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A Summary of Research Targeted at Computer-Aided Decision Support in Endoscopy of the Gastrointestinal Tract

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A Summary of Research Targeted at Computer-Aided Decision Support in Endoscopy of the Gastrointestinal Tract

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Abstract

Today, medical endoscopy is a widely used procedure to inspect the inner cavities of the human body. The advent of endoscopic imaging techniques – allowing the acquisition of images or videos – created the possibility for the development of the whole new branch of computer-aided decision support systems. Such systems aim at helping physicians to identify possibly malignant abnormalities more accurately. At the beginning of this work we give a brief introduction to the history of endoscopy, followed by introducing the main types of endoscopes which emerged so far (flexible endoscope, wireless capsule endoscope, and confocal laser endomicroscope), followed by an overview of systems developed to assist medical experts but not aiming at diagnosis support. We then give a brief introduction to computer-aided decision support systems specifically targeted at endoscopy in the gastrointestinal tract. Then, after presenting general facts and figures concerning computer-aided decision support systems, we summarize work specifically targeted at computer-aided decision support in the gastrointestinal tract. For this purpose we present the research activities grouped into coarse categories with respect to the the part of the gastrointestinal tract and the pathology the respective approach is targeted at. This summary is followed by a discussion of some common issues concerning the approaches reviewed and suggestions of possible ways to resolve them.

Keywords: Endoscopy, Wireless Capsule Endoscopy, Confocal Laser Endomicroscopy, Gastrointestinal Tract, Computer-aided Decision Support

1. Introduction

The first time the term endoscope was used was in 1806, when Philipp Bozzini developed the first kind of medical endoscope which he called "Licht-

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leiter". By using this device he already made the first attempts to examine the inner cavities of the human body. But endoscopes, as we know them today, significantly differ from the one Bozzini developed. In the early days of endoscopy the devices were lit by external light sources (a candle in the case of by Bozzini's apparatus) and not flexible. Thus, these devices were somewhat limited in terms of their usability. Modern endoscopes are very compact devices, including a light source, and a CCD or CMOS chip for taking pictures.

Nowadays the areas for using endoscopes are manifold. Besides medical procedures, endoscopes are also used to inspect airplane turbines, pipes in buildings or industrial machinery, car engines, tanks in ships, and for veterinary endoscopy. However, from now on when using the terms "endoscope" and "endoscopy" we always refer to the medical device and procedure, respectively.

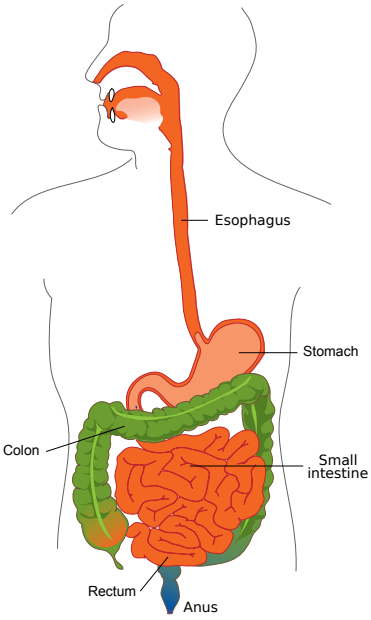


Figure 1: A schematic illustration of the human GI tract.

Since endoscopy is a minimally invasive and relatively painless procedure, allowing to inspect the inner cavities of the human body, endoscopes play an important role in modern medicine. While we restrict this review to the gastrointestinal tract (GI tract), there are also other organs regularly inspected by using an endoscope such as the respiratory tract, the urinary tract, and the female reproductive system. Based on endoscopy, physicians are able to detect severe diseases already in early development stages and therefore the mortality rate for many diseases has been lowered drastically. This especially accounts for different types of cancer. Some examples of conditions which are known to be pre-malignant or to increase the risk of cancer in the GI tract are adenomas, Barrett's esophagus, Crohn's disease, celiac disease, GI bleeding, and a Helicobacter pylori infection. The parts of the human GI tract, which are most commonly inspected with an endoscope, are illustrated in Figure 1.

The advent of endoscopes with the ability to take digital pictures created the whole new field of computer-aided decision support systems (CADSSs) in medical endoscopy. Such systems are designed to detect and/or classify abnormalities and thus assist a medical expert in improving the accuracy of medical diagnosis. In addition, different methods have emerged which do not directly provide decision-support. Instead they aim for example at enhancing image quality, detecting degraded images, or provide endoscope navigation support. Throughout this work we use the term "supportive systems" for such methods.

To highlight the relevance of CADSSs and supportive systems we conducted

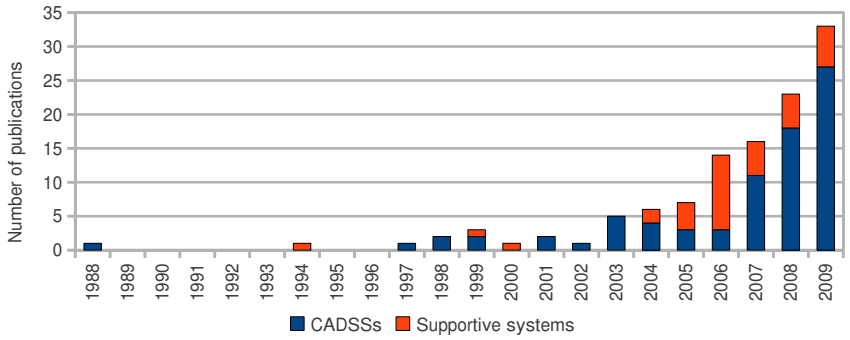


Figure 2: Number of publications between 1988 and 2009 found on PubMed and ScienceDirect when searching for publications dealing with CADSS or supportive systems for medical endoscopy (search was conducted on the 26^{th} of May, 2010).

an exhaustive search for publications dealing with these topics (on PubMed [1] and on ScienceDirect [2]), which yielded the search results presented in Figure 2. In order to find relevant publications our search was based on key terms corresponding to different endoscopic techniques and pathologies (the respective search queries used can be found in the Appendix). The results show that there is a rising interest in this research topic, starting about one decade ago.

The remaining part of this work is structured as follows: Section 2 reviews the technological advances in endoscopy. In Section 3 we give an overview of existing supportive systems. We then discuss CADSS in more detail in Section 4. This discussion includes a brief overview of CADSS, general facts and figures, and a detailed review of proposed CADSSs found in literature. Problems inherent to CADSSs and possible ways to cope with them are discussed in Section 5. Section 6 concludes this work.

2. Technological advances in endoscopy

Medical endoscopy, as we know it today, is performed using a flexible endoscope (Figure 3(a)), sometimes also referred to as videoscope.

This type of endoscope has been introduced in the mid 1960s. In contrast to modern devices, which are usually equipped with a digital imaging chip, the first endoscopes used fiber optics and an eyepiece lens to visualize cavities in the human body. But the basic concept did not change very much since those days.

Modern endoscopes contain a light source at the distal tip and are equipped with an accessory channel, which allows the entry of medical instruments for

[1] PubMed located at `http://www.ncbi.nlm.nih.gov/pubmed`
[2] ScienceDirect located at `http://www.sciencedirect.com`

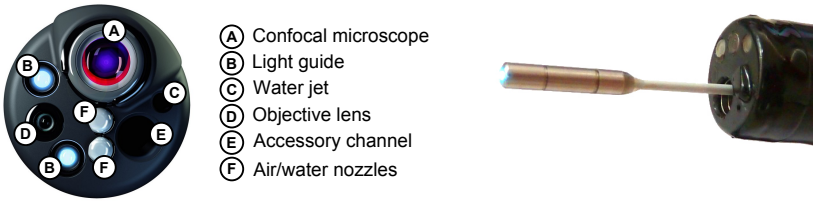
(a) Flexible endoscope (b) WCE capsule

Figure 3: (a) A flexible endoscope (Image courtesy of Olympus) and (b) an example of a WCE capsule (Image courtesy of Given Imaging).

example to take tissue samples, perform cleansing of poorly prepared areas, perform polypectomies, and perform endoscopic resections without any invasive surgery involved. Besides that, modern endoscopes may be used to take digital pictures and video sequences due to the digital imaging chips used.

If color dyes are topically applied onto the mucosal surface, superficial patterns are enhanced and can be observed more easily (e.g. vascular patterns), allowing to distinguish between normal and abnormal lesions. This procedure, which is essential for the diagnosis of certain diseases and allows targeted biopsies, is commonly referred to as chromoscopy or chromoendoscopy. But since topical staining is time-consuming and needs an experienced endoscopist there has been much research effort to develop systems which are easier to be used. One such recently developed method is Narrow Band Imaging (NBI) (Emura et al., 2008; Gross and Wallace, 2006; Inoue et al., 2008; Rey et al., 2007). Similar to chromoendoscopy, NBI allows to enhance the contrast of vascular patterns on the mucosal surface. But instead of using color dyes this system enhances the contrast in the capillary patterns by using rotating filters in front of the light source, which narrow the spectrum of the visible light to narrow bands of blue and green, resulting in a pseudo-colored image. Compared to topical staining, NBI is easier to be used because such systems feature a simple button to switch between white-light endoscopy and NBI. In terms of enhancement quality the results are very similar to chromoendoscopy. Besides that, a study by Su et al. (2006) showed that the diagnostic accuracy is at least equal to that of chromoscopy. Other systems similar to NBI, like FICE (Fujinon Intelligent Chromoendoscopy) or I-scan, use computer algorithms to post-process endoscopic images. Systems like NBI, FICE, or I-scan are referred to as "virtual chromoendoscopy".

Endoscopes allowing to zoom in at interesting regions are called zoom-endoscopes. These devices offer a significant advance since smaller and finer details in the region to be examined get uncovered (Hurlstone et al., 2004; Kato et al., 2006; Konishi et al., 2003; Stergiou et al., 2006; Tung et al., 2001). While standard endoscopes provide a magnification factor of approximately 30, zoom-endoscopes allow a magnification factor of up to 150. Another possibility to obtain images with a higher level of detail are high definition (HD) endoscopes,



(a) Dedicated system (b) Probe-based system

Figure 4: (a) The tip of an eCLE system (Image courtesy of Pentax) and (b) a probe-based system (Image courtesy of Mauna Kea Technologies).

which also provide images of higher resolutions and therefore allow to detect subtle changes in the mucosa. But according to a study by East et al. (2008) it seems that this does not automatically lead to higher detection rates of polyps or adenomas.

Another recent advance in endoscopy is confocal laser endomicroscopy (CLE) (Gheorghe et al., 2008; Kiesslich and Neurath, 2007; Nguyen and Leong, 2008; Vercauteren et al., 2008). This procedure allows to inspect the mucosal surface in a highly detailed manner. This is achieved by a laser-based endomicroscope which scans the surface of the mucosa. By using this technique it is even possible to inspect sub-surface features up to a depth of 250 microns by adjusting the focal point of the laser. Since this method relies on fluorescent light, the tissue to be examined is usually treated with fluorescent dyes. The resulting images have a resolution corresponding to a magnification factor of 1000, making "smart" biopsies possible, thus avoiding random and possibly unnecessary biopsies. Currently there exist two different types of CLE systems: probe based systems where a CLE probe is passed through the accessory channel of an endoscope (pCLE) and dedicated systems which integrate the endomicroscope at the distal tip of the endoscope (eCLE). In Figure 4 tips of an eCLE and a pCLE system are shown. In order to obtain high-magnification images, a region of particular interest is identified using the standard magnification of a white-light endoscope. Once such a region is reached, the tip of the endoscope (or the probe) is placed such that it gently touches the tissue of interest. Then the endoscopist is able to switch to the CLE view. It has already been shown that the diagnostic accuracy of CLE is comparable to histology (Buchner et al., 2010; Gómez et al., 2010; Wallace and Kiesslich, 2010).

