48] and is purely diagnostic and polyps finally must be removed during an endoscopy procedure.

The main contribution of this work is a semi-automatic method that delineates the polyp and estimates its size in a video sequence, using a local spatio-temporal characterization and an automatic defocus strategy.In this approach, an initial manual delineation in a single frame is propagated using a per-pixel motion descriptor built while the camera is moving, assuming only a statistical dependence with the precedent frame. An additional Bayes strategy couples the per-pixel motion descriptor with prior motion information, approximating the shape during occlusion phases. The polyp size is then estimated from the resulting polyp delineation, using a focused estimation of the whole sequence with a calibrated camera model. This paper is organized as follows. In section 2.2 describe the proposed strategy, in section 2.3 present the evaluation and result of method, in section 2.4 is the discussion of proposed approach and in section 2.5 the conclusions and the future work.

2.2 Proposed Approach

The present strategy segments, tracks and measures polyps during an endoscopy procedure. An initial manual polyp delineation in the first frame captures the main features to be used. This characterization and the motion history endoscopy coarsely follow the polyp in the sequence. Afterwards, a classical second order kalman filter, a bayesian tracking strategy, is used to refine the polyp segmentation, obtained from the spatio-temporal characterization. Once a polyp is identified and segmented, the polyp size is computed using an offline depth defocus strategy. The pipeline of the proposed approach is illustrated in Figure **2-1** and further described in the following subsections.

2.2.1 Radial distortion correction

In general, radial endoscopy distortion produces non linear incremental deformations from the optical center to the outer regions, affecting the object relative size and position [31, 28]. The wide-angle lens distortion (barrel's effect) was corrected by estimating the camera parameters using a bank of artificial images (see Figure 1(c)). Assuming an orthogonal coordinate system, every point in the image space $\mathbf{x}$ is related to the real world $\tilde{\mathbf{x}}$ by a pinhole model defined as $\mathbf{x} = \frac{f}{z}\tilde{\mathbf{x}}$, where f is the focal length and z the distance from the object to the camera lens. This model estimates the focus camera length, the scale factor, the distortion coefficient and the optical center point. This nonlinear distortion was aproximated by power series and corrected as $r_n = r_d(1 + k * r_d^2)$, being k the radial distortion coefficient and r_d the image with the corrected distortion.

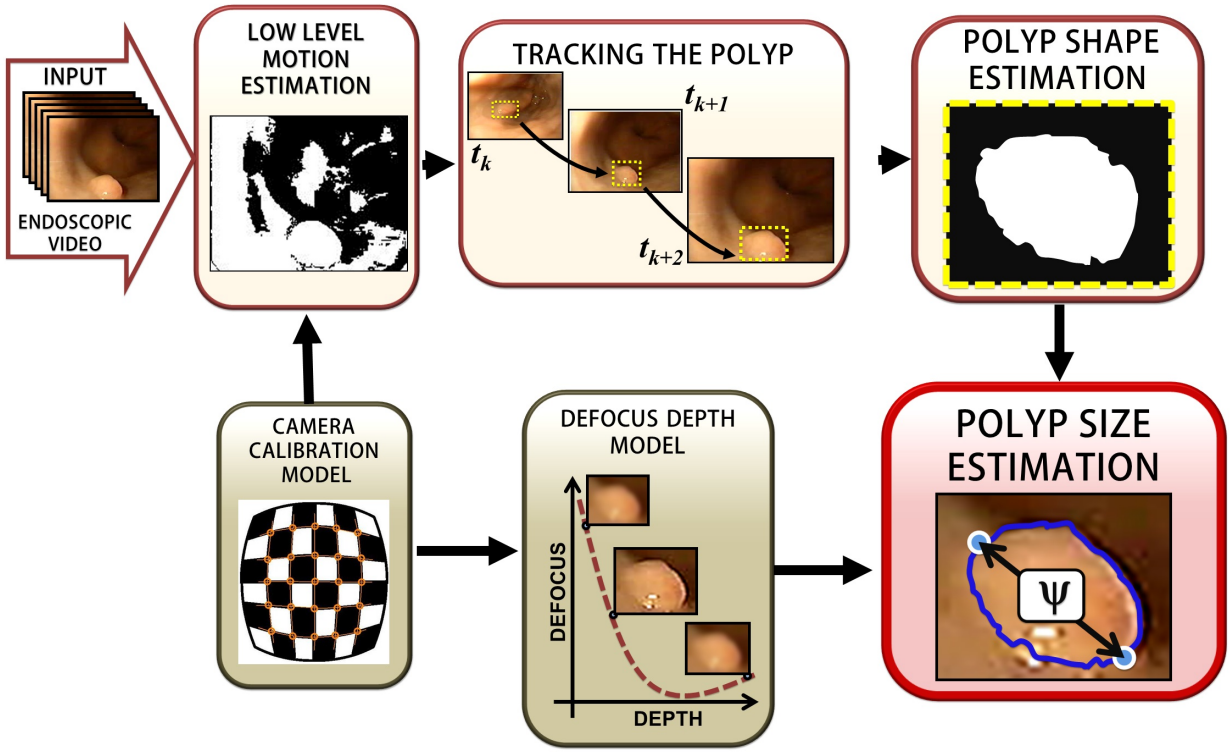


Figure 2-1: Pipeline of the proposed approach. The method is composed of four main steps. Firstly in (a), a spatio-temporal characterization allows to coarsely follow the polyp. In (b) a polyp tracking strategy was then used to refine the polyp segmentation. Finally a camera calibration model (c) and a depth defocus strategy (d) was used to measure the maximum size diameter of the polyp segmentation obtained.

