Features for Classification of Polyps in Colonoscopy

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Abstract. Colonoscopy is the gold standard for detection of colorectal polyps that can progress to cancer. In such an examination physicians search for polyps in endoscopic images. Thereby polyps can be removed. To support experts with a computer-aided diagnosis system, we compare different methods for automatic detection. Comparable to traditional pattern recognition systems, features are initially extracted and a classifier is trained on such data. Afterwards, unknown endoscopic images can be classified with the previously trained classifier. In this contribution we concentrate on the extension of the feature extraction module in the existing system. New detection methods are compared to existing techniques. Several features are tested, such as Graylevel Co-Occurrence Matrices (GLCM), Local Binary Patterns (LBP), and Discrete Wavelet Transform features. Different modifications on those features are applied and evaluated. We extend feature detectors to use color in different color spaces. We also compare different classifiers such as Support Vector Machines (SVM) and k-Nearest Neighbor classifier.

1 Introduction

Colonoscopy is the accepted gold standard for screening colon cancer or colorectal polyps, but there is a 6–12 % miss rate for adenomas that are 1cm or larger; the miss rate for smaller adenomas is up to 25 %. It is desirable to develop a system that marks polyps reliably during the screening process leading to a significantly decreased miss-rate.

Features for polyps are mostly from shape or from texture, or combined methods, as we outline in the following.

Krishnan et al. [1] approach is based on finding contours of abnonormalities in the colon. The method of Hwang et al. [2] relies on the elliptical shape of colon polyps by applying watershed image segmentation. Wang et al. [3] propose a feature extraction method called Local Binary Pattern (LBP) which is a local texture descriptor. Karkanis et al. [4] propose a scheme which uses textural descriptors based on second order gray-level statistics called Graylevel Co-occurence Matrices (GLCM), intitially proposed by Haralick [5]. Karkanis et al. [6] propose a new color feature extraction scheme named Color Wavelet Covariance based on a fixed size sliding window. Further investigations are made here into these approaches.

All in all the results of these methods are hardly comparable because of the usage of different data bases, which are beside this often too small to make reliable predictions.

2 Materials and Methods

The data base in this contribution consists of four hours of video data from different colonoscopies initially used in [7]. It has been evaluated by medical specialists to obtain ground-truth data. Four scenes are extracted with polyps under varying illumination, view angle and distance. Each of the scenes has approximately 400 single frames and a resolution of 800×800 pixel. From the four scenes a heterogenous set of 130 frames is randomly chosen for further testings.

To represent ground-truth data image masks are created as depicted in Fig. 1. The white region describes the exact location, size and shape of a polyp.

The image is divided into overlapping patches. For each patch, a feature vector is computed and classified as *polyp* or *non-polyp* by considering the number of white pixels in the mask images, which must be larger than a certain threshold (≥ 625 pixel) to count as *polyp*. We extend [7] as we now use all patches and introduce new features.

The classification of the features is evaluated by the area under the ROC curve (AUC) value. Therefore, a data mining software called WEKA[1] and the classification library LibSVM[2] provide adequate means.

[1] http://sourceforge.net/projects/wekaclassalgos
[2] http://www.csie.ntu.edu.tw/ cjlin/libsvm

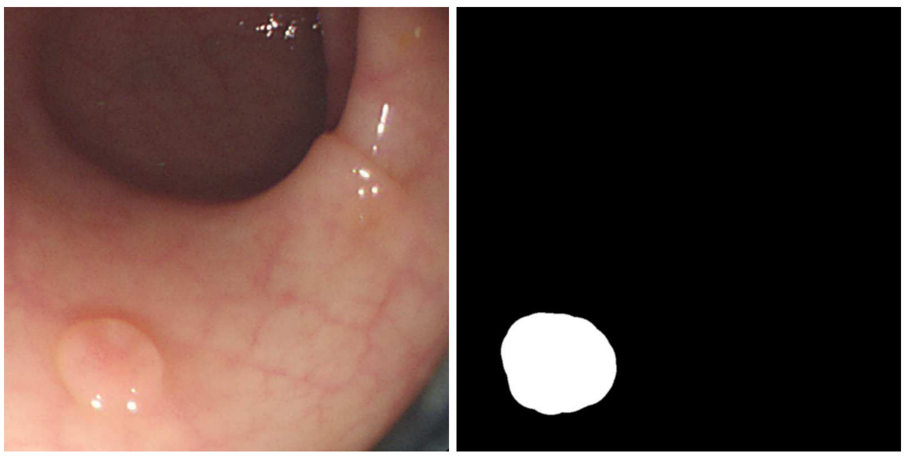

Fig. 1. Endoscopic image and its reference mask.

Table 1. Overview over the implemented features and their highest AUC value. Several properties are listed such as the dimensions of the feature vectors, color or gray information and patch size.