Figure 5 shows a schematic illustration of standard endoscopy, zoom-endoscopy, and CLE. As can be noticed from this figure the distance of the endoscope tip to the mucosa under inspection differs between these techniques. This is due to the different focal depths inherent to the different techniques. As a result, the field of view (FOV) differs also between the devices. While standard endoscopes usually have FOVs between 120° and 170°, zoom-endoscopes have rather limited FOVs between 50° and 70°. This naturally affects the size of the visible mucosa

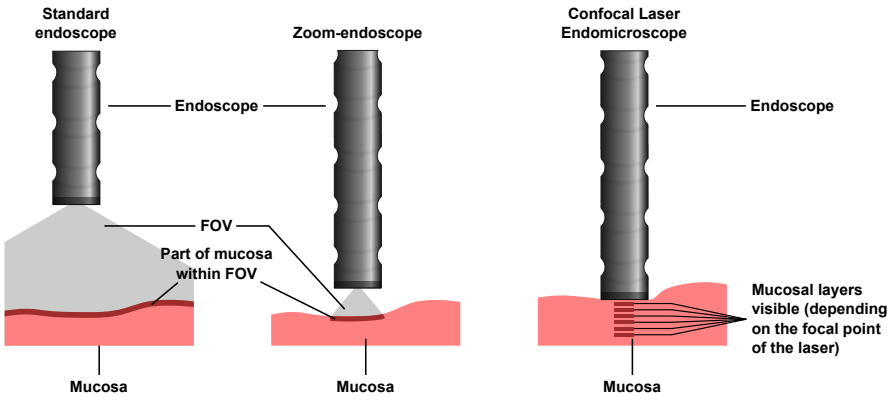


Figure 5: Schematic illustration of the different endoscopic techniques.

regions. In case of CLE the FOV is even more limited, resulting in a visible region of about $500 \times 500 \mu m$. Nevertheless, the limited FOV comes along with the advantage of higher image resolutions.

Although this work is restricted to endoscopy in the GI tract there also exist other cavities within the body which are regularly inspected with an endoscope, such as the lower respiratory tract (bronchoscopy), the nose (rhinoscopy), the urinary tract (cystoscopy), or the female reproductive system (gynoscopy) including the cervix (colposcopy) and the uterus (hysteroscopy). Common to these procedures is the fact that they are performed through natural orifices. But there also exist procedures which are performed through small incisions to reach cavities which are normally closed, such as for the example the abdominal or pelvic cavity (laparoscopy), the interior of a joint (arthroscopy), or organs of the chest (thorascopy).

Another novel field, which has emerged throughout the last years and is still in the initial stages, is natural orifice transluminal endoscopic surgery (NOTES) (Hochberger et al., 2009). While standard surgical procedures are invasive, requiring incisions to be made, NOTES aims at minimally invasive surgical procedures through natural orifices (transvaginal, transgastral, transcolonic, or transvesical). Despite the fact that this method may revolutionize the field of digestive endoscopy and offers several potential benefits for patients, such as lack of scars and faster recovery, there are still ethical concerns and numerous technical limitations.

One thing common to all procedures based on flexible endoscopes is the fact that inspecting the inner cavities of the human body is rather uncomfortable for a patient. In addition, by using a flexible endoscope there are potential side effects, such as perforation of organs, infection, and hemorrhage. As a consequence there has been much research effort to cope with these problems. To make endoscopic procedures less risky and more comfortable for a patient one focus of research are self-propelled endoscopes. In (Glozman et al., 2010)

the authors propose a system allowing to advance an endoscope into a body tube using an earthworm-like locomotion. To achieve peristaltic motion serially interconnected inflatable balloons are used.

The small intestine is especially problematic since it is very long and convoluted. Therefore a traditional flexible endoscope cannot be used to inspect the entire length of the small intestine. However, a rather new technique, called double-balloon enteroscopy (Fry et al., 2009), may be a prospective alternative to cope with this restriction. Another way to overcome this limitation and to make endoscopic procedures more safe, less invasive, and more comfortable for the patient, is wireless capsule endoscopy (WCE) (Coimbra et al., 2007; Qureshi, 2004), which has been developed recently. To perform WCE the patient swallows a small capsule (Figure 3(b)), which basically contains a light source, lens, camera, radio transmitter, and batteries. The capsule then travels through the digestive system, propelled by peristalsis, and automatically takes a huge number of pictures during a traveling time of about eight hours. Since approximately two pictures per second are taken, the resulting set of images contains more than 50 000 images. More recent capsules provide higher frame rates yielding even more images, which are transmitted wirelessly to a recorder worn outside the body. The quality of these images is still low compared to flexible endoscopy and needs to be improved (Arnott and Lo, 2004; Hara et al., 2005; Mylonaki et al., 2003; Swain, 2008). Initially developed as a better diagnosis tool for the small intestine and limited to the investigation of the GI tract, it has become a valuable tool, especially for detecting the cause of gastrointestinal bleeding (Eliakim, 2004; Iddan et al., 2000; Lewis and Goldfarb, 2003; Mylonaki et al., 2003). But there are also other areas of interest for examination in the GI tract such as the colon (Fireman and Kopelman, 2007; Iobagiu et al., 2008) or the esophagus (Eliakim et al., 2004).

A potential problem with WCE is an eventual retention, for example, in case of strictures or obstructions within the bowel, making a surgery necessary to remove the capsule. Besides that, WCE does not provide the possibility to treat lesions directly, obtain biopsy samples, clean poorly prepared areas, control the orientation and motion of the camera, which are major drawbacks compared to flexible endoscopes (Hara et al., 2005). To cope with such limitations there is already a lot of research going on. In (Carpi et al., 2006; Quirini et al., 2007), for example, prototypes of capsules with controlled motion are presented. Arena et al. developed a capsule prototype with an external power supply and tiltable optics to extend the field of view (Arena et al., 2005). Furthermore, a comprehensive review of recent patents on WCE is given in Moglia et al. (2008), which shows that many research groups aim at improving the usability of capsule endoscopes. Another, more recent advance is a prototype of a capsule, which can be navigated through the stomach using a joystick and an artificially generated magnetic field (Magnetically guided capsule endoscopy) [3]. Apart

[3] `http://www.siemens.com/press/pool/de/pressemitteilungen/2010/Healthcare/H20101001e.pdf`.

from that, there exists a project called VECTOR [4] which is funded by the European Commission. The primary goal of this project is the development of a novel capsule endoscopy device, offering a user-controlled navigation through the body, taking biopsy samples, and treating lesions. One result of the VECTOR project is presented in Carta et al. (2009). In this work the authors present preliminary results for a self-propelled capsule prototype.

Despite the current limitations of WCE this new technique has already proven to be an effective diagnostic modality for detecting small bowel tumors and small bowel lesions (Cobrin et al., 2006), and may also become an important tool to detect other abnormalities in the GI tract (El-Matary, 2008).

Another recent advance in endoscopy is virtual endoscopy (Bielen and Kiss, 2007; Blachar and Sosna, 2007; Wood and Razavi, 2002) (VE), also referred to as computed endoscopy. This method differs completely from flexible endoscopy and WCE as it is completely non-invasive (apart from insufflating the bowel as a preparation step). The data to be analyzed is acquired using helical or spiral computer tomography (CT) or Magnetic Resonance imaging (MRI). This usually results in a huge number of slice images, which are sometimes used directly for a decision support system. But it is also common practice to use the slices to create 3D models, which are then used for further inspection by medical experts. Due to the almost completely non-invasive nature of this procedure, the fact that no sedation is required, and since it is rather fast, it is a comfortable procedure for the patient. However, one major drawback of virtual endoscopy is the lack of structural and color information (i.e. the texture pattern of the colonic mucosa) since the underlying data for the 3D model basically implies positional information only. Apart from that, very small abnormalities may easily be missed due to the limited resolution of the underlying image acquisition techniques.

Since virtual endoscopy differs significantly from all other techniques described above in terms of the underlying imaging technique, the remaining part of this work is focused on flexible endoscopy and WCE only.

3. Supportive systems

The main focus of this work lies on CADSSs. But there also exist other types of systems which, while not fitting in the category of decision support systems, also aim at supporting medical experts during the task of establishing a diagnosis or support the operation of CADSSs. In this work we refer to such systems as supportive systems.

From Figure 6 we notice that the first work on such a system has been published in 1994, based on flexible endoscopy. It gets also apparent that the number of supportive systems increased rapidly with the advent of WCE (starting in 2005). From this point on the majority of such systems has been developed for WCE (about 72% in total). The remaining methods have been developed to

[4] http://www.vector-project.com

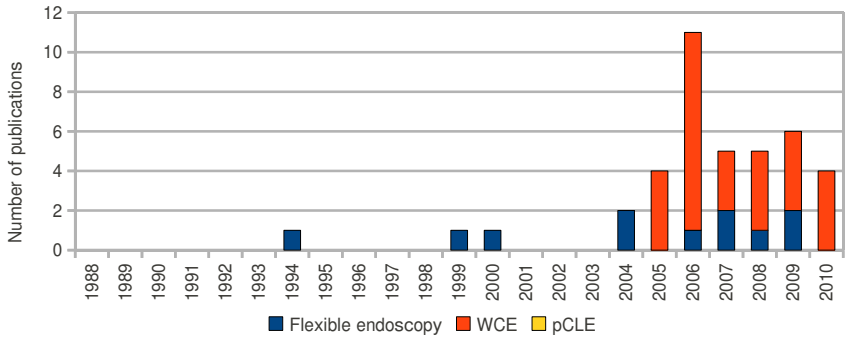


Figure 6: Number of publications on supportive systems throughout the last two decades.

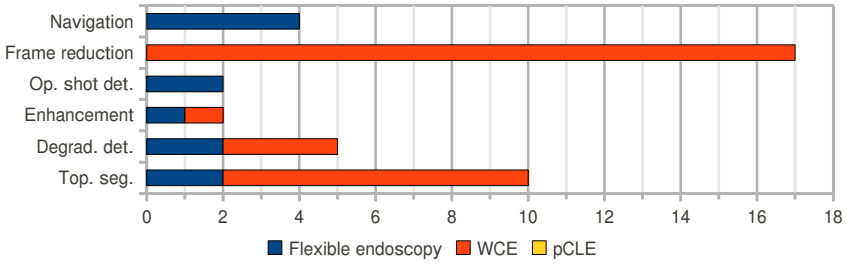


Figure 7: Number of supportive systems aiming at endoscopy in the GI tract found throughout literature.

support flexible endoscopy (about 28% in total). We also notice that there exist no supportive systems for pCLE in the GI tract so far.

Figure 7 gives an overview of the number of different supportive systems found in literature. Obviously the most frequently addressed tasks are frame reduction and topographical segmentation, which are very specific to WCE. Throughout this section we briefly summarize the different types of systems we were able to identify in literature.

3.1. Navigation support

The idea behind such systems is to aid the physician in advancing the endoscope through the body cavities, which is a fairly complex task. A common assumption in case of such systems is, that distant regions within the cavity correspond to dark regions within the image taken by the endoscope. As a consequence most work found in this area is developed in order to find the lumen center (Krishnan et al., 1994, 2000; Kwoh et al., 1999). But there exists also work aiming at biopsy site retargeting (Atasoy et al., 2009).

At the time of this writing such work is solely focused on flexible endoscopy, since WCE does currently not allow to control the motion and orientation of the capsule.

3.2. Operation shot detection

This is a field also dedicated to flexible endoscopy since WCE does not allow to take biopsies or perform endoscopic procedures like for example polypectomies. Basically such systems aim at detecting so-called operation shots in endoscopy videos. These are specific parts of videos which show endoscopic instruments such as snares, biopsy forceps, or balloons (Cao et al., 2004a, 2007).

By detecting such sequences in videos automatically the reviewing time for videos can be lowered drastically. The main area of application for such systems is teaching or simply providing the ability to review endoscopic operations.

3.3. Topographic segmentation

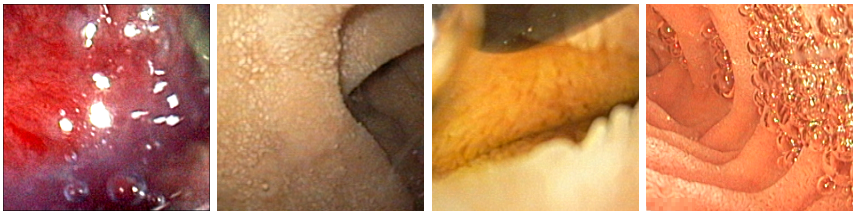
This type of systems aims at performing a segmentation of endoscopic videos with respect to the different GI tract parts. In other words, such systems automatically annotate the different parts of the GI tract. This enables a medical expert to browse faster to a part of interest. Consequently, such systems allow to save time and therefore cost associated with the usual reviewing time. Especially in case of WCE such systems are of particular use, since, due to the vast amount of images generated per WCE session, inspection of such videos is time consuming and therefore expensive in terms of the time raised by a medical expert (Coimbra et al., 2007; Swain, 2003). Hence, it is not surprising that the majority of the approaches found, aiming at topographic segmentation, is based on WCE (Berens et al., 2005; Coimbra et al., 2006a,b; Cunha et al., 2008; Lee et al., 2007; Mackiewicz et al., 2006, 2008; Vu et al., 2010). But also in case of flexible endoscopy such systems may be helpful to for example assess the quality of an endoscopic procedure (Oh et al., 2009) or automatically detect anatomical landmarks (Cao et al., 2004b).

