Detection of Lesions in Colonoscopic Images: A Review

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Abstract— **Colonoscopy is one of the best methods for screening colon cancer and still is the "gold standard" despite advancements in the field of virtual endoscopy based on computer-tomographic imaging. As the automatic detection of polyps in endoscopic images is a challenging task for image processing, a variety of research groups have proposed methods that try to fulfill this task to develop a system which supports the doctors during examination. However, the problem can still not be assumed to be solved. This paper provides a review of the state of the art in detection methods published within the last decade. We found out that the major drawback of many approaches is the lack of representative video data, which hinders comparison and evaluation of the published methods.**

Keywords— **Computer-Aided Detection, Colonoscopy, Classification, Review**

I. Introduction

According to the World health organization (WHO), colorectal cancer is the third most common form of cancer [1]. With approximately 639,000 deaths per year worldwide it is also on the second place regarding cancer-related death in the western countries. In about 80% of cases, colonic polyps (adenomas) are the precursors of colorectal cancer making the early detection of such polpoid lesions a highly important goal of regular screening programs. However, the effectiveness of the screening strongly depends on the quality and thoroughness of the examination [2]. Within the tight schedule for the screening in clinical practice the recognition of small, immersed and flat neoplasia is very difficult and the reported rates for missing such lesions is quite high with a range of 15-25% [3,4].

This alarming statistics emphasizes the demand for computer systems supporting the doctors during examination. Three main causes that lead to misses can be distinguished:

- The endoscopist does not cover all parts of the colon (parts remain "unseen" by the endoscope),
- the polyp appears on the screen and the doctor sees it but does not identify it as a polyp,
- the polyp appears on the screen but the doctor does not look at the screen in this moment.

The first error is hard to tackle with computer systems, as it addresses 3D-reconstruction of non-rigid shapes from only one camera. To address the second type of errors, CADx-systems (Computer-Assisted Diagnosis) are needed that compare conspicious structures to a database of structures that already have a verified diagnosis. Most work has been done on the third problem, the Computer-Aided Detection (CADe) or on combined CADx/CADe-systems. Our work focuses on a review of current available techniques of polyp detection, i.e. on CADe systems.

II. State of the art

The problem of automated polyp recognition has been an active field of research since over 10 years now and still is of interest to various research groups. In the following we give an overview of the different approaches applied so far.

A. General structure of CADe-systems

In general methods for automatic detection of colorectal polyps and cancer are structured as follows: At first colonoscopic images or videos containing normal and abnormal cases are needed. In addition to that, ground truth information that labels the abnormalities is necessary. Extracted feature-data from the images are used to train a classifier which should be tested on a different set of images. Classifiers such as self organizing maps (SOM), support vector machines (SVM), neural networks (NN), or fuzzy approaches have been suggested.

Good classification results primarily depend on appropriate features that characterize polyps and cancer to distinguish between abnormal and healthy areas within an image. Training and testing of classifiers should be based on large sets of images showing different polyps, due to the high diversity of their appearances. In general one can distinguish two classes of approaches to polyp detection. These are shape and texture based methods such as the ones described in the following sections.

B. Shape-based methods

Krishnan et al. presented a method to detect abnormalities through curvature analysis. They use a thresholding method to segment the darker image regions, that are supposed to represent the intestinal lumen, and compute parameters such as perimeter, boundary area, and a form factor describing the irregularity of the enclosed region [5]. Later they used an edge detection approach, that is performed to extract contours, which are smoothed afterwards to make them suitable for curvature computation [6]. A similar approach by Hwang et al. is based on the elliptical shape that is common for nearly all small colon polyps. It is observed whether elliptical shapes fit into segmented regions by utilizing a watershed-based image segmentation and ellipse fitting algorithms. New techniques are proposed to distinguish the ellipses of polyp regions from those of non-polyp regions by matching curve direction, curvature, edge distance, and intensity [17].

The techniques adopted by Dhandra et al. are based on segmentation of color endoscopic images in HSI color space followed by morphological watershed segmentation. The output of the process indicates whether the endoscopic image is normal or abnormal based on the number of watershed regions present in the image [18]. Kang et al. proposed a real-time image processing system for endoscopic applications. After detecting edges using the Canny-operator [19], a morphological operation is employed to thicken the edges and connect disjoint edges that are closer together. The emerging segments are classified as either a polyp or a non-polyp by extracting three features: area size, color and shape [20].