Feature	dim	color	gray	patch size	AUC LibSVM	AUC k-NN
ColorGLCM	72	×		32 × 32		0.843
L_8^{subset}	59	×		64 × 64	0.835	
ColorLBP	192	×		64 × 64	0.834	
OC-GLCM	108	×		64 × 64	0.832	
Color Wavelet	144	×		128 × 128	0.820	
OC-LBP	576	×		64 × 64	0.818	
WaveletDecomp	36	×		128 × 128	0.799	
$L_{16}^{subset,ri}$	54	×		64 × 64	0.799	
L_8^{ri}	108	×		64 × 64	0.792	
LBP	64		×	64 × 64	0.760	
GLCM6	6		×	64 × 64	0.740	
GLCM16	16		×	64 × 64	0.735	

We introduce new features based on texture such as ColorGLCM and ColorLBP, which are applications of GLCMs/LBPs on each RGB-color channel. The ColorGLCM method $F_m(P_{d,\theta}(I^i))$ produces for each channel i of the patch I four GLCMs $P_{d,\theta}$ with distance $d = 1$ and angle $\theta = 0°, 45°, 90°, 135°$. Then for each of the twelve GLCMs, six statistical measures m are extracted, namely energy, correlation, IDM, entropy, cluster shade and cluster prominence leading to a 72 dimensional feature vector. The Opponent-Color-GLCM (OC-GLCM) feature relates pairs of color channels by calculating GLCMs from the pixels of different color channels. Furthermore, several versions of rotation invariant LBPs and Subset LBPs [8] are tested.

Our wavelet features called ColorWavelet and WaveletDecomp also use GLCMs for representing texture after applying a three-level discrete wavelet transform to each patch and color channel. Again, statistical measurements are computed from the GLCMs which serves as input for the feature vector.

3 Results

Comparing the classification results from the SVM with the k-NN classifier leads to the conclusion that with less exceptions the SVM output has higher AUC values. No scheme could be investigated in which cases the latter performs better. Comparing the best classification results for each of the twelve features, the SVM holds the better results in eleven cases as shown in Tag. 1, which also clearly shows the advantages of using color. The best AUC result of all applied tests resulted from the ColorGLCM feature with a small patch size. The k-NN classifier performed best in this case with an AUC of 0.843.

4 Discussion

The published methods use very different image material. In this work, a very heterogenous set of images is chosen, containing frames from different scenes and different polyp types to make comparisons easier. We extend [7] by different texture descriptors and combine them to new features, incorporating wavelet transform, GLCMs and LBPs:

– Including color led to a significantly higher detection rate (+0.10 AUC for GLCM features). The single color methods performed equally well for the chosen data set. Only 0.05 AUC range lie between the best and the worst color method.
– The combination of all color channels of the RGB color space led to the best results.
– The discrete wavelet transform does not have the expected positive impact on polyp detection.
– The local binary pattern and the GLCM and their implemented variants perform equally well.
– The support vector machine classifier holds superior results in comparison to k-NN, considering the number of higher classification results.

Possible future extensions for a comprehensive polyp detection system are:

– Scale invariant features: Examine the resolution level of the texture by storing an additional parameter, which describes the distance to the intestinal wall during colonoscopy. An image normalization could be applied to achieve scale invariance.
– Over-complete wavelet transform: Compute translation invariant features by using the over-complete version of the wavelet transform (OCWT) [9].
– Preprocessing: Remove artifacts from endoscopic images such as shifted RGB color channels or glossy spots.
– Tracking: Prediction of a polyp's location to the next frame might help in classification.

References

1. Krishnan SM, Yang X, Chan KL, et al. Intestinal abnormality detection from endoscopic images. Proc IEEE EMB. 1998;2:895–8.
2. Hwang S, Oh J, Tavanapong W, et al. Polyp detection in colonoscopy video using elliptical shape feature. Proc IEEE ICIP. 2007;(2):465–8.
3. Wang P, Krishnan SM, Kugean C, et al. Classification of endoscopic images based on texture and neural network. Proc IEEE EMB. 2001;4:3691–5.
4. Karkanis SA, Magoulas GD, Grigoriadou M, et al. Detecting abnormalities in colonoscopic images by textural description and neural networks. Proc Work Mach Learn Med Appl. 1999; p. 59–62.
5. Haralick RM, Dinstein I, Shanmugam K. Textural features for image classification. IEEE Trans Sys Man Cybern. 1973 11;3:610–21.

6. Karkanis SA, Iakovidis DK, Maroulis DE, et al. Computer-aided tumor detection in endoscopic video using color wavelet features. IEEE Trans Inf Technol Biomed. 2003;7(3):141–52.
7. Ameling S, Wirth S, Paulus D, et al. Texture-based Polyp Detecion in Colonoscopy. In: Proc BVM; 2009. p. 346–50.
8. Mäenpää T, Ojala T, Pietikäinen M, et al. Robust texture classification by subsets of local binary patterns. In: Proc. ICPR; 2000.
9. Bradley AP. Shift-invariance in the discrete wavelet transform. In: Proc Digit Image Comput Tech Appl; 2003. p. 29–38.