2.2.2 Preprocessing and polyp initialization

A polyp is an intestinal protuberance whose appearance may be easily confounded with the surrounding tissues, leading most segmentation procedures to fail. The proposed approach starts by an expert delineation of the polyp contour in the first frame to capture specific polyp features. The polyp contour $\mathbf{X_t}$ is represented as a parametric curve defined as: $\mathbf{X_t} = \left\{\{\mathbf{x}_t\}_{i=0}^{n}, (\bar{x}, \bar{y})\right\}$, where $\{\mathbf{x}_t\}_{i=0}^{n}$ is a set of n points contouring the polyp with its centroid defined in $(\bar{x}, \bar{y})$. Such delineation defines a neighbour RoI around the lesion, the RoI_t with size $\{RoI_t = \mathbf{X_t} + \xi\}$, being ξ a tolerance value. Afterwards, the histogram of the whole sequence was equalized and a gaussian filter, with $\sigma = 0.7$, was applied to remove the granular noise.

2.2.3 Quantifying the polyp motion patterns

During an endoscopy navigation, the expert always tries to track the polyp with translational movements, attempting to generate a depth perception by amplifying the motion of nearby structures[1]. Using a background subtraction strategy, the proposed approach estimates the region with more motion, within which the polyp shape is approximated by those pixels with the largest temporal variance [30]. For so doing, a per pixel history motion $M_t(x, y)$ (reference model), storing those pixels that are relatively motionless and correspond to the background, is firstly calculated as $M_t(x, y) = M_{t-1}(x, y) + sign(I_t(x, y) - M_{t-1}(x, y))$, where I_t is a particular frame at time t. A likelihood function $\Delta_t(x, y)$ measures the instantaneous pixel motion at time t w.r.t the background history motion, being $\Delta_t(x, y) = \left|M_t(x, y) - I_t(x, y)\right|$. The lesion is then the set of pixels with a relevant motion defined by the bidirectionally likelihood function, i.e., in the forward and backward temporal directions of the whole video-sequence (causal and anti-causal analysis). The bidirectional computation of the motion pixels recovers the lesion at each time as: $\mathbf{\Delta_t}(\mathbf{x}, \mathbf{y}) = (\alpha_t)\Delta_t^{forward}(x, y) + (1 - \alpha_t)\Delta_t^{backward}(x, y)$, where $\alpha = \frac{t}{N}$ is a temporal weight parameter. Finally, moving pixels that better represent the polyp shape are selected by simple thresholding the estimation $\mathbf{\Delta_t}(\mathbf{x}, \mathbf{y})$ with a learned scalar parameter τ as: $Sb_t(x, y) = \mathbf{\Delta_t}(\mathbf{x}, \mathbf{y}) \geq \tau$, yielding the motion segmentation.

2.2.4 Tracking the Region of Interest (RoI)

The initial position of the RoI_t that bounds the polyp delineation is then propagated to the rest of the image space and motion history sequences. For doing so, the motion history is correlated for every pair of consecutive frames [27], as:

$$RoI_t(x, y) = \arg\max_{RoI_t} \sum_{i=0}^{(n-1)} \sum_{j=0}^{(m-1)} \mathbf{\Delta_t}(\mathbf{i}, \mathbf{j}) * RoI_{t-1}(x - i, y - j) \tag{2-1}$$

Where $RoI_t(x, y)$ is an estimation of the polyp location corresponds then to that maximally correlated RoI.

Such RoI in the motion history space is mapped to the image space, where a minimal per-pixel euclidean distance w.r.t. the precedent RoI_{t-1}, allows to obtain an additional polyp segmentation $Si_t(x, y)$, the intensity segmentation. Then, an improved segmentation is obtained by fusing the two mentioned segmentations as the intersection of the intensity $Si_t(x, y)$ and motion $Sb_t(x, y)$ (defined in the previous subsection), $Z_t = \{Si_t(x, y) \oplus Sb_t(x, y)\}$.

Additionally, a classical morphological operator removes the remaining noise, basically groups of isolated polyp regions. Finally, The obtained segmentation is transformed to a polar space, where a simple smoothing preserves the global shape.

[1] classically known as motion parallax (right-left movements) [39] and kinetic depth perception (rear-front movements) [46]

2.2.5 Tracking the polyp

During an actual endoscopy procedure, a polyp may be missed because of some abrupt camera motions or presence of some digestive fluid that might partially occlude the intestinal tract. With a proper frame-rate capture, it is reasonable to assume a relatively smooth polyp motion, even when the polyp is partially occluded.

A bayesian strategy estimates and tracks the polyp, modeling the probability $p(\widehat{\mathbf{X_t}}|Z_t)$ of the state of the polyp delination $\widehat{\mathbf{X_t}}$ at time t, given the spatio-temporal observations $\mathbf{Z}_t = (Z_1, \ldots, Z_N)$. This model is assumed markovian, i.e., the current state of the system stores the relevant information. Such Bayesian strategy requires a model of the dynamics $p(\mathbf{X_t}|\mathbf{X_{t-1}})$ and a likelihood function $p(Z_t|\mathbf{X}_t)$ that maps the estimated polyp to the spatio-temporal space. Once this information is avaible, the polyp delineation at a particular state, is calculated in two steps:

- *Prediction.* A particular state $\mathbf{X}_t$ is computed by updating the previous belief $\widehat{\mathbf{X}}_{t-1}$, after a prediction given by the Chapman-Kolmogorov equation: $\widehat{\mathbf{X}}_t = \int p(\mathbf{X}_t|\mathbf{X}_{t-1})\widehat{\mathbf{X}}_{t-1} d_{\mathbf{X}_{t-1}}$
- *Update.* The predicted belief $\mathbf{X}_t$ is adjusted after observations: $\mathbf{X}_t \propto \widehat{\mathbf{X}}_t p(Z_t|\mathbf{X}_t)$

For the sake of computational efficiency, a second order kalman filter models the polyp delineation $\widehat{\mathbf{X}}_t$ by using the first and second statistical moments as $\mathbf{X}_t \sim \mathcal{N}(\mu_t, \Sigma_t^2)$, where μ_t is the mean distribution and Σ_t^2 is the covariance matrix of the state t. This kalman estimator is computationally optimal because it linearizes the system with a first order taylor series expansion.