3.4. Frame reduction

Basically, similar to topographic segmentation, the main aim of frame reduction is to save time and, hence, reduce the costs associated with the reviewing process of endoscopic videos.

There exist different types of such systems. One branch aims at filtering out video frames which are of no value for a medical expert due to certain degradations. Another branch aims at reducing the viewing time of endoscopic videos by condensing information (e.g. summarizing frames showing similar content) (Iakovidis et al., 2010; Tsevas et al., 2008), viewing the videos at variable frame rates, depending on the similarity of consecutive frames (Vu et al., 2006, 2009a), or detecting video parts belonging to certain events of interest (e.g. intestinal contraction detection for motility assessment) (Igual et al., 2007; Spyridonos et al., 2005, 2006; Vilariño et al., 2005a,b, 2006a,d,e, 2010; Vu et al., 2007, 2009b). But there also exist approaches to transform WCE videos into another form of visual representation, allowing to identify abnormalities faster and more easily (Szczypinski et al., 2009).

Common to all these approaches is the fact that the respective methods found in literature are focused solely on WCE, since this procedure generates a



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

Figure 8: Examples of different kinds of degradations which are quite frequently visible in endoscopic images and videos (a) specular highlights and reflections, (b) inhomogeneous light conditions, (c) blurry images, and (d) bubbles.

vast amount of video frames and, hence, offline reviewing is a time-consuming and tedious task in case of WCE.

3.5. Degradation detection and enhancement

Images acquired during endoscopy often suffer from various kinds of degradations (Hanna and Cuschieri, 2001) (some examples are shown in figures 8 and 9). Hence, in many cases pre-processing is necessary prior to any further use of the image data. In this work we distinguish between two different sorts of degradations: those which can be observed in endoscopic images but are not specific to endoscopy (e.g. noise, blurry images, inhomogeneous brightness and contrast) and those which are typically seen in endoscopic images. It must be noted, that, while there exists some work which is dedicated solely to degradation detection or image enhancement, in most cases such procedures are implemented as small parts of a bigger system.

In the following we first discuss common degradations, followed by degradations typical for endoscopic images and ways to cope with them.

3.5.1. Common types of degradations

Due to the fact that modern endoscopes are equipped with digital imaging chips (either CMOS or CCD) these devices are prone to sensor noise (e.g. thermal noise). This is especially noticeable when images contain areas of low intensity, resulting in grainy image parts. In addition current endoscopes do not provide the ability to focus. Therefore, moving the camera at the tip of the endoscope too close to the mucosa or too far away from the mucosa may result in blurred images (out-of-focus blur). A rapid movement of the endoscope tip usually also results in motion blur. Especially in the case of magnified endoscopy a rather small movement of the camera may result in noticeable motion blur. But blurry frames may also be caused by peristalsis.

Usually these types of degradations are fought by applying well-established image processing algorithms (denoising and deblurring algorithms operating either in the spatial domain or in the frequency domain). In (Vécsei et al., 2009), for example, it has been shown that by applying a Laplace filter kernel to endoscopic images, the classification results of the system proposed can be increased.

Vécsei et al. also concluded that for this kind of deblurring the filter size may be crucial, since by using kernel sizes which are chosen too small present noise most likely will get amplified.

Another commonly seen degradation is poor contrast and poor illumination in some parts of an image. This is caused by the fact that endoscopes are not necessarily facing perpendicular to the surface under inspection. Especially in the case where an endoscope is advanced through a cavity such as for example the colon, the endoscope is often facing towards the lumen center. As a result the regions farther away from the light source appear darker compared to the surface in the proximity of the endoscope tip. In some cases this may be helpful and give important cues (e.g. for lumen center detection). However, in general either texture descriptors invariant against global illumination changes are used (e.g. the LBP operator (Ojala et al., 1996)) or some sort of enhancement is applied to the images.

Enhancing such images by a global contrast enhancement will most likely fail and produce no significant enhancement. In this case operators working on local image regions are the more promising choice, e.g. Contrast Limited Adaptive Histogram Equalization (CLAHE) (Zuiderveld, 1994). In (Gschwandtner et al., 2010; Häfner et al., 2008b, 2009b, 2010d; Kwitt and Uhl, 2007, 2008a,b,c; Häfner et al., 2009e), for example, CLAHE has been used successfully to enhance the contrast in endoscopic images.

In (Li and Meng, 2006) the authors propose a contrast enhancement method specifically targeted at endoscopic images. For this purpose the authors start by analyzing the structure tensor of an image. Then a non-linear diffusion is applied taking into account the direction and strength of the structure tensor.

3.5.2. Specular reflections and highlights

Specular reflections and highlights are also image defects characteristic of endoscopy. Since the light source of an endoscope is usually facing into the same direction as the camera they can hardly be avoided due to the moistness of the tissue under examination. Such artifacts may vary in size significantly, ranging from small white spots to big white blobs.

The detection of such highlights is not always easy, since they do not necessarily correspond to the brightest areas within an image. Therefore histogram based techniques using a global threshold tend to produce unreliable results.

In the past several different methods have been proposed to cope with this problem. In (Gevers and Stokman, 2000) the authors use color gradient methods to detect highlight edges and fill closed contours of these areas. Another approach, proposed in (Vogt et al., 2002), is based on simple thresholds for saturation and illumination in the HSV color space (Gonzalez and Woods, 2007).

A more involved method, based on multi-thresholding, is proposed in (Oh et al., 2007). Oh et al. distinguish between areas of absolute brightness (usually larger regions with brightness above a certain threshold) and areas of relative brightness (smaller regions which are relatively bright compared to the surrounding pixels). After transforming an image to the HSV color space, areas of absolute brightness are detected if the brightness (value in the HSV model)

exceeds a certain threshold and the saturation is lower than some certain threshold. The detection of relatively bright areas is more involved. After segmenting the image into regions of similar texture and color, Oh et al. are searching for outliers (pixels brighter than the adjacent pixels) within these regions. Pixels which exceed a threshold based on the outliers and contain a saturation which is lower than some certain threshold are regarded as belonging to a relatively bright area (if these pixels have not been assigned to a region of absolute brightness already).

Once specular reflections have been detected, the corresponding image areas may be masked out from further processing steps or – if they are small enough – they may be removed using image inpainting methods. In (Stehle, 2006) specular reflections are removed from endoscopic images by first creating a reflection mask using thresholding based on a luminance histogram. Then spectral deconvolution is used to estimate the contents of the reflection areas. However, the authors report that their method generates block artifacts in areas with a high density of reflection spots. In addition, it is reported by the authors that their method in some cases destroys information surrounding a specular reflection, which is also an undesired behavior.

Another application of specular reflection detection is a pre-classification of images as out-of-focus images if the reflections have no distinct boundaries and the respective image is therefore not suitable for a subsequent feature extraction (Oh et al., 2007).

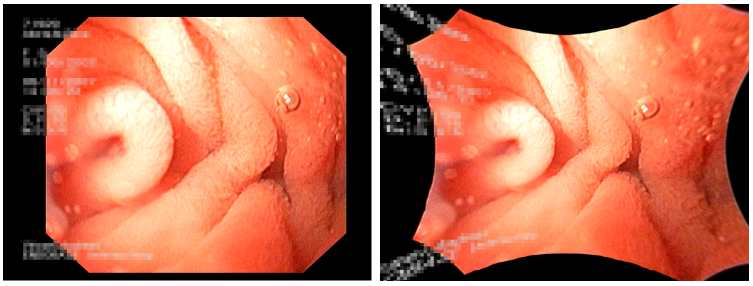
3.5.3. Fecal materials

This problem is especially apparent in colonoscopy (in flexible endoscopy as well as in capsule endoscopy). Due to poorly cleansed areas within the colon fecal materials may be visible during an endoscopic procedure. This may lead to an inaccurate diagnosis by a medical expert because of abnormalities eventually covered by fecal materials, which may be missed during colonoscopy (Church, 2008). Moreover, a CADSS may also get hampered by such image degradations.

To cope with this problem Hwang et al. proposed a system for automated stool detection in colonoscopy videos (Hwang et al., 2008). The aim of this system is to have a tool at hand which is able to automatically assess the quality of the colonoscopy procedure. For this purpose an image is subdivided into smaller blocks, for each of which the mean color is computed. Furthermore, a color histogram is computed for the input image. Then, using these features and the SVM classifier (Burges, 1998; Duda et al., 2000; Hsu et al., 2003), an initial mask showing stool regions is created. After applying the majority filter and a binary opening to the initial mask, the ratio of the pixels in stool regions to the non-stool pixels is computed and thresholded to obtain the final decision.

3.5.4. Intestinal juices and bubbles

During flexible endoscopy an expert is able to flush away residual foods or intestinal juices to clean poorly prepared areas within the GI tract. However, as already mentioned earlier, WCE lacks this ability, which is one major drawback of this technique. Hence, WCE suffers from video frames exposing intestinal



(a) (b)

Figure 9: Correction of a barrel-type distortion. (a) Example of a distorted endoscopic image and (b) the same image after applying distortion correction. As mentioned in the text, distorted texture can be observed especially in the outer regions of the image (i.e. the corners).

juices, turbid layers on tissue, and bubbles. As a result, a rather high number of unusable frames is generated (approximately 10 000 frames per WCE session, which corresponds to approximately 20% of all images taken). Since these frames contain no valuable information for a medical expert, an automated filtering of such frames is desired to be able to reduce the WCE video inspection time.

A work aiming at detecting intestinal juices with a bubble-like appearance is presented in (Vilariño et al., 2006b). To achieve this, Vilariño et al. compute Gabor filter bank responses at different scales and directions and use a thresholding to classify a frame as a bubble or non-bubble frame.

In (Bashar et al., 2010) a system to detect such uninformative frames is proposed. For this purpose the authors distinguish between highly contaminated non-bubbled (HCN), significantly bubbled (SB), and informative frames. To detect HCN frames color histogram based features in conjunction with the SVM classifier are used. In order to detect SB frames, Bashar et al. use Laguerre Gauss circular harmonic functions at multiple scales and Otsu's thresholding to decide whether a frame contains bubbles or not. If a frame is neither a HCN frame nor a SB frame, it is considered to be an informative frame.

3.5.5. Barrel-type distortions

In contrast to the previously mentioned degradations Barrel-type distortions constitute a special case. While the degradations discussed above are not necessarily present in all endoscopic images, Barrel-type distortions are present in all endoscopic images due to the wide-angle (fish eye) nature of optics used in endoscopes (although the strength of the distortions varies depending on the endoscope used).

Such distortions are claimed to affect diagnosis (Borcharrt et al., 2009) since they introduce nonlinear changes in the image. These distortions are especially noticeable in the outer regions of endoscopic images which are perceived considerably smaller than they actually are. Hence, properties of observed lesions

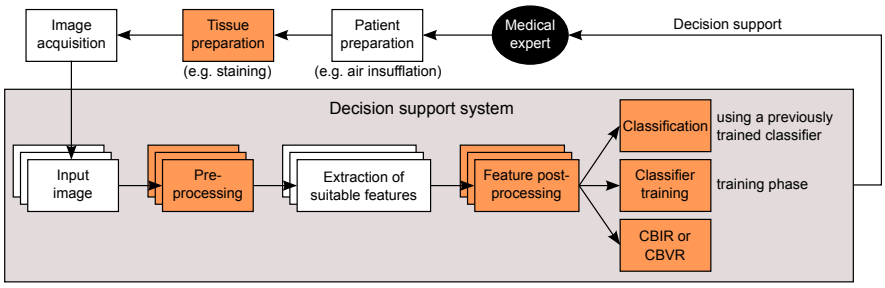


Figure 10: This figure illustrates common steps involved in a decision support system (colored boxes denote optional steps). Layers depict the possibility that multiple frames from an endoscopic video may be processed simultaneously to exploit inter-frame relationships.