C. Texture-based methods

Wang et al. developed a method for classification of endoscopic images based on texture and Neural Networks. The Local Binary Pattern describes the spatial structure of local texture. Combining this pattern with average intensity leads to a two-dimensional histogram. A self-organizing map is applied for the classification process [7]. Li et al. proposed to represent the image regions using multi-size patches simultaneously. The features extracted from these patches include the means and standard deviations of the absolute value of the approximating and detail coefficients from a two-level Discrete Wavelet Transform decomposition of the image patches in the three channels of CIE-Lab color space. Other features include one-dimensional histograms of luminance L and two-dimensional histograms of the a and b components. An ensemble is constructed based on a set of individual Support Vector Classifiers to categorize patches as normal or abnormal [22].

Tjoa et al. proposed to use homogeneity histograms for segmentation of colonoscopic images [8] which serve as a basis for further classification. In a later work they extract different statistical measures from the texture spectra in the chromatic and achromatic domains. Furthermore, color features for a selected region of interest from each color component histogram are extracted. The feature vector's dimension is reduced using Principal Component Analysis. For evaluation, Back-propagation Neural Networks are used [9].

Alexandre et al. presented a method subdividing each image into small subimages with a fixed size of 40×40 pixels. The used features are RGB-values and coordinates of each pixel. As SVMs are able to deal with high-dimensional input spaces, learning and classification is performed on this raw data sets [12]. Coimbra et al. are investigating the potential of selected MPEG-7 descriptors for event detection (such as polyps) in colonoscopic images. Some of the used features among others are: color structure, homogenous texture and scalable color [29].

Karkanis et al. proposed a scheme based on features extracted from the grey-level co-occurrence matrix (GLCM). To distinguish between normal and cancer regions a multilayer feed-forward neural network is employed [21]. The same GLCM features were used by Magoulas et al. and different learning and classification techniques were investtigated [23, 24, 25]. An extension proposed by Karkanis et al. based on GLCM-features and discrete wavelet transform [26] was implemented in CoLD (colorectal lesions detector) [11]. Another extension by Karkanis et al. utilizes covariances of the GLCM-features calculated over the wavelet frame transformation of different color bands and linear discriminant analysis (LDA) [10]. Iakovidis et al. presented different approaches, all based on features (wavelet energy, correlation signature, …) computed from subimages and tested on several color spaces. SVMs handle the classification of the feature vectors computed from every single subimage [28]. Maximizing the use of available detection methods, Zheng et al. presented a fusion-based decision support system [27].

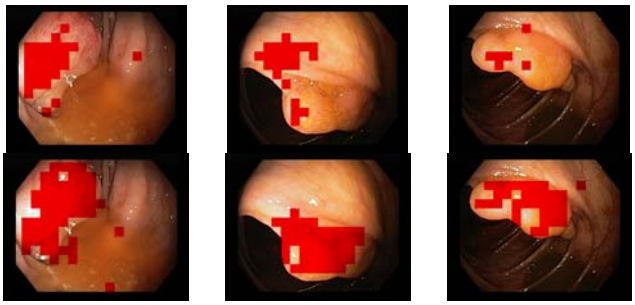

Fig. 1 Detection results: Modified color vector method according to [12] (first row), sum- and difference histograms [15] SVM (second row)

Common to all of these approaches is that a combination of color and texture information is aimed for which nevertheless only the work by Karkanis et al. [10] is doing in a way that captures direct correlations of texture and spectral information. Palm et al. [13,14] integrated spatial and spectral information by calculating the co-occurrence matrix directly from pair-wise adjacent chromatic planes in different color channels. This principle was adopted by Münzenmayer et al. [15] for the computation of inter-plane sum- and difference histograms that can be computed much more efficiently and thus are capable for realtime applications. Shevchenko et al. [16] used inter-plane sum- and difference-histograms together with an SVM-classifier to detect polypoid lesions on a database of 153 images, see. Fig. 1.

pagation neural network. Karkanis et al. [10,11], who also used textural methods for the detection of lesions in colonoscopic video sequences, report a specificity of 97% and a sensitivity of 90% for the detection of adenomatous polyps which is based on 1200 single frames from digitized video sequences. Alexandre et al. [12] also achieved classification rates up to 93% on a dataset consisting of 4630 regions of interest obtained from 35 single image frames.