2.2.6 Polyp size estimation

A polyp size is estimated from the obtained temporal segmentation at a fixed depth position of the camera, as a function of the focused image [16] [2] and the pinhole camera parameters (See in section 2.1).

The depth was herein estimated by a defocus strategy [25] that assumes each frame is contaminated with an unknown gaussian blur with standard deviation σ^o, proportional to the object distance to the camera. This unknown Gaussian blur is estimated by convolving the image with a known Gaussian blur and computing the difference between gradients of the original (unknown blur) and blurred (known blur) images. This gradient ratio R_t is proportional to the unknown standard deviation as $\sigma_t^o = \frac{1}{\sqrt{R^2-1}}\sigma_t^b$, where σ^b is a known standard deviation of a blurred gaussian.

[2] a well known psychophysical theory states that the distance to the camera is a function of the image blur[16]

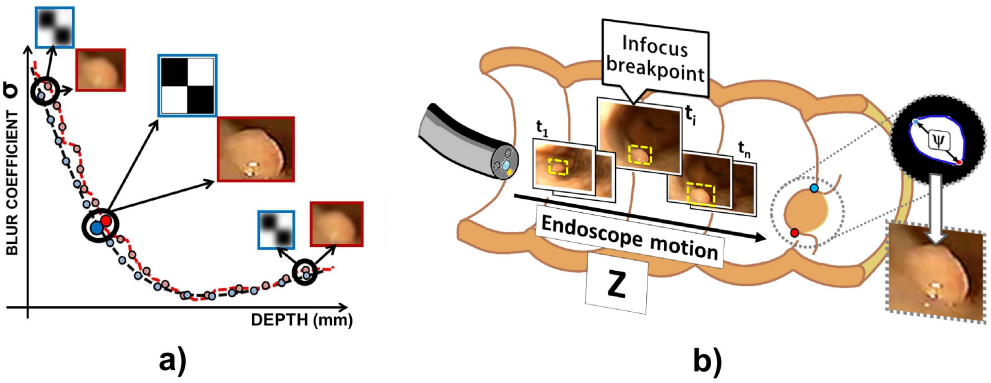


Figure 2-2: the off-line depth defocus learned model is presented (a) an artificial grid image with known defocus-depth relationship. Using this learned representation, a depth estimation in endoscopy images finds an optimal depth distance (infocus breakpoint) and computes the maximum polyp size (b).

In an off-line posterior training step, the blur coefficients, a set of correspondences between the blur levels of a phantom image[3] and actual camera depths (see in Figure 2(a)), are computed. A single blur coefficient is then associated to the infocus breakpoint image $IB_{off-line}$ (the clearer cut-frame) and serves as a reference depth since this is the minimum estimated blurring with a unique depth correspondence. Such relationship - the blur coefficients - was herein used within the endoscopic RoI_t to estimate the unblurred polyp by computing the corresponding infocus ROI breakpoint. The unblurred polyp size (ϕ) is then estimated from the segmentation previously obtained.

2.2.7 Dataset

The dataset herein used is composed of a set of videos captured using an *Olympus EVIS EXERA (GIF-1TQ160)* gastrovideoscope device, provided with a field of view of 140° and a focal length of $(357.3, 325.5)$. Each sequence was recorded in color, with a spatial resolution of 720 per 480 pixels and a temporal resolution of 30 frames per second. Two different groups of videos were captured for training and evaluation. The first dataset was captured under controlled conditions using an artificial phantom grid superimposed to a set of images captured at different angles, estimating thereby the intrinsic and extrinsic camera parameters. The depth function was trained with captures of the artificial phantom grid, as illustrated in Figure 1(c). The grid is placed at different depth distances, using a custom platform that is displaced in steps of 1 *mm*, with a maximum distance of 30 *mm*. Additionally, as shown in Figure 3, a tubular structure emulated the digestive tract while a set of spheres of known size, the polyps. Four navigations within this structure were recorded to test the proposed approach in controlled conditions. The second dataset included real endoscopic procedures and

[3] An artificial grid phantom was adapted for this task

presence of polyp lesions. Ten videos were captured and four gastroenterologists annotated the videos, segmenting the polyps and estimating their size.

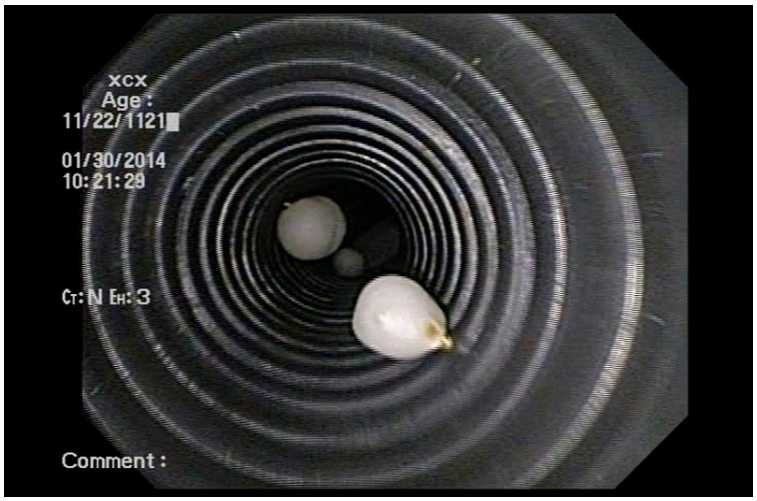


Figure 2-3: Custom tubular structure that emulates the tract with spheres of known sizes that simulate polyps.