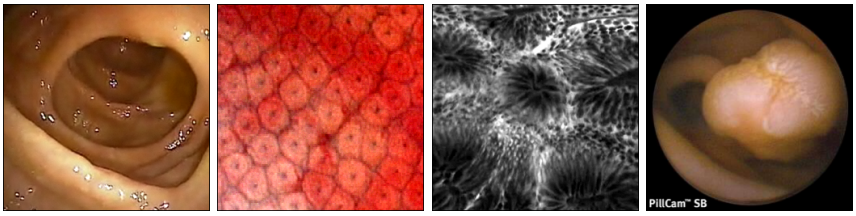
(e.g. perimeter or area) can be significantly incorrect, depending on their position within the image. In terms of pattern recognition this might also lead to corrupted features, as stated in (Haneishi et al., 1995). Since this seminal work on distortion correction of endoscopic images several distortion correction procedures have been developed for this application domain (Asari et al., 1999; Helferty et al., 2001; Sun et al., 2008). Figure 9 shows an example of a barrel-distorted endoscopic image and the same image after distortion correction. It can be easily seen that the distortion correction compresses image parts near the image center, while the outer parts get stretched (the stretching is especially noticeable in the image corners).

The only work so far, addressing the impact of distortion correction on an automated classification of endoscopic imagery, is given in (Gschwandtner et al., 2010). The aim of the experiments conducted in this work is to assess whether distortion correction has an impact on the diagnostic accuracy of an automated celiac disease detection system. The distortion correction used is mainly based on the work proposed in (Zhang, 2000).

4. Computer-aided decision support systems

This type of systems aims at providing a diagnosis. More specifically, such systems are designed to detect and/or classify abnormal pathologies.

A rough overview of common steps involved in a decision support system for medical endoscopy is shown in Figure 10. In many cases the first step is a preparation of the tissue region to be investigated (e.g. staining, treatment with fluorescent dyes). After an image has been acquired, pre-processing may be required in order to enhance the quality of possibly degraded images (as already described in more detail in Section 3.5). Then, depending on the aim of the application, suitable features have to be found and extracted. Sometimes a post-processing of the features is also necessary (e.g. removing invalid feature combinations in the case of high-level features). If the decision support system is targeted at classification (e.g. polyp detection, cancer detection) the features



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

Figure 11: Images acquired by using different endoscopic techniques (a) endoscopy (Kelsey, 2005), (b) zoom-endoscopy, (c) confocal laser endomicroscopy (Kiesslich, 2007), and (d) WCE (Copyright © 2005-2010, Given Imaging. All Rights Reserved).

are used for a classification of the image, using a previously trained classifier. But there exist also other systems which base their decisions directly on the features without using an intermediate classifier (e.g. by using feature thresholds) (Hwang et al., 2007). Similar to classification, some systems are targeted at content based image retrieval (CBIR) or content based video retrieval (CBVR). The main difference between automated diagnosis systems and CBIR/CBVR systems is the fact that, in case of an automated diagnosis, the output of such a system is a suggestion of the final diagnosis. CBIR/CBVR systems on the other hand present an expert a number of similar images or videos, from which the expert is able to decide by himself on the final diagnosis. In many cases the expert is also able to interact with the system, allowing to refine the result. Hence, CBIR/CBVR systems have an interactive nature, mainly suited for offline processing, while fully automated diagnosis systems may potentially be suited for realtime environments.

As already pointed out in Section 2, each endoscopic procedure generates images which exhibit specific characteristics depending on the technique used. Therefore, computer systems targeted at decision support must be designed accordingly. As can be seen from Figure 11(a) an image taken with a traditional flexible endoscope does not allow to see details of the tissue under examination. A zoom-endoscope, on the other hand, allows to examine the fine structures and details of tissue too (see Figure 11(b)). This, however, comes along with a rather limited field-of-view, which makes navigation more difficult. This problem is even more apparent in the case of CLE due to the high magnification nature of this technique (see Figure 11(c)). But this technique produces images which contain clear and detailed structures. In case of WCE the image resolution is often considerably lower compared to the aforementioned techniques (see Figure 11(d)). In addition, WCE suffers from the inability to control the motion and position of the capsule, which raises new difficulties for CADSSs.

From the example images shown in Figure 11 it is clear that – even in case of the same pathology – images taken with different endoscopic techniques will in general differ significantly.

In the next section we present general facts and figures for CADSSs. We

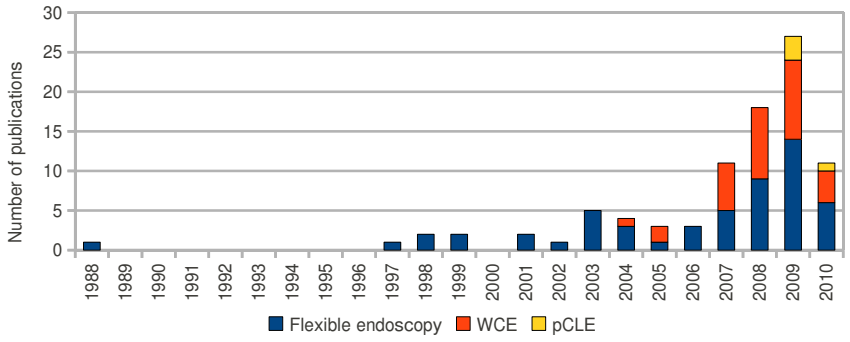


Figure 12: Number of publications on CADSSs throughout the last two decades.

discuss the spread of the different endoscopic imaging modalities across CADSS-related literature. This is followed by presenting facts and figures focusing on the the medical perspective of CADSSs. In the course of this discussion we first give an overview of the different parts of the GI tract which CADSSs have been developed for in the past. We then outline the different pathologies under investigation along with some medical background, also showing the importance of respective detection and classification systems. Finally, we discuss approaches found in literature from the image processing and classification perspective, providing details such as the transformations, features, and classifiers used.

4.1. Facts and figures

In Section 2 we already covered the main endoscopic techniques which currently exist to examine the GI tract. From these technologies flexible endoscopy is the most commonly used one. Since this technique has been developed about half a century ago, it is no surprise that the first CADSSs, which appeared in the 80's and 90's, were solely focused on this imaging modality.

This however changed with the development of WCE. As can be noticed from Figure 12 in the year 2004 the first methods focusing on WCE appeared. Since then, a fair amount of WCE-related work has been published.

Because of the fact that CLE is the most recent technique, the number of respective CADSSs targeting this technique is still low. The methods which can be found at the time of this writing are even only based on pCLE. Hence, up to our knowledge, there exists no CADSSs related work based on eCLE so far.

Figure 13 shows the number of publications found in literature dealing with CADSSs using the different endoscopic imaging modalities. This figure shows that flexible endoscopy is clearly the most frequently targeted endoscopic technique (about 60%), followed by WCE (about 35%), and pCLE (about 5%).

4.1.1. Areas for CADSSs in the GI tract

As already indicated in Section 1, the human GI tract consists of different parts. The parts of the GI tract which are most commonly inspected using an

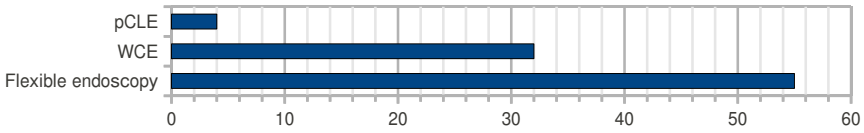


Figure 13: Number of diagnosis-related publications found for the different endoscopic image modalities.

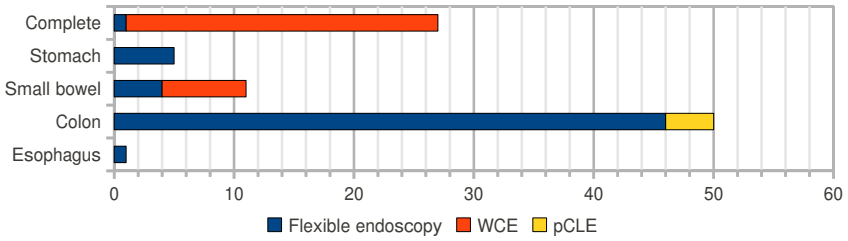


Figure 14: Number of CADSS-related publications per GI tract part.

endoscope are the esophagus, the stomach, the small intestine, and the colon. Figure 14 shows the distribution of the methods found in literature with respect to the different GI tract parts and the endoscopic techniques used. About 71% of the CADSS-related literature focuses on one particular part of the GI tract only. But there also exists a lot of work which aims at examining the complete GI tract and looking out for abnormal pathologies (denoted as "Complete" in Figure 14). As one can easily see, the majority of these approaches is based on WCE. This is quite natural as the capsule travels through the whole GI tract and therefore a WCE based CADSS is able to search for abnormal pathologies in almost the complete GI tract (basically only restricted by the endurance of the on-board battery).

It is also quite interesting to see that, besides examining the complete GI tract, the colon is obviously the most frequently targeted part of the GI tract (about 53% of the CADSS-related publications). This is most probably due to the fact that colon cancer in the third most common malignant disease in western countries. As a consequence, finding abnormalities within the colon is considered a very important field of research. Some of these abnormalities are known to either develop into cancer or to be precursors of colon cancer, hence, an early detection of such pathologies can lower the mortality rate drastically. But also the complete inspection of the GI tract amounts to a rather high share of CADSS-related publications (about 29%). As we have already seen in Figure 14, the endoscopic imaging modality most frequently used in this case is WCE.

4.1.2. Pathologies under investigation - the medical perspective

These days endoscopy is used to detect various types of pathologies, as already indicated in Section 1. As a consequence there exists a variety of pathologies which are targeted by different CADSSs. Roughly spoken, such systems

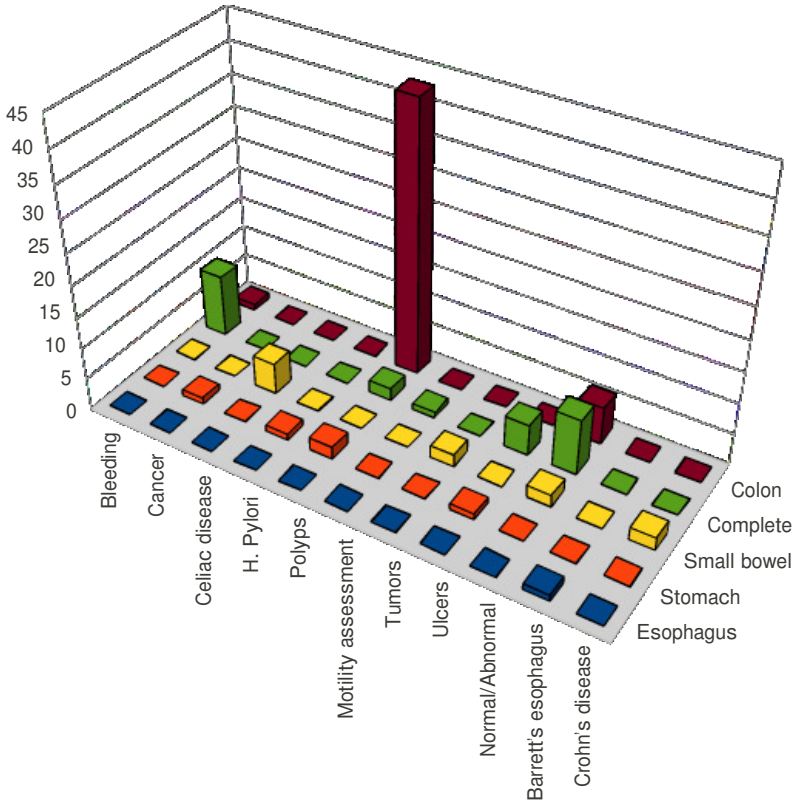


Figure 15: Number of CADSS publications per pathology category and GI tract part.

either try to detect or detect and classify certain pathologies.

It must be noted that there exist additional disorders which are currently not specifically addressed by CADSS-related research (although it is possible that work, distinguishing between normal and abnormal cases, may by targeted at some of them).

In the following we discuss the different pathologies which are in the focus of CADSSs-related research.

Polyp detection and classification

Polyps are masses of abnormal growth which are protruding out of the mucosa of a hallow organ such as the GI tract. While most polyps are benign, they can also be malignant. As can be seen from Figure 15, the detection and classification of polyps is a dominant field of research. In case of polyps, the GI tract part of particular interest is the colon. This stems from the fact that colonic polyps have a high prevalence, although other parts of the GI tract may also develop polyps (e.g. esophageal

polyps). In addition, adenomas are a special type of polyps which, while being benign, carry a high risk of developing into cancer.

Thus, as already discussed earlier, an early detection is imperative to lower mortality rates. In addition, a distinction between benign, pre-malignant, and malignant polyps is important for a medical expert to be able to choose the right treatment for a such a lesion.

With respect to CADSSs there is a difference between polyp detection and polyp classification. While a classification also implicitly performs a detection, polyp detection systems aim at the detection of polyps only, usually making no prediction on the malignant potential of a polyp.