However, the expressiveness of these results can be called into question due to several facts. First, except for a few cases, the sample sets used for testing and training usually are relatively small. It is also of high importance what kind of evaluation scheme was used. In cases where cross-validation of image regions extracted from the same image sequences (or the same patient) have been used, the generalization of methods seems to be questionable. That means, there is a high risk of over-adaption to a certain sample set, so that the classifier would not be able to correctly detect lesions on different image material. A reliable classification system should be based on a huge set of images containing many different types of abnormalities. Beyond quantity, the quality is an important factor, i.e. the modalities of image acquisition influenced by the optics, the sensor chip, quality and image enhancement settings of the video processor, standardization of illumination as well as final digitization and coding have to be optimized. Of course, in future, high definition (HD) colonoscopy will be standard so that digiti-

Table 1 Overview of different polyp detection methods described in current literature.

Research group	Methods / Fetures	Feature Class	Classifier	Datasets (#img; size)	Literature
Krishnan et al.	form factor, curvature	shape	-	9; 256 x 256	[5]
Krishnan et al.	curvature analysis	shape	-	2 normal, 4 abnormal	[6]
Hwang et al.	curve direction, curvature, edge distance, intensity	shape, color	-	27 polyps	[17]
Dhandra et al.	number of regions after morphological watershed transformation	shape, color	-	50 normal, 50 abnormal	[18]
Kang et al.	area, colour and shape of segments	shape, color	-	-	[20]
Wang et al.	Local Binary Pattern, intensity	texture, color	NN	3 images	[7]
Li et al.	Wavelet coefficients, Lab histograms	texture, color	SVM	12 normal, 46 abnormal; 256 x 256	[22]
Tjoa et al.	texture spectrum, colour histograms	texture, color	NN	12 normal, 54 abnormal	[9][8]
Alexandre et al.	RGB values and coordinates of each pixel	-	SVM	35; 514 x 469	[12]
Coimbra et al.	MPEG-7 descriptors	texture, color	-	899	[27]
Karkanis et al.	GLCM features, Wavelets	Texture	NN	2, 10, 4, 2, 8; 512 x 512	[21,24,23,25]
Karkanis et al.	Colour Wavelet Co-variance	texture, color	LDA, SVM	1380, 15000; 320 x 240	[10,26]
Iakovidis et al.	(Color) Wavelet Energy, Wavelet Correlation Signatures, (Opponent Color) Local Binary Patterns	texture, color	SVM	15000; 320 x 240	[26,28]
Shevchenko et al.	Sum- and difference histogram	texture, color	SVM	153	[16]

To provide an overview of all mentioned methods, the main aspects are summarized in Table 1. Additionally, a column ‘datasets’ describes the data used for demonstrating or testing the methods in the corresponding approach.

III. Discussion

According to literature, the mentioned methods achieve remarkably good classification results. For example, the work of Tjoa et al. [9] report a classification accuracy of 97% on a data set of 66 images with 54 abnormal and 12 normal cases based on a combination of texture and color features with a principal component analysis and back-pro-

zation and interlacing artifacts should now really become a problem of the past.

IV. CONCLUSIONS

In this paper we presented an overview of colon polyp detection approaches proposed by several research groups. The benefits of automated lesion detection could be numerous as the effectiveness of preventive colonoscopy is very dependent on the quality of the examination. Thus, this research topic still is of high interest. In our opinion, the major problem today is the lack of a representative database that contains enough annotated lesions. Each relevant lesion should be delineated by a clinical expert and its relevance verified, e.g. by histological evaluation. These lesions should be captured from several hundreds of patients, to also capture individual differences. Thus, new methods could be evaluated against a valid "gold standard" and also compared to each other to really advance the field. Only with such a basis systems that are really clinically relevant can be developed.

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