2.3 Evaluation and Results

The performance of the proposed approach was assessed in two different tasks: segmentation and estimation of the polyp size. Four expert gastroenterologists delineated and estimated the polyp size in phantom and real endoscopy sequences.

2.3.1 Polyp segmentation

Figure **2-4** illustrates the segmentation results in actual endoscopic videos. The yellow contour stands for the ground truth delineation. In the second row, the red polyp delineation is computed using an alternative tracking strategy introduced as a baseline, the classical exponentially weighted moving average EWMA [18], for which an actual polyp delineation is propagated along the sequence using the bhattacharyya coefficient and a set of exponentially decreasing weights obtained from previous frames. Despite this strategy takes into account the motion histoy, and the polyp is relatively well localized within the analysis RoI, the method misses polyp changes resulting from abrupt camera movement, leading to a wrong segmentation. In contrast, in the third row, the blue delineation is obtained with the proposed approach, showing a reliable overlap during those periods with a relatively slow motion. When the camera abruptly moves, the polyp appearance and size result modified, but the proposed approach follows the lesion more accurately than the tracking observed with the EWMA.

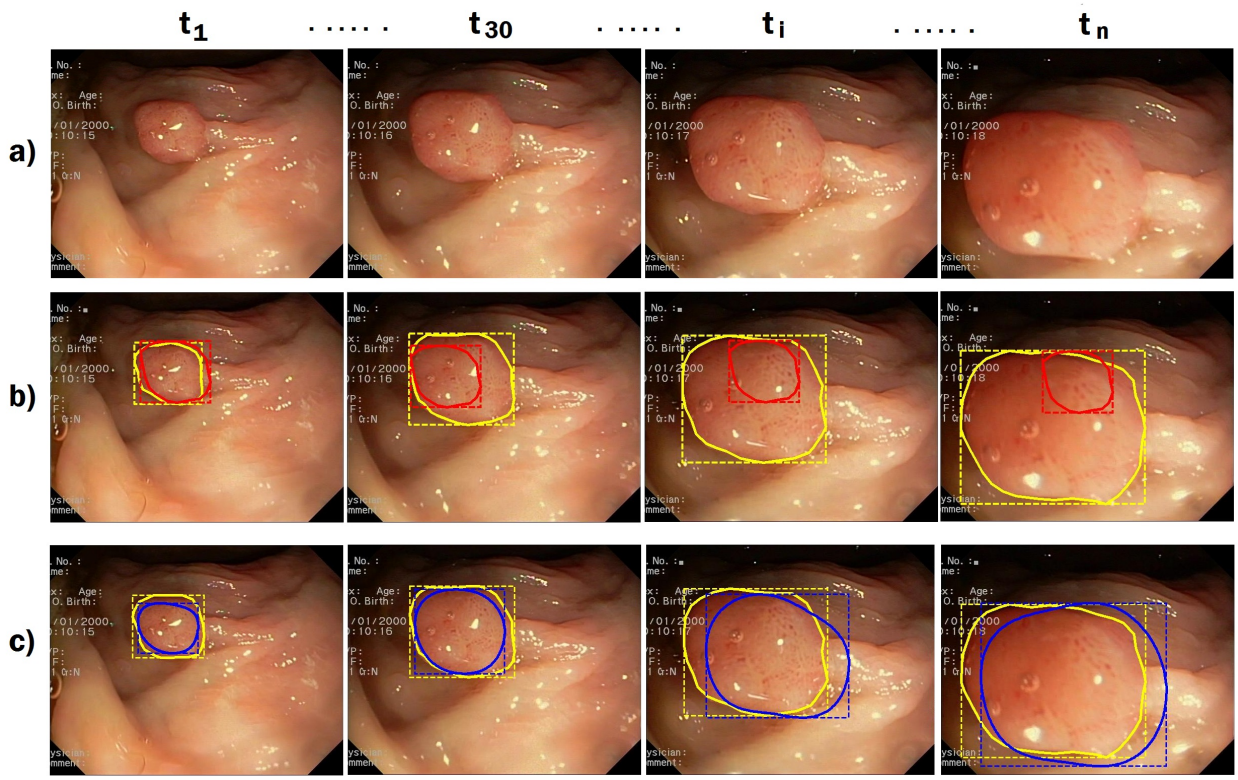


Figure 2-4: Illustration of a polyp segmentation in a real sequence. First row, the original sequence, second row: EWMA and third row, the proposed method.

Two quantitative metrics were used for assessing the segmentation task: the Dice coefficient (DSC) and the Hausdorff distance (HD). The $DSC(A, b)$ is $\frac{2(A \cap B)}{A+B}$[9], where A and B represent the obtained polyp area and the expert ground truth delineation, respectively. The Hausdorff measure $H(A, B)$ [22] computes the maximum distance between two sets of points as $\max(h(A, B), h(B, A))$ and $h(A, B) = \max_{a \in A} \min_{b \in B} \|a - b\|_2^2$. In this case, each set of points represents the polyp delineation at each frame. This measure allows to indirectly assess the compactness of the segmentation since outliers are penalized. In videos captured within the artifitial tubular structure (see in Figure 3) a DSC of 0.96 was obtained when the phantom polyps were segmented, under controlled illumination conditions. Table 1 shows the performance obtained by the proposed approach and the EWMA tracking when segmenting 1040 frames.