Systems proposed solely for polyp detection purposes can be found in (Alexandre et al., 2007, 2008; Ameling et al., 2009; Cheng et al., 2008; Gross et al., 2009a; Iakovidis et al., 2004, 2005, 2006; Kang and Doraiswami, 2003; Karargyris and Bourbakis, 2009a; Magoulas et al., 2004a). In contrast to a detection, the systems proposed in (André et al., 2009a,b; André et al., 2010; Gross et al., 2009b; Häfner et al., 2006a,b, 2007a,b,c, 2008a,b, 2009a,b,c,d,e, 2010a,b,c,d; Karkanis et al., 1999, 2001a,b; Karkanis, 2003; Kwitt and Uhl, 2007, 2008a,b,c; Kwitt et al., 2010; Liedlgruber and Uhl, 2007; Maroulis et al., 2003; Stehle et al., 2009; Tischendorf et al., 2010) perform a classification of polyps found. The granularity of the classification (i.e. the number of classes considered) varies among these approaches. One share of these approaches performs a classification using two classes only. In (André et al., 2009a,b; André et al., 2010; Gross et al., 2009b; Häfner et al., 2010c; Karkanis et al., 1999, 2001a,b; Karkanis, 2003; Maroulis et al., 2003; Stehle et al., 2009; Tischendorf et al., 2010) the goal is a classification between non-neoplastic and neoplastic lesions. The remaining approaches in (Häfner et al., 2006a,b, 2007a,b,c, 2008a,b, 2009a,b,c,d,e, 2010a,b,d; Kwitt and Uhl, 2007, 2008a,b,c; Kwitt et al., 2010; Liedlgruber and Uhl, 2007) are based on the pit pattern classification scheme initially developed by Kudo et al. (1994, 1996). Besides a categorization of colonic lesions into non-neoplastic and neoplastic polyps, this classification scheme allows a more detailed classification into six classes (normal mucosa, hyperplasia, three classes of adenomas, and highly indicative for cancer).

While almost all of these methods are targeted at the colon, Iakovidis et al. propose a system specifically targeted at the stomach (Iakovidis et al., 2005) and another system, which they evaluated for images from the stomach as well as for images from colonoscopy (Iakovidis et al., 2006). Another exception are the methods proposed in (Kang and Doraiswami, 2003; Karargyris and Bourbakis, 2009a), which do not impose a restriction to a particular part of the GI tract.

From Figure 16 it is obvious that the most frequently used endoscopic technique for polyp detection and classification is flexible endoscopy. Only a few approaches are based on either WCE (Karargyris and Bourbakis,

2009a) or pCLE (André et al., 2009a,b; André et al., 2010).

Tumor detection and classification

Similar to a polyp, a tumor represents an abnormal proliferation of tissues, resulting from an abnormal cell growth. But while polyps appear on mucosal layers only, tumors may develop in various anatomic structures. In analogy to polyps, tumors can be either benign, pre-malignant, or malignant. Tumors of the latter type are in fact cancerous.

As we see from Figure 15, the number of CADSSs targeted at tumor detection is quite low. Apart from that, all work found in literature focuses on small bowel tumors only (Barbosa et al., 2008, 2009). Moreover, from Figure 16 we see that all this work is based on WCE. This is due to the already previously mentioned inability of flexible endoscopy to investigate the whole small bowel due to its lengthy nature.

Cancer detection

In contrast to tumors or polyps, which may be either benign or malignant, cancer is a malignant condition. As we notice from Figure 15, CADSS approaches specifically targeted cancer detection are rare. The only work we were able to identify in this specific field of research is presented in (Sousa et al., 2009).

Motility assessment

The investigation of intestinal motility allows a medical expert to detect the presence of different intestinal dysfunctions. Usually motility assessment is performed using rather invasive methods such as intestinal manometry. As can be seen from Figure 15, computer-assisted motility assessment is still very rare, although there exists a plenty of methods which are the basis for such systems (Igual et al., 2007; Spyridonos et al., 2005, 2006; Vilariño et al., 2005a,b, 2006a,c,d,e, 2010). In (Seguí et al., 2008) the authors analyze motility patterns with the aim of characterizing such dysfunctions.

Ulcer detection

Gastrointestinal ulcers are mucosal erosions exceeding a certain size. They may arise in several parts of the GI tract, such as for example the esophagus, the stomach, or the small intestine. Ulcers may lead to complications like GI bleeding or perforation of the mucosal wall. In combination with Helicobacter pylori there is also a higher risk of developing cancer.

In the past different methods for an automated ulcer detection have been developed. The first work, presented by Kodama et al. (1988), is based on flexible endoscopy and dates back to 1988. More recent approaches are solely based on WCE (Karargyris and Bourbakis, 2009b; Li and Meng, 2008b, 2009b,c; Szczypiński and Klepaczko, 2009).

Barrett's esophagus

Barrett's esophagus is a disorder specific to the esophagus. In case of

this disorder the mucosa in the esophagus is injured due to a chronic reflux disease, also called gastroesophageal reflux disease (GERD). Since the Barrett's esophagus is known to be a pre-cancerous condition it is imperative to detect this disease in its early stages already.

Despite the fact that Barrett's esophagus may develop into cancer, the number of CADSSs focused at an automated detection of this disorder is rather low, as can be seen from Figure 15. The only work we were able to identify in this field of research is presented in Münzenmayer et al. (2009).

Helicobacter pylori infection detection

Helicobacter pylori (H. pylori) is a bacterium which may inhabit several regions within the stomach. Approximately 50% of the world's population carry this bacterium. However, about 80% of these cases remain asymptomatic. An infection with this bacterium may cause an inflammation of the gastric lining and is therefore strongly associated with the development of duodenal and gastric ulcers and carcinomas.

Despite the rather high prevalence of H. pylori, the number of CADSSs focused at an automated detection of such an infection is rather low, as can be seen from Figure 15. The only work we were able to identify in this field of research is presented in Huang et al. (2008).

Celiac disease detection

Celiac disease, commonly known as gluten intolerance, is a complex autoimmune disorder that affects the small bowel in genetically predisposed individuals of all age groups after introduction of gluten containing food. Characteristic for the disease is an inflammatory reaction in the mucosa of the small intestine. During the course of the disease the mucosa looses its absorptive villi and hyperplasia of the enteric crypts occurs leading to a diminished ability to absorb nutrients.

Endoscopy with biopsy is currently considered the gold standard for the diagnosis of celiac disease, but also WCE seems to be a prospective alternative. This is also reflected by the approaches found in literature, aiming at an automated diagnosis of celiac disease (see Figure 16). While the methods proposed in (Gschwandtner et al., 2010; Hegenbart et al., 2009; Vécsei et al., 2008, 2009) are based on flexible endoscopy, more recent work aims at a diagnosis based on WCE (Ciaccio et al., 2010).

Crohn's disease detection

Similar to celiac disease, Crohn's disease is thought to be an autoimmune disorder. Although a combination of genetic predisposition and environmental factors is suspected to cause this disease, the exact cause for Crohn's disease still remains unclear. Characteristic for this disease is a patchy inflammation of the GI tract which may affect all parts of the GI tract. However, the most frequently affected parts are the ileum and the colon.

The gold standard for the diagnosis of Crohn's disease is endoscopy, but WCE seems to be a prospective alternative. Hence, the methods proposed in (Bejakovic et al., 2009; Girgis et al., 2010) are both based on WCE.

GI bleeding detection

Gastrointestinal bleeding may be an indication for many diseases such as, for example, colon cancer, Crohn's disease, esophageal cancer, small intestine cancer, or the typhoid fever. Depending on the location within the GI tract where the bleeding is observed one distinguishes between upper GI bleeding and lower GI bleeding.

Following from the fact that GI bleeding may occur in any part of the GI tract it is no surprise that most CADSS-related approaches found in this area do not focus on any specific part of the GI tract (see Figure 15) (Al-Rahayfeh and Abuzneid, 2010; Giritharan et al., 2008; Jung et al., 2008; Karargyris and Bourbakis, 2008; Lau and Correia, 2007; Li and Meng, 2008a, 2009a,b; Pan et al., 2010; Penna et al., 2009). On exception is the work presented in (Krishnan et al., 1999), which aims at the detection of GI bleeding within the colon. Furthermore, from Figure 16 we see that work aiming at GI bleeding detection is almost always based on WCE. However, this is not surprising either since the capsule is currently the only endoscopic device able to reach all parts of the GI tract, while flexible endoscopy is somewhat limited in this sense.

Distinction between normal and abnormal lesions

This category of approaches does not focus on a particular pathology. Moreover, work found in literature, not mentioning any specific target pathology, falls into this group (about 18% of all diagnosis-related approaches). In contrast to previously mentioned approaches, methods falling into this category distinguish between normal and abnormal cases only, without being specific about the underlying pathology (Bonnel et al., 2009; Khademi and Krishnan, 2007; Kodogiannis, 2004, 2007; Kodogiannis et al., 2007; Kodogiannis and Boulougoura, 2005, 2007; Kodogiannis and Lygouras, 2008; Krishnan and Goh, 1997; Krishnan et al., 1998a,b, 1999; Li and Meng, 2007; Lima et al., 2008; Magoulas et al., 2004b; Tjoa et al., 2002; Tjoa and Krishman, 2003; Wadge et al., 2005).

4.2. Image processing techniques and classification in CADSSs

In this Section we cover work on CADSSs found in literature in some detail. For this purpose we review the different approaches separated by pathology, grouped by the part of the GI tract the respective methods are targeting. This is done from the image processing and classification perspective. Hence, we provide details on for example transformations, features, and classifiers used throughout these approaches.

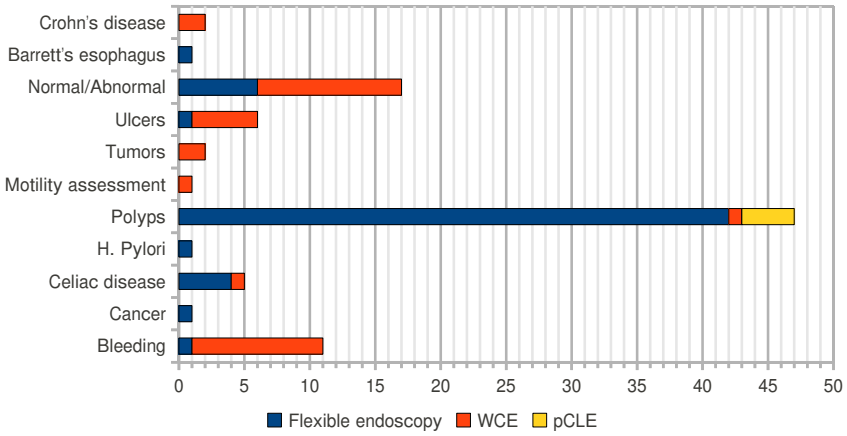


Figure 16: Number of CADSS publications per pathology category.

4.2.1. Esophagus

In (Münzenmayer et al., 2009) a CBIR system based on flexible endoscopy and targeted at the discrimination between benign epithelium and Barrett's esophagus is proposed. For this purpose a multi-scale image pyramid is created from an endoscopic gray-level image. Then, using a set of equally-spaced thresholds, binary images are created, which are subsequently subject to a blob analysis and used to extract statistical features. To account for color, an extension combining binary images from different color channels is used. The proposed system includes a relevance feedback mechanism, allowing an expert to refine the retrieval process and steer a search into the right direction.

4.2.2. Stomach

The methods presented in (Huang et al., 2008; Iakovidis et al., 2005, 2006; Kodama et al., 1988; Sousa et al., 2009) aim at the detection of different disorders within the stomach (all these approaches are based on flexible endoscopy).

Helicobacter pylori

In (Huang et al., 2008) the authors propose a system aiming at the detection of Helicobacter pylori. To achieve this, statistical color features and smoothness estimates are used along with statistical features obtained by a Discrete wavelet transform (DWT) applied to different color channels in different color spaces. After applying a feature subset selection algorithm, images are classified using a SVM classifier.

Polyps

The approaches proposed in (Iakovidis et al., 2005, 2006) both aim at the comparison of well-known texture features for the classification of gastric polyps. However, while the work in (Iakovidis et al., 2005) is restricted to gastric polyps,

(Iakovidis et al., 2006) also targets colonic polyps. In (Iakovidis et al., 2005) the features compared are Local Binary Patterns (LBP) histograms (Ojala and Pietikäinen, 1999), Texture Spectrum histograms (TS) (Wang and He, 1990), statistics based on color histograms and the texture spectrum (TSCHS) (Tjoa and Krishman, 2003), and Color Wavelet Covariance (CWC) (Karkanis, 2003). The features compared in (Iakovidis et al., 2006) are CWC, Opponent Color LBP (OCLBP) histograms (Mäenpää et al., 2002), Wavelet Correlation Signatures (de Wouwer et al., 1999), and DWT-based features. Both approaches are based on the SVM classifier.