An additional comparison with the Hausdorff Distance allows the compactness of the polyp delineation to be assessed, since this measure penalizes those pixels far from the ground truth, reporting in such a case a small value. Overall, the proposed approach outperforms the baseline in terms of overlapping and compactness (small Hausdorff distance). Some segmentation errors may be caused a certain polyp occlusion is present or in cases in which abrupt motions may change the appareance, size and shape of the polyp.

Score	EWMA tracking	Proposed approach
DSC	0.52 ± 0.05	0.71 ± 0.12
HD	0.55 ± 0.08	0.38 ± 0.14

Table 2-1: Performance of the proposed approach using Dice Score (DM) and Hausdorff distance (HD)

2.3.2 Polyp size estimation

Estimation of polyp size is a challenging task and high intra and inter expert variability has been reported in previous work. The variance of 12 expert measuring 240 gastric lesions was reported [17], obtaining a mean difference of 11 ± 17 *mm*. Additionally, a kappa coefficient of 0.4 and an agreement of only a 50.0% in series with three gastroenterologists were also reported [34]. In consecuence, a second experiment aimed to evaluate the accuracy of the estimated polyp size. This task is much more challenging because of the multiple sources of distortion, but also more useful from a clinical standpoint since the gastroenterologist usually has no reference to establish an actual polyp size. Results are shown in Figure **2-5**, the blue lower and upper boxes stand for the spread of the estimated sizes reported by four experts (interquartile range), while the maximum and minimum values are shown as the vertical dotted lines. A total of four endoscopy phantom sequences, with 4 spheres whose size varied between 5 and 15 *mm*, were evaluated. A part of the experiment required the gastroenterologist to simulate a procedure with similar gestures to an actual endoscopy, the camera moved abruptly and the navigation patterns were complex. In spite of the controlled conditions, experts showed a large variability in their estimation, as illustrated in Figure **2-5**, where yellow diamonds correspond to the ground truth measure per video. Interestingly, results evidence a very large variability of the obtained measures with respect to the reference. In average, the standard deviation was about ± 5.4 *mm*, confirming the high inter expert variability. In contrast, the proposed metod (green circles) systematically achieved estimations much closer to the actual value. In this case, the method accomplished an accurate segmentation of the phantom polyps and also a proper estimation of the break focus frame.

Overall, it has been tradionally acknowledged that the expert estimation is the most reliable information source in real endoscopy procedures and therefore the ground truth reference. Figure 6 shows the obtained estimations by the proposed approach (green circles) and the gastroenterologists (interquartile range). In average, the gastroenterologists showed a variance of ± 3.63 *mm* with respect to polyps that varied between 5 and 20 *mm*. In case of real endoscopies, the mean expert estimation -the red line- amounts to the ground truth. As illustrated in figure **2-6**, the estimated size of the proposed approach is within the range of variability observed for the the group gastroentelogists and no significant differences were found when statistically evaluated (Anova test with $p < 0.01$).

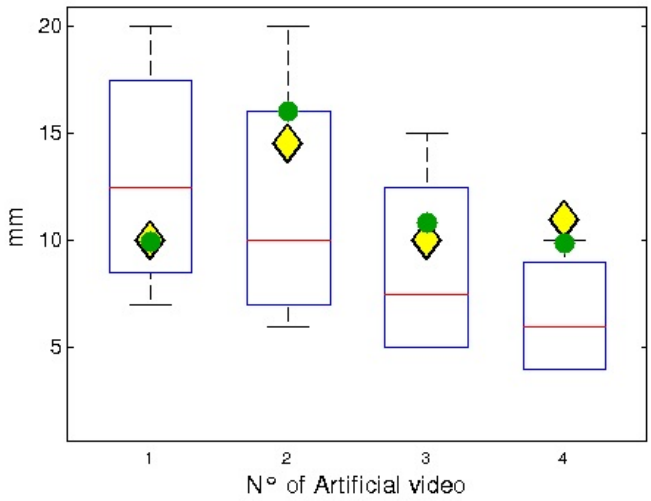


Figure 2-5: Size estimation of phantom polyps in an artificial tubular tract. The yellow diamonds represent the real measure of each recorded phantom polyp. The box plot represents the obtained measures by a group of four expert gastroenterologists. The green circles show the estimation with the proposed approach in each video.

2.2

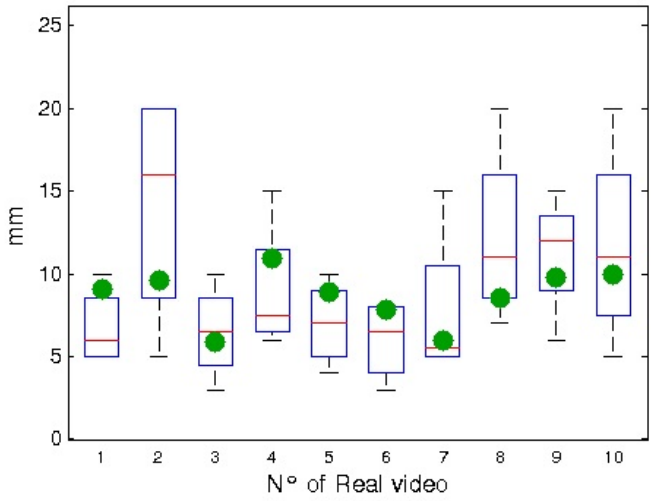


Figure 2-6: Size estimation by the experts is summarized in the statistical box plots, where the upper and bottom blue lines represent the quartiles (μ= 9.25 mm; σ = $\pm$3.63 mm). The green circle stands for the size estimation obtained by the proposed approach.

The quality and fidelity of measurements obtained for any method is always affected by a noise. The quality of the estimation was herein weighted by the noise as the SNR-like measurement, using a logarithmic scale and measuring the difference between the expected control data and the predicted values. This SNR-like measurement was defined as $SNR-like = 10\log_{10}\frac{\sigma^2}{RMSE}$, where σ^2 is the largest delineation variance among the group of experts and $RMSE$ is the root mean squared error, the computed error of the proposed approach w.r.t. the ground truth estimation. Table 2 shows the results obtained by the proposed approach in terms of this SNR-like measure. In summary, the proposed approach achieves a gain of 37.48 dB, indicating that the proposed approach estimates the polyp, with a high degree of confidence, within the interval defined by the estimations of the experts. Table 2 also reports the mean and the standard deviation of the Error (RMSE), indicating a high accuracy of the estimation in artificial videos and a size estimation within the interval defined by expert variablity, in real videos.

Dataset	RMSE (mm)	SNR-like (dB)
Artificial	0.89 ± 0.56	53.8 ± 16.4
Real	4.7 ± 3.2	37.48 ± 8.06

Table 2-2: Performance of the proposed approach using Root mean square error (RMSE) and the SNR-like measurements

2.4 Discussion

This work introduces a novel approach that segments polyps and estimates their sizes during video-endoscopy procedures. The method starts with an initial expert delineation that is warped along the sequence by using information obtained from both a motion and an appearance per-frame analysis. The resultant coarse shape is then refined by a second order Kalman filter, a bayesian strategy that uses the motion history as observation. From such segmentation, the maximum polyp size in pixels is computed and then transformed to real-world coordinates by a combination of camera parameters and computation of an optimal depth distance.

Every polyp, found during a colonoscopic procedure, must be extirpated, but those polyps whose size exceeds the 10 mm are sent for further pathological examination [26, 1, 40]. In spite of the demonstrated importance of quantifying the polyp size, the colonoscopic measure so far consists in comparing the observed lesion with micro-scales introduced within the endoscopy tube, a very highly expert-dependent procedure. Hence, reliable, efficient and reproducible measurements that estimate the polyp size are required. As mentioned before, this problem is particularly challenging since the procedure is by nature the result of abrupt motions, the exploration is carried out under uncontrolled illumination conditions and the

complex anatomy introduces a huge variability of the polyp appearance and shape. Several computational strategies have been proposed to cope with identification, characterization and measure of polyps. Regarding polyp delineation, Ganz et al. [14] used a multiespectral endoscopic imaging to highlight the region that bounded the polyp, according to certain expected histological properties. Then, the boundary is detected using a prior shape term as regularizer. In terms of overlapping, this strategy achieved an average Jaccard index of 0.52 for the segmentation task. This method requires a special device to characterize the polyp, that is to say, to define the set of histological characteristics that might be associated to the lesion. Hence, this approach results dependent on a very large database that can store the high shape variability. In contrast, the presented approach characterizes the polyp in standard endoscopic sequences, without whatsoever prior shape, achieving an overlapping score of 0.71 over 1040 frames in 10 videos. On the other hand, for estimating the polyp size, Chadebecq et al [6]. proposed a semi-automatic method that started by manually placing a bounding box surrounding the polyp, followed by a conventional affine registration that propagates such initial guess to the whole sequence and estimates the best focused region by a depth learning procedure. Unlike our approach, this break focus is determined on the entire bounding box, with the consequent error coming from calculating the polyp distance as a linear function of the estimated depth within the box. Likewise, the rigid registration is very limited to follow abrupt changes of the camera view.

The proposed approach has presented a framework that performs polyp segmentation and size estimation, during colonoscopy procedures. One of the main advantages of the proposed approach is the adaptability to different polyp shapes, with different appearances, depending only of the required initial characterization. Additionally, the deep estimation was computed only within the polyp regions, obtaining more accurate approximations. The proposed approach was evaluated on phantom and real endoscopy videos, showing in general an appropriate performance in both tasks, polyp segmentation and size estimation, i.e., an overlapping average of 0.82 ± 0.09 for segmentation and a RMSE of $0.89 \pm 0.56\, mm$ in phantom polyps varying from 5 to 20 mm and a RMSE of $4.7 \pm 3.2\, mm$ in real sequences, when estimating sizes. In summary, the proposed approach shows adequate sensitivity and reproducibility so that it may potentially be useful in clinical applications as a tool to support the diagnosis.

The average time spent by the proposed approach in a test set of 15 sequences at 30 frames per second was 21.2 s, discriminated as follows: 1) the pre-processing step 4.1 s, 2) the expert delineation 7.2 s, 3) the polyp shape estimation 5.7 s and 4) the polyp size estimation 4.2 s.

2.5 Conclusions and Perspectives

This work has introduced a novel approach to segment and estimate the polyp size in colonoscopy video sequences. The proposed method uses a combination of local motion information and the appearance of polyp features. The results show a reliable segmentation

and tracking of the polyp throughout the video sequence. The approachalso is capable of dealing with video artifacts and the high degree of variability in appearance.Additionally, the real polyp size estimation was obtained in millimeters and results demonstrated these measurements were comparable to those obtained by experts.In a future work, a strategy to automatically initialize the segmentation will be integrated, based on machine learning strategies while the segmentation will be refined with alternative polyp appearance descriptors.