Ulcers

The work proposed in (Kodama et al., 1988) focuses on the detection of gastric ulcers in the stomach and outlining them by applying edge detection followed by morphological operations (Gonzalez and Woods, 2007), based on an image after noise removal.

Cancer

Sousa et al. (2009) aim at detecting stomach cancer. The authors employ a combination of adaptive histograms and uniform LBP (LBPU) (Ojala et al., 2002) to achieve this. The features are then evaluated using a set of classifiers (decision trees, k-NN classifier, SVM, and the Bayes classifier (Duda et al., 2000)).

4.2.3. Small bowel

The detection of disorders in the small bowel is the goal of the methods proposed in (Barbosa et al., 2008, 2009; Bejakovic et al., 2009; Bonnel et al., 2009; Ciaccio et al., 2010; Girgis et al., 2010; Gschwandtner et al., 2010; Hegenbart et al., 2009; Khademi and Krishnan, 2007; Vécsei et al., 2008, 2009).

Tumors

The detection of tumors within the small bowel (based on WCE) is the goal of the methods presented in (Barbosa et al., 2008, 2009). In (Barbosa et al., 2008) each color channel of an input image is decomposed using the DWT, discarding subbands containing a low amount of information only. From the remaining subbands a new image is synthesized, which is used to compute a co-occurrence matrix and obtain a subset of Haralick features (Haralick et al., 1973). The more recent work, presented in (Barbosa et al., 2009), uses the Curvelet transform to obtain statistical features from an endoscopic image. In addition the authors exploit the statistical dependence between color channels by computing a covariance measure across different color channels. For the classification both approaches use a multilayer perceptron neural network.

Celiac disease

An automated diagnosis of celiac disease is the aim of the methods presented in (Ciaccio et al., 2010; Gschwandtner et al., 2010; Hegenbart et al., 2009; Vécsei

et al., 2008, 2009). While the work in (Ciaccio et al., 2010) is based on WCE, the remaining work is based on flexible endoscopy.

In (Vécsei et al., 2008) statistical features based on color histograms are compared against some of the statistical wavelet-based features already proposed in (Liedlgruber and Uhl, 2007) using the k-NN and the SVM classifier. In the follow-up work (Vécsei et al., 2009) the authors evaluate statistical features based on the Fast Fourier transform (FFT). In addition a genetic algorithm is used to optimize the set of features used. Apart from that, in this work the authors added the Bayes classifier to the set of classifiers used for the feature comparison. The work presented in (Hegenbart et al., 2009) also utilizes features from the frequency domain which have already been proposed earlier (Häfner et al., 2009b; Kwitt and Uhl, 2007, 2008a; Liedlgruber and Uhl, 2007; Vécsei et al., 2009). In addition, this work analyzes the impact of different image capturing techniques on the classification accuracies. Apart from the classifiers already used in (Vécsei et al., 2008), this work also uses the Bayes classifier and a classifier ensemble in order to obtain a more robust classification. A more recent work, presented in (Gschwandtner et al., 2010), aims at assessing the impact of correcting barrel-type distortions on the classification accuracy. In the course of this work features computed from the frequency domain (Häfner et al., 2009b,e; Liedlgruber and Uhl, 2007) are evaluated as well as spatial domain features (Huang et al., 2004; Kwitt and Uhl, 2007; Tan and Triggs, 2007; Vécsei et al., 2009) and shape features (Häfner et al., 2010c,d). In contrast to previous work this work utilizes the k-NN classifier only. Up to our knowledge, the work presented in (Gschwandtner et al., 2010) is the first published work which not only aims at a binary classification, but also classifies according to a more challenging reduced Marsh classification (four classes).

Another recent work, proposed by Ciaccio et al. (2010), also aims at the detection of celiac disease. For this purpose each frame of a WCE video is subdivided into non-overlapping blocks. For each of these blocks different statistical measures are computed. These measures are then averaged over several frames (for each block). The resulting features are used with a non-linear discriminant classifier to detect the presence of celiac disease and analyze small bowel motility.

Crohn's disease

The detection of lesions characteristic to Crohn's disease is the aim of the methods proposed in (Bejakovic et al., 2009; Girgis et al., 2010), which are both based on WCE images. While both methods employ MPEG-7 features as proposed earlier by Coimbra et al. (2006a), in (Bejakovic et al., 2009) these features are combined with a subset of Haralick features. In (Girgis et al., 2010), in contrast, a Mean-Shift algorithm is used to detect candidate regions showing inflammation. Then subwindows are extracted from the candidate regions and MPEG-7 features are combined with color histogram statistics in order to assemble the final feature set. For the classification step both methods rely on the SVM classifier.

Normal and abnormal

The methods proposed in (Bonnel et al., 2009; Khademi and Krishnan, 2007) are also based on WCE. However, in contrast to the previously mentioned approaches there is no clear statement made about the pathology these approaches are aiming to detect. Instead there is only a discrimination made between "normal" and "abnormal" cases, which however could be related to several different pathologies as already pointed out in Section 4.1.2. In (Khademi and Krishnan, 2007) the authors compute Haralick features from co-occurrence matrices based on subbands resulting from a SIDWT decomposition (a shift-invariant DWT variant), which are also directionally aligned to the according subbands. While the method in (Khademi and Krishnan, 2007) is based on grayscale imagery, Bonnel et al. (2009) additionally consider the relationship between different color channels by constructing one co-occurrence matrix for each possible pair of color channels. Furthermore, co-occurrence matrices of different orientations are averaged within each wavelet subband to obtain a semi-rotation invariant representation. The classification in (Bonnel et al., 2009) is done using a threshold of 1D features resulting from a feature selection, while in (Khademi and Krishnan, 2007) the classification is done by employing Linear Discriminant Analysis (LDA).

4.2.4. Colon

While the vast majority of approaches summarized in this section is based on flexible endoscopy, using traditional classification methods, the methods presented in (André et al., 2009a,b; André et al., 2010) are targeted either at CBIR or CBVR, based on pCLE.

Polyps

André et al. (2009a) propose a system designed to discriminate between benign and neoplastic polyps. The authors slightly modify the Bag of Visual Words (BVW) method (Zhang et al., 2007) to obtain a scale invariant texture descriptor by using multiple SIFT descriptors (Lowe, 2004). To capture local features over a complete image a dense grid of salient feature detectors is used. The classification is carried out using the k-NN classifier. In (André et al., 2009b) this method is extended by a co-occurrence matrix based on the adjacency of visual words in order to exploit relationships between local feature regions. By using the mosaicing method proposed in (Vercauteren et al., 2006), temporal information is also considered, allowing to query mosaics. The follow-up work presented in (André et al., 2010) extends the BVW method to generate signatures for video sequences, making it possible to query videos too.

The method proposed in (Krishnan et al., 1999) is based on flexible endoscopy and aims at labeling parts of an endoscopic image into regions belonging to background, polyps, or bleeding. After a segmentation based on scale-space filters and histograms, a set of fuzzy rules is used to discriminate the different types of image regions.

In order to detect polyps, the method proposed in (Alexandre et al., 2007) uses the color of all pixels along with the respective pixel coordinates as features

in conjunction with the SVM classifier. In (Alexandre et al., 2008) this method is compared against well-established features (LBP and CWC), again using the SVM classifier.

Another approach aimed at polyp detection is presented in (Ameling et al., 2009), which is also the only work we were able to identify using images taken with a HD colonoscope. In this work the authors compare LBP features, OCLBP features, and a subset of the Haralick features. The classifier used is the SVM classifier.

Karkanis et al. (1999) also use Haralick features to discriminate between benign and neoplastic polyps. But their work is based on grayscale images and employs a neural network classifier. In (Cheng et al., 2008) these features are extended to color images, aiming at polyp detection. Cheng et al. also introduce features exploiting relationships between different color channels and use the SVM classifier. In a follow-up work to (Karkanis et al., 1999), the authors extend their previous work to extract Haralick features from co-occurrence matrices based on the detail subbands of a one-level DWT (Karkanis et al., 2001a). This type of features has also been used in (Maroulis et al., 2003) for polyp detection. A comparison between different features (Haralick features in the spatial domain, run-length features, wavelet-based features (Karkanis et al., 2001a), and an estimate of texture roughness) is given in (Karkanis et al., 2001b). Similar to (Karkanis et al., 1999), the methods presented in (Karkanis et al., 2001a,b; Maroulis et al., 2003) are also restricted to grayscale images. All these methods employ a neural network classifier for the classification.

The approaches proposed in (Karkanis, 2003; Iakovidis et al., 2004) use color-based features, similar to the ones proposed in (Karkanis et al., 2001a). But, in addition to color awareness, these approaches extend the feature extraction process by using a sliding window, generating more localized features. Apart from that the CWC features are proposed. These features are based on a DWT decomposition followed by computing the co-occurrence matrices from subbands and computing a subset of the Haralick features on these matrices. To account for relationships between different color channels, the covariances between features originating from different channels are computed and serve as final features. While Karkanis (2003) uses LDA for a discrimination between non-neoplastic and neoplastic lesions, Iakovidis et al. (2004) use the SVM classifier to detect adenomatous polyps. Based on (Iakovidis et al., 2004) a comparison of different texture features (including LBP and OCLBP) is given in (Iakovidis et al., 2006). In addition, this work also aims at the detection polyps in the stomach.

In (Magoulas et al., 2004a) another approach, similar to the method proposed in (Karkanis et al., 1999), is presented. But while (Karkanis et al., 1999) aims at a discrimination between benign and neoplastic polyps, the work by Magoulas et al. is focused on polyp detection. In addition, the features extracted are clustered using the k-Means clustering algorithm and a separate neural network acts as a local expert on each resulting cluster.

In contrast to the previously mentioned approaches, which are based on colonoscopes without zoom capabilities, the work presented in (Häfner et al.,

2006a,b, 2007a,b,c, 2008a,b, 2009a,b,c,d,e, 2010a,b,c,d; Kwitt and Uhl, 2007, 2008a,b,c; Kwitt et al., 2010; Liedlgruber and Uhl, 2007) is based on images acquired using a zoom-colonoscope. Moreover, each of these approaches aims at the discrimination of colonic polyps, based on the pit pattern classification scheme. Hence, most of this work either tries to discriminate between non-neoplastic and neoplastic polyps (two-classes case) or tries to classify unknown endoscopic images into the respective pit pattern classes (six-classes case). Exceptions are presented in (Häfner et al., 2008b, 2009a, 2010c; Kwitt et al., 2010). In (Häfner et al., 2010c) and (Häfner et al., 2008b, 2009a) only the two-classes case and the six-classes case are considered, respectively. In addition to the two-classes, the method proposed in (Kwitt et al., 2010) also makes a distinction between benign, non-invasive, and invasive colonic lesions. The features used in these approaches include spatial domain features (LBP histograms, color histograms, or Haralick features) (Häfner et al., 2006a, 2007c, 2009c), frequency domain features (statistical wavelet features, model parameters of wavelet detail subband coefficient distributions, or features based on FFT or DCT coefficients) (Häfner et al., 2006b, 2007a,b, 2008a,b, 2009a,b,e, 2010a,b; Kwitt and Uhl, 2007, 2008a,b,c; Kwitt et al., 2010; Liedlgruber and Uhl, 2007), and shape based features (triangulation based features or shape description features) (Häfner et al., 2010c,d). In (Häfner et al., 2009d) a subset of all these features is compared in terms of classification performance. To obtain an optimal subset of features a feature optimization is carried out in some cases (a feature subset selection in (Häfner et al., 2007a,b, 2008a,b, 2009b, 2010b,d; Kwitt and Uhl, 2008a,b) and a Principal Component Analysis in (Häfner et al., 2007c)). The most commonly used classifier throughout these approaches is the k-NN classifier, which is used in (Häfner et al., 2006a,b, 2007c, 2008a,b, 2009a,b,c,d,e, 2010a,c,d; Kwitt and Uhl, 2007, 2008a,b,c; Kwitt et al., 2010; Liedlgruber and Uhl, 2007). Other classifiers, like the SVM classifier, the Bayes classifier, or neural networks, are used in (Häfner et al., 2007c, 2009d, 2010b; Liedlgruber and Uhl, 2007), (Häfner et al., 2007a,b, 2009b,d, 2010b; Liedlgruber and Uhl, 2007), and (Häfner et al., 2007c), respectively. To make the classification process more robust an ensemble classification setup is employed in (Häfner et al., 2008b, 2009a,d,e; Kwitt and Uhl, 2008c).