3 A 3D endoscopy reconstruction as a saliency map for analysis of polyp shapes

Presented on the "10th International Symposium on Medical Information Processing and Analysis" SIPAIM 2014, October 2014

A first diagnosis of colorectal cancer is performed by examination of polyp shape and appearance during an endoscopy routine procedure. However, the video-endoscopy is highly noisy because exacerbated physiological conditions like increased motility or secretion may limit the visual analysis of lesions. In this work a 3D reconstruction of the digestive tract is proposed, facilitating the polyp shape evaluation by highlighting its surface geometry and allowing an analysis from different perspectives. The method starts by a spatio-temporal map, constructed to group the different regions of the tract by their similar dynamic patterns during the sequence. Then, such map was convolved with a second derivative of a Gaussian kernel that emulates the camera distortion and allows to highlight the polyp surface. Results show reliable reconstructions, with a salient 3D polyp structure that can then be better observed.

3.1 Introduction

The colorectal cancer is worldwide the seventh cause of death [37]. A morphological analysis of the polyp is the first sign of its malignancy and also the element that decides the surgical management [34, 40, 38, 1]. Nevertheless, a full exploration of the polyp surface during the endoscopy is really difficult because of the constant motility and secretion of the tract. In addition, this task is highly dependent on the expert training and the limited 2D perspective may make some important malignancy details may be lost [25]. Hence, reliable and efficient strategies to observe the polyp surface are required.

Several strategies have been proposed to reconstruct the tract during an endoscopy sequence, classically using geometric and brightness depth assumptions. For instance, Hong et al [20] propose a strategy to semi-automatically reconstruct the tract by introducing tubular prior shapes and using a sequence of images as observations. However, such prior restriction is highly restrictive and folds and small polyps may be lost or confounded with the background. In addition, this strategy starts with a manual intervention that introduces variability. Kaufman et al. [25] proposed a 3D representation by using object shadows in each frame and iteratively refine the reconstruction during the sequence. This method is highly noisy because the assumption that the light source is in the center of the camera. On the other hand, Alcantarilla et al. [2] uses a set of salient points as information to reconstruct the digestive tract, a procedure that may fail because the presence of noise and the abrupt changes of the camera during the sequence.

The main contribution of this work is an automatic strategy that fully reconstructs the digestive tract by using a spatio-temporal map computed from the instantaneous motion of the sequence. Such representation highlights the regions pointed out during the navigation, i.e., the polyp lesions. Then, the saliency reconstruction is refined, focusing in the polyp, by convolving the spatio-temporal map with a second Gaussian kernel.

3.2 Proposed Approach

The strategy herein introduced is based on a temporal intestinal tract characterization, using routine gastrointestinal video sequences. During a typical endoscopy, the polyp is moved towards the observer and this projection, in a short period of time, can be used as a depth perception from the optical expansion. The motion perception is here characterized from a local per-pixel analysis, in which pixels with less motion as considered as deeper. This spatio-temporal map is then highlighted by focusing in the polyp region, using a second derivative of Gaussian kernel, which also emulates the camera distortion.

3.2.1 Spatio-temporal tract map from motion information

The visual system is able to perceive 3D information from different motion patterns, a phenomenon known as kinetic depth effect [44, 46]. During an endoscopy navigation, the expert always follows the polyp with translational movements, useful to generate a depth perception of different structures. The proposed approach estimates motion patterns from an endoscopy sequence by analysing the temporal history of each pixel, i.e., a temporal coherence is captured by computing the variance of the intensity values during a sequence the [30]. For doing so, it was firstly computed the relative motionless digestive tract as:

$$M_t(x,y) = M_{t-1}(x,y) + sign(I_t(x,y) - M_{t-1}(x,y)) \tag{3-1}$$

where $I_t(x,y)$ is a particular frame at time t. Then, a first spatio-temporal map by computing the instantaneous pixel motion at time t w.r.t the history motion as:

$$\Delta_t(x,y) = \big|M_t(x,y) - I_t(x,y)\big| \tag{3-2}$$

This spatio-temporal map can be considered as an initial depth perception of the intestinal tract.

3.2.2 Polyp saliency map

In general, radial endoscopy distortion produces nonlinear incremental deformations from the optical center to the outer regions. Such distortion was emulated by convolving the spatio-temporal map with a second derivative Gaussian kernel, defined as:

$$\psi(t) = \frac{2}{\sqrt{3\sigma}\pi^{\frac{1}{4}}}\big(1 - \frac{t^2}{\sigma^2}\big)e^{\frac{-t^2}{2\sigma^2}} \tag{3-3}$$

where σ is the standard deviation and allows to emulate the amplitude of the signal. The extreme peaks of the signal, the central peak, allows to highlight the salient structure, i.e., the polyp lesion. The central peak of the kernel is aligned w.r.t the identified polyp, which is salient from the spatio-temporal map. From this kernel, a clear-cut visual map was obtained, aimed to perform a better observation of the polyps by expert gastroenterologist.

3.2.3 Dataset

The dataset used includes a set of 10 videos captured using an *Olympus EVIS EXERA (GIF-1TQ160)* gastrovideoscope device captured in real endoscopy procedures. Each sequence was recorded in color, with a spatial resolution of 720 per 480 pixels and a temporal resolution of 30 frames per second.

3.3 Evaluation and Results

Evaluation of the proposed strategy is illustrated in Figure 1. The dataset includes a large variability of endoscopies with real problems of contrast, saturation and non-controlled motion navigation (see in Figure 1 (a)). For a complete sequence, it was computed the spatio-temporal map from a local per-pixel analysis (see in Figure 1 (b)). Such motion analysis is robust to appearance variation and typical noise, present in endoscopies. In Figure 1(c) the obtained tract reconstruction is illustrated. Such map reconstruction is focused on the polyp surface to improve the lesion examination. The red color in this map represents the regions near to the camera while the blue color stands for those regions far from the optical reference.