The methods presented in (Gross et al., 2009a,b) are also targeted at the classification or detection of colonic polyps. But in contrast to previous work, Gross et al. base their experiments on NBI colonoscopy images. This allows an investigation of blood vessels on polyps as these can be more easily identified when using NBI. Gross et al. (2009b) propose features which allow to describe vessels visible in endoscopic images (number of blood vessel pixels, average perimeter of vessels, and intensity based features). The classification robustness of these features is assessed by comparing them against LBPU features (using a k-NN classifier). While this work is based on a manual segmentation of polyps, a follow-up work, presented in (Gross et al., 2009a), aims at the segmentation of polyps. This is achieved by iteratively applying nonlinear diffusion filtering to an endoscopic image and using the Canny edge detector to get an edge image. The edge image is then used in a shape template matching process to find polyp

candidates for a subsequent classification based on (Stehle et al., 2009).

While the work by Gross et al. is based on NBI endoscopy, the work in (Stehle et al., 2009; Tischendorf et al., 2010) is based on NBI zoom-endoscopic images. Stehle et al. compare two different algorithms to detect blood vessels. The first algorithm is based on the Hessian matrix in combination with a directional stamping algorithm, while the second algorithm is based on phase symmetry features and fast marching. For the classification features describing vessel properties (similar to the ones proposed in (Gross et al., 2009b)) are used. Based on this work and (Gross et al., 2009b), Tischendorf et al. (2010) present a study to assess the feasibility of polyp classification based on vascularization features.

Normal and abnormal

In contrast to the previously presented approaches, in (Krishnan and Goh, 1997; Krishnan et al., 1998a,b; Tjoa et al., 2002; Tjoa and Krishman, 2003; Magoulas et al., 2004b) there is no clear statement made about the targeted pathology. Instead the authors use a vague differentiation between "normal" and "abnormal" cases. In (Krishnan and Goh, 1997) a fuzzy edge detection is used to find a seed point for a fuzzy region growing algorithm. Based on the resulting region is characterized by different features (statistical color features, boundary perimeter, center of mass, irregularity, and area of the enclosed region) in order to discriminate between normal and abnormal cases. The work in (Krishnan et al., 1998b) is based on an edge detection performed on followed by analyzing the curvature of edge segments in order to detect abnormalities, which disturb the usually smooth shape of the contours of creases within the colon. Krishnan et al. (1998a) apply thresholds to histograms based on chromatic components of an endoscopic image in order to segment the image. Based on the segmentation result, features are extracted (mean chromatic components and a parameter describing the shape of the lumen). The subsequent classification is carried out using different flavors of neural networks.

The method proposed in (Tjoa et al., 2001) uses histograms representing local edge variations against pixel intensities. A segmentation is performed based on a thresholding of these histograms and the hue value within regions. The final segmentation result is obtained by merging regions based on their perceptual similarity. Tjoa et al. (2002) extend this segmentation method by a background removal algorithm, which is based on the minimum cross entropy.

In (Tjoa and Krishman, 2003) the authors compute statistical features based on texture spectrum histograms. These features are complemented by color histogram features. The final features are obtained by applying PCA on the intermediate feature set. The classification is then carried out using a neural network classifier.

While Magoulas et al. (2004b) also use a neural network classifier, the authors employ Haralick features for the classification. In addition the neural network used follows an online learning strategy. In this setup the learning rate of the classifier used is adaptive. Moreover, the weights of the neural network are adapted over time, using evolutionary strategies.

4.2.5. Complete GI tract

Throughout this section we summarize diagnosis-related work not focused on a particular part of the GI tract. Except for the work presented in (Kang and Doraiswami, 2003), which is based on flexible endoscopy, all approaches targeting the complete GI tract are based on WCE.

GI bleeding

In (Al-Rahayfeh and Abuzneid, 2010) bleeding regions are detected within WCE frames by simply counting pixels which exhibit certain color properties (e.g. reddish). If the number of pixels exceeds some predetermined threshold, the respective pixel is considered a bleeding pixel. Similarly, in (Pan et al., 2010) the detection is carried out on a per-pixel-basis. But instead of counting bleeding pixels, the pixel colors are used as features for a classification based on a Probabilistic Neural Network (PNN).

Color component histograms (in HSV space) are used along with the dominant color (Manjunath et al., 2001) and co-occurrence matrix features (based on the dominant colors) to detect bleeding in WCE frames in (Giritharan et al., 2008). For the classification a SVM ensemble is used. To account for possible illumination variations over time a temporal filtering is applied to the ensemble outcome.

Jung et al. (2008) detect bleeding regions by first removing very dark and very bright regions by a simple thresholding. After transforming the image, such that reddish color gets highlighted, another thresholding followed by morphological operations is performed to obtain the final bleeding regions. Similar to (Jung et al., 2008), the first step in (Penna et al., 2009) is a removal of dark pixels, carried out by thresholding. To eliminate the influence of edges to the actual blood detection, edges are masked out using the Mumford-Shah functional (Mumford and Shah, 1989). Then, after applying another thresholding to detect reddish or dark image parts, an anomaly detection algorithm is applied, followed by morphological operations, to detect the final blood regions. Another approach based on thresholding is proposed in (Lau and Correia, 2007). Based on the assumption that image parts containing bleeding patterns are more saturated, a pre-classification of frames as bleeding frames is done by dividing the image into non-overlapping blocks. If at least one block exceeds some predefined saturation threshold the frame is pre-classified as bleeding frame. The classification is then refined by a pixel-based multi-level thresholding. Similar to (Al-Rahayfeh and Abuzneid, 2010), a frame is finally classified as bleeding frame if the number of pixels labeled as bleeding pixels exceeds some threshold.

The detection of different blood-based abnormalities (bleeding, angioecstasia and erythema) based on WCE images is the goal of the method presented in (Karargyris and Bourbakis, 2008). This work is based on a previously presented approach by Bourbakis (2005). In this work Karargyris et al. carried out a segmentation on the smoothed and decorrelated RGB color channels using a fuzzy segmentation algorithm. The segmentation result is then used to create a Local-Global graph (L-G graph) (Bourbakis et al., 1999). The basic idea behind the L-G graph is to represent information within an image in a hierarchical

manner. This is achieved by combining local information extracted from regions (resulting from a segmentation) with global information describing relationships between the regions. In (Karargyris and Bourbakis, 2008) such a graph is used to merge segmented regions of certain similarity and replace these regions with the original content based on the input image.

The approaches presented in (Li and Meng, 2008a, 2009a,b) are very similar. Each work uses features based on chromaticity moments and compares them against other features in terms of the classification accuracy. All these approaches compare these features against CWC features, proposed in (Karkanis, 2003). In addition, statistical features based on color histograms are evaluated in (Li and Meng, 2009b). While in (Li and Meng, 2008a) LBPU histograms are evaluated, the work presented in (Li and Meng, 2009a) additionally evaluates the performance of rotation-invariant LBPU histograms (LBPRIU) (Ojala et al., 2002). Throughout (Li and Meng, 2008a, 2009a,b) the classification is always carried out using a neural network classifier. In contrast to (Li and Meng, 2008a, 2009a) the work in (Li and Meng, 2009b) is not only restricted to the detection of bleeding but also ulcers.

Motility assessment

The only work aiming at the analysis of intestinal motility, aiming at a diagnosis, is presented in (Seguí et al., 2008). This work is split up into two parts. The first part focuses on detecting intestinal contents (e.g. intestinal juices), analyzing the movement of the intestine and the camera, and analyzing contractile activity (Vilariño et al., 2010). The analysis of the wrinkle patterns occurring in the contracted lumen is based on the work proposed in (Spyridonos et al., 2006). Based on the frame-based information obtained in the first part, in the second part different statistical features are computed, which are then used for a subsequent classification using SVM.

Polyps

A detection of polyps, based on flexible endoscopy, is proposed in (Kang and Doraiswami, 2003). This work is based on the Canny edge detector applied to each color channel of an input image. From the resulting edge map statistical texture features as well as shape features (based on the Hough transform) are extracted to detect polyps. Karargyris and Bourbakis (2009a) propose a method which is based on WCE and also aims at the detection of polyps. The methodology is based on the segmentation of the result of Log-Gabor filtering and an edge detection using the SUSAN edge detector (Smith and Brady, 1997). The outputs of these algorithms are used to obtain more reliable contours for polyp candidates by employing an active contour method. By applying simple rules to the resulting regions the polyp detection part is carried out.

Ulcers

Detecting ulcers in WCE frames is the aim of the method proposed in (Karargyris and Bourbakis, 2009b). Similar to the work in (Karargyris and Bourbakis, 2009a), Log-Gabor filters are used to obtain a binary image, from which medium

sized regions are used as ulcer candidates. Then, based on the work proposed in (Bourbakis, 2005), the final ulcer regions are obtained. These regions are then used for a subsequent feature extraction (statistical color features and Haralick features). The final classification is carried out using SVM. Another work, also aimed at ulcer detection, is proposed in (Li and Meng, 2008b, 2009c). After applying the Curvelet transform to an input image, Li et al. apply the LBPRIU operator to the respective coefficient image and compute statistical features from the resulting histogram. The features are then used for a classification, using either a neural network classifier or the SVM classifier. While the focus of the work presented in (Szczypiński and Klepaczko, 2009) lies in selecting discriminative features for WCE images, the authors also show that the features found can be used for the detection of ulcers. The set of features, which serves as a basis for this work, is extracted using a previously developed software and consists of more than 1 000 possible features. The actual selection of optimal features is then carried out based on a convex hull method. The evaluation of the features (i.e. the classification) is then done using a RBF network classifier (Witten and Frank, 2005).

Normal and abnormal

Contrasting to the previously presented approaches there is no clear statement made about the pathology the work proposed in (Kodogiannis, 2004, 2007; Kodogiannis et al., 2007; Kodogiannis and Boulougoura, 2005, 2007; Kodogiannis and Lygouras, 2008; Li and Meng, 2007; Lima et al., 2008; Wadge et al., 2005) is targeted at. Instead the authors use a differentiation between "normal" and "abnormal" cases only.

In (Kodogiannis, 2004; Kodogiannis and Lygouras, 2008) statistical features are used for a classification based on Fuzzy Interference Neural Networks (FINN). A separate FINN is used for each color channel. These classifiers are then fused based on Fuzzy Integrals (FI) to obtain the final decision of the system. But while in (Kodogiannis, 2004) the features are obtained directly from the color channels, the channels are transformed using fuzzy segmentation (based on surface uniformity) in (Kodogiannis and Lygouras, 2008). The features are then extracted from the transformed channels.

The methods proposed in (Kodogiannis, 2007; Kodogiannis et al., 2007; Kodogiannis and Boulougoura, 2005, 2007) are based on statistical features extracted from color channels, after transforming them using the texture spectrum transform. The differences throughout these approaches are mainly associated with the classification method used. In (Kodogiannis and Boulougoura, 2005) an Extended Normalized Radial Basis Function network (ENRBF) is used for the classification. This classifier has been extended in (Kodogiannis, 2007) by adding support of neuron splits to the network, allowing to dynamically changing the structure of the neural network used. The method proposed in (Kodogiannis et al., 2007; Kodogiannis and Boulougoura, 2007) is different in the sense that the ENRBF network is replaced by and adaptive fuzzy logic system (AFLS). Such a fuzzy logic system has the the advantage that, while the knowledge is still represented by simple rules (like in a traditional fuzzy logic

system), the underlying rules can be derived and extracted from training data. In all these approaches the classification is performed using a classifier ensemble (one classifier per color channel considered is used). In (Wadge et al., 2005) the features used in (Kodogiannis, 2007; Kodogiannis et al., 2007; Kodogiannis and Boulougoura, 2005, 2007) are compared against statistical features gathered from color histograms. In addition the authors provide a comparison between different neural network classifiers.

The work presented in (Li and Meng, 2007) is based on computing two averaged 3D color histograms, one for the normal and one for the abnormal cases. The average histograms are based on images which have been quantized to reduce memory consumption of the histograms. The classification is based on the similarity the 3D histogram of a patch under consideration with the reference histogram.

Another work, proposed in (Lima et al., 2008), is similar to the work proposed in (Karkanis, 2003) with respect to the features used. However, in addition to the CWC features, the authors compute higher order moments which are also included into the feature vectors. The classification is then carried out using a RBF network classifier.

5. Discussion

As we have seen in the previous section, there exist various different approaches aiming at assisting a medical expert during the process of decision-making. Apart from that, in Section 4 we already pointed out that the interest in the field of CADSSs has increased throughout the past two decades. Nevertheless, despite the vast amount of approaches found in literature some common weaknesses exist among a big share of these approaches. In this section we will discuss these issues and propose possible ways to cope with them.

5.1. Different image databases

When it comes to the assessment of techniques for CADSSs a common problem are the images or videos used. Although there exist publicly available image databases containing medical images or videos from the GI tract, almost each working group bases their experiments on their own image database, which in most cases has been created in a collaboration with only a few medical experts. As a consequence, work found throughout literature cannot be compared directly. Moreover, it gets nearly impossible for other working groups to verify results presented in this field or to assess the quality of the images used throughout a work (i.e. the medical expertise of the involved experts is usually not known). In Table 1 we give a short overview of available image databases

Name	Modality	V	I	Regions	Case details
DB-1	Various	804	N/A	E, ST, SB, C	✓
DB-2	Various	3521	N/A	E, ST, SB, C	✓
DB-3	Various	<75	>1000	E, ST, SB, C	
DB-4	Various	N/A	1076	E, ST, SB, C	✓
DB-5	WCE	85	85	E, SB, C	

Table 1: Overview of publicly available image databases dealing with endoscopy in the GI tract. The columns V and I indicate the number of videos and images available, respectively. In the column "Regions" E, ST, SB, and C are abbreviations for Esophagus, Stomach, Small bowel, and Colon, respectively (information collected on the 25$^{\text{th}}$ of November, 2010).

(abbreviated as DB-1 [5], DB-2 [6], DB-3 [7], DB-4 [8], and DB-5 [9]).

Another issue, which can be frequently observed throughout literature, is the use of a quite limited number of images in some approaches. This is a severe problem as results based on a few images only must be doubted due to a limited significance. Throughout the work found the number of images used varies significantly as shown in Table 2. This table shows the number of methods which base their experiments on a number of images within a certain range (in absolute values as well as the respective proportions). Since WCE-based work is usually using complete videos, leading to a higher number of images available for experiments, we present these numbers separated by the underlying endoscopic technique (either WCE or flexible endoscopy, including pCLE-based systems). As we notice from this table, most approaches are based on image databases consisting of between 100 and 500 images (44% and 42% in case of WCE and flexible endoscopy, respectively). But there is also work which lacks any information on the quantity of the imagery used or, at least, make no clear statements about the number of images used for training and testing (denoted by "N/A" in Table 2). Such problematic examples can be found in (Kang and Doraiswami, 2003; Karargyris and Bourbakis, 2008; Kodama et al., 1988; Krishnan et al., 1998b, 1999; Maroulis et al., 2003; Tjoa et al., 2002). A special case is constituted by approaches which provide information about the number of videos used but do not give any information about the total number of frames used from these videos (Iakovidis et al., 2004) (denoted by "Videos" in Table 2).

Image databases consisting of less than 100 images are not suitable to estimate the accuracy of a diagnosis-related system. Using between 100 and 500 images may already be sufficient to support presented results. While using more than 500 images seems to be more appropriate in order to achieve reliable and significant results (used in about 34% and 22% of all work in case of WCE and

[5]DaveProject, `http://daveproject.org`
[6]The Gastrointestinal Video Atlas, `http://www.gastrointestinalatlas.com`
[7]Endoskopie-Atlas, `http://www.endoskopiebilder.de`
[8]The Atlas of Gastrointestinal Endoscopy, `http://www.endoatlas.com`
[9]Given Imaging Image Atlas, `http://www.capsuleendoscopy.org`

# of images	WCE		Flexible endoscopy	
< 100	6	19 %	14	24 %
$100 - 500$	14	44 %	25	42 %
> 500	11	34 %	13	22 %
Videos	0	0 %	1	2 %
N/A	1	3 %	6	10 %
	32	100 %	59	100 %

Table 2: Number of approaches which are based on the given number of images along with the respective proportions.

flexible endoscopy, respectively), we have to point out that the sufficiency also depends on the number of image classes used in a work.

While in other fields of research (e.g. biometrics) the use of well-established databases is already common practice, this is still not the case in the field of CADSSs. Nevertheless, it is absolutely necessary to establish commonly used image databases (depending on the underlying endoscopic technique), containing a sufficient amount of images and made available to researchers in this field. Especially in cases where a visual inspection is common practice to obtain the ground truth information, involving several different medical experts in the process of creating such a database would be necessary to lower the inter-observer disagreement.

As a consequence of the usually limited image databases many methods are not evaluated on two distinct image sets (one for the training and one for the validation of the underlying classifier). Different sets are only used in about 44% of all methods found in literature. The remaining work is either based on some variant of cross-validation (Duda et al., 2000) (in about 49%) or the authors provide no clear information about the training- and validation-strategy used (in about 7%). While cross-validation is a common way to deal with small image databases there also exist pitfalls. One problem is a possible overfitting if two or more images in the database originate from the same patient and have been taken in the very same region within the GI tract. Depending on the features used, the feature vectors for such images are likely to exhibit a high similarity. To cope with this problem the Leave-One-Patient-Out (LOPO) cross-validation is an option, ensuring that the training set does not contain images from patients in the validation set. However, this type of cross-validation is rarely used throughout literature (in only about 5% of the methods using cross-validation). Another pitfall arises when some sort of feature selection is used along with cross-validation. In this case it is important to perform the cross-validation on each feature candidate set in order to avoid overfitting (inner cross-validation).

5.2. Ground truth establishment

Basically there exist two different ways of obtaining ground truth information for experiments. The numbers may be gathered either by a visual inspection of endoscopic imagery, or based on histological findings.

If the ground truth is obtained by visual means there is no profound knowledge about the real pathology for a given image. In addition, the judgment on the pathology in case of a visual inspection may differ significantly between different experts (i.e. the inter-observer agreement may be rather low, depending on the level of expertise of the experts).

For WCE-based CADSS there is usually no other option than to rely on visual inspections by one or more medical experts, since taking biopsies is not possible with current capsule endoscopes.

In case of flexible endoscopy the ground truth can be gathered histologically since taking biopsies is possible. But even if histological findings are available, an endoscopic image does not necessarily correspond to the biopsy site due to slight movements of the endoscope tip, which for example may be the result of the preparation for taking a biopsy (especially in case of magnified endoscopy).

A special case is constituted by CLE since this technique allows in-vivo histologies due to the high level of magnification. As already stated earlier, it has already been shown that the diagnostic accuracy of CLE is comparable to histology (Buchner et al., 2010; Gómez et al., 2010; Wallace and Kiesslich, 2010). Hence, the inter-observer agreement is also expected to be similar to the agreement in case of histology.

Considering the methods presented in Section 4.2 which are based on flexible endoscopy (including pCLE), 7 out of 59 methods base their experiments on a visually obtained ground truth (about 12%), while the vast majority of the methods (40 out of 59) is based on histological findings (about 68%). However, there are also quite a few approaches which do not unveil the way the ground truth has been obtained (12 out of 59 approaches, which corresponds to about 20%) (Iakovidis et al., 2005; Karkanis et al., 2001a; Kodama et al., 1988; Krishnan and Goh, 1997; Krishnan et al., 1998a,b, 1999; Magoulas et al., 2004a,b; Maroulis et al., 2003; Tjoa et al., 2002; Tjoa and Krishman, 2003).

Making a recommendation concerning this issue is not easy, since the best way of obtaining the ground truth information very much depends on the endoscopic technique used. While in case of WCE a visual inspection is usually the only way a ground truth can be obtained, in case of pCLE a visual ground truth gathering is likely to be sufficient due to its closeness to histology. In case of the remaining work based on flexible endoscopy a histological ground truth is highly desired due to its accuracy over visual inspection. However, no matter how the ground truth has been obtained, each method published in this field of research should be accompanied by this information to make it possible for a reader make his own judgments on the value of the results presented.

5.3. Comparison of accuracies among systems

Since the approaches presented in Section 4.2 do not only focus on different parts within the GI tract but also target different pathologies, a direct comparison in terms of the respective classification performance is not possible. Despite the fact that there exist different ways to measure the accuracy of a system, we also identified diagnosis-related work in the literature which does not provide

Target of work	Accuracy	
Barrett's esophagus	81	Münzenmayer et al. (2009)
Bleeding	87 - 98	Al-Rahayfeh and Abuzneid (2010)
Cancer	91	Sousa et al. (2009)
Celiac disease	72 - 98	Vécsei et al. (2008, 2009)
Crohn's disease	87 - 96	Bejakovic et al. (2009)
H. pylori	87	Huang et al. (2008)
Motility assessment	-	
Normal/Abnormal	85 - 100	Kodogiannis (2004); Krishnan et al. (1998a)
Polyps	74 - 99	Häfner et al. (2008a, 2009c, 2010a); Karkanis et al. (2001a)
Tumors	-	
Ulcers	74 - 92	Li and Meng (2009c)

Table 3: The ranges of reported overall accuracies among the diagnosis-related work found in literature (given in percent). The work reporting the respective maximum value is given in brackets.

any results at all (7 out of 91 approaches, which corresponds to about 8%) (Kang and Doraiswami, 2003; Karargyris and Bourbakis, 2008; Kodama et al., 1988; Krishnan and Goh, 1997; Krishnan et al., 1998b, 1999; Tjoa et al., 2002). This makes a comparison against other methods impossible. However, even if some sort of accuracy information is given this does not automatically imply that the proposed systems are comparable. This stems from the fact that a number of different measures to rate a system have been established throughout literature. These measures include the overall classification accuracy, the sensitivity (also known as recall), the specificity, and area under ROC curves.

While the overall accuracy allows us to get an idea of how well a method performs there is no evidence about the false positives or false negatives produced by the system, which however is of particular interest for medical experts. ROC plots also give an idea of the overall system performance by the investigation the area under the curve.

To make comparison among different systems feasible it is therefore necessary to establish a set of measures which are then used to assess the classification performance throughout diagnosis systems (e.g. overall classification rate, specificity, and sensitivity). But even if the same measures are used a direct comparison of different approaches is not meaningful due to the diversity of image databases used, although at least a rough comparison would be possible. Using limited or unbalanced datasets is also problematic as in such cases the results are usually of low significance or biased.

In Tables 3, 4, and 5 we give an overview of the overall accuracies, specificity values, and sensitivity values, respectively, which have been reported in work targeted at diagnosis (no distinction is made between detection and classification). These tables contain the respective ranges of the reported values. In addition, the references of the approaches which achieved the highest values are given. As we notice from Table 3 there are some pathologies which are already detected (or classified) with a rather high accuracy (above 95%). These

Target of work	Specificity	
Barrett's esophagus	-	
Bleeding	86 - 93	Li and Meng (2009a)
Cancer	-	
Celiac disease	84 - 100	Vécsei et al. (2009)
Crohn's disease	93	Girgis et al. (2010)
H. pylori	-	
Motility assessment	100	Seguí et al. (2008)
Normal/Abnormal	82 - 98	Kodogiannis et al. (2007)
Polyps	67 - 99	Häfner et al. (2006a, 2009a); Karkanis (2003); Kwitt and Uhl (2008a)
Tumors	96 - 97	Barbosa et al. (2009)
Ulcers	73 - 93	Szczypiński and Klepaczko (2009)

Table 4: The ranges of reported specificity values among the diagnosis-related work found in literature (given in percent). The work reporting the respective maximum value is given in brackets.

Target of work	Sensitivity	
Barrett's esophagus	-	
Bleeding	83 - 93	Jung et al. (2008); Pan et al. (2010)
Cancer	-	
Celiac disease	53 - 100	Vécsei et al. (2008)
Crohn's disease	70 - 80	Girgis et al. (2010)
H. pylori	-	
Motility assessment	95	Seguí et al. (2008)
Normal/Abnormal	65 - 97	Bonnel et al. (2009); Kodogiannis et al. (2007)
Polyps	56 - 100	Häfner et al. (2009d); Karargyris and Bourbakis (2009a)
Tumors	97 - 99	Barbosa et al. (2008)
Ulcers	75 - 94	Szczypiński and Klepaczko (2009)

Table 5: The ranges of reported system sensitivity values among the diagnosis-related work found in literature (given in percent). The work reporting the respective maximum value is given in brackets.

include GI bleeding, celiac disease, polyps, and the distinction between normal and abnormal cases. Also in case of the sensitivities and specificities reported we already see rather high values (always above 90%). But as already pointed out above a comparison of these results must be taken with caution, as the results are based on different image databases. Hence, the