The results herein reported show reliable surfaces of the digestive tract, highlighting the polyp shape which is the most important region to determine the malignancy of the tumor and also to define the surgical procedure. The applied kernel is appropriate to the emulation of the camera distortion without losing any definition of the polyp visualization. In addition the proposed strategy processes the information in terms of milliseconds, facilitating the introduction of this tool as support to the diagnosis during endoscopy process.

3.4 Conclusions

In this work a novel approach that reconstructs a digestive tract is presented, highlighting the polyp surface to improve the gastroenterologist exploration. The proposed strategy is fully automatic and obtains a depth estimation from a spatio-temporal analysis. Future work includes the evaluation in a large dataset and the validation with artificial structures.

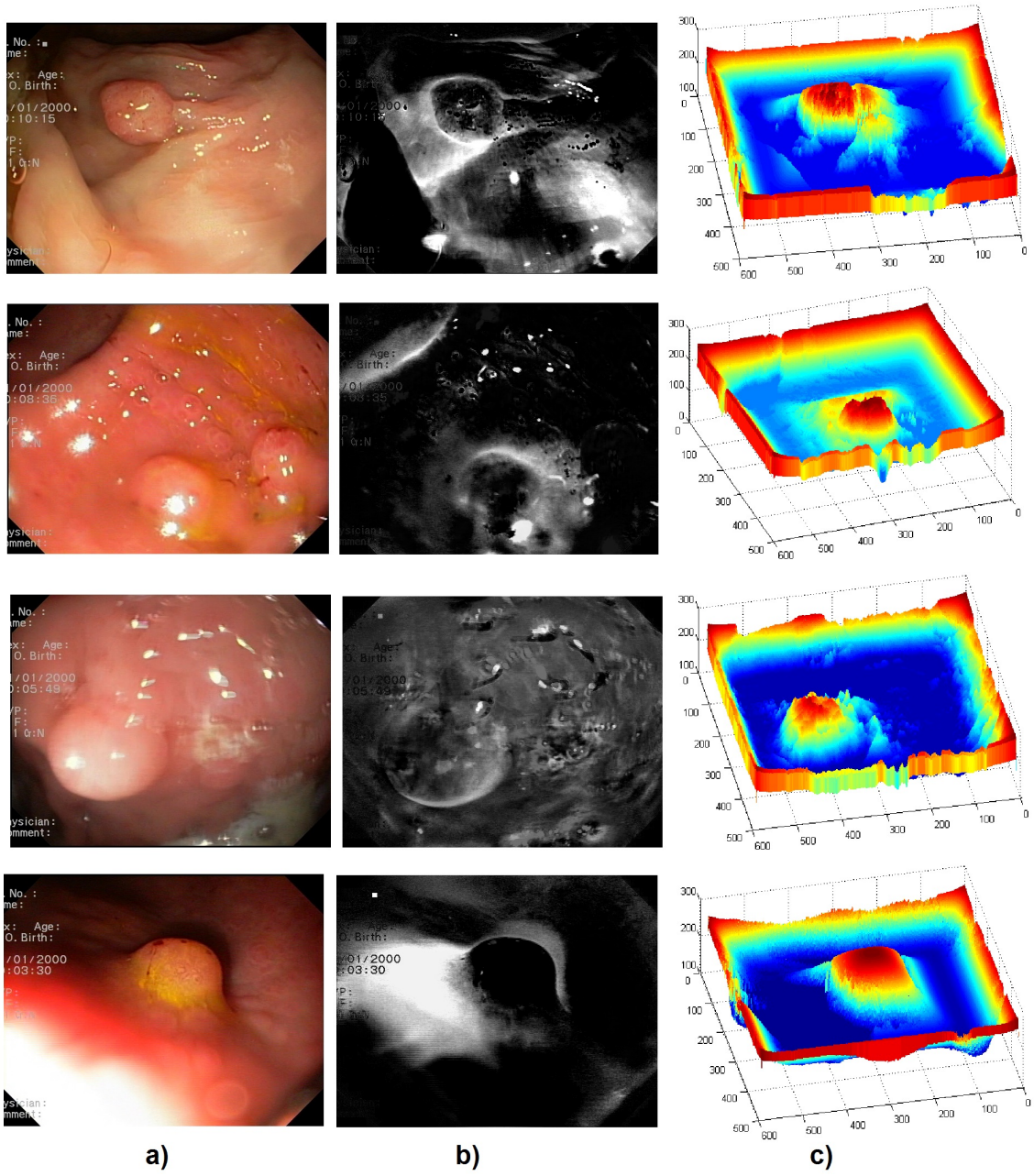


Figure 3-1: Figure 1. (a) shows the original frame and (b) the corresponding spatio-temporal map obtained from the local motion analysis. Panel (c) depicts the obtained reconstruction from the proposed strategy.

4 Conclusions and future work

This thesis has explored the problem to determine the malignancy of the neoplasic lesions from polyp size estimation in endoscopy sequences. To achieve this task, semi-automatic method was proposed using a combination of local motion information and appearance polyp features showing a reliable segmentation, tracking and size estimation of the polyp during a endoscopy video sequence. Additionally, a 3D endoscopy saliency map was reconstructed, facilitating the polyp shape evaluation by highlighting its surface geometry and allowing an analysis from different perspectives. In a future work, a strategy to automatically initialize the segmentation will be integrated, based on machine learning strategies while the segmentation will be refined with alternative polyp appearance descriptors. Subsequently, the complete method can be use as supporting diagnostic tool for the specialist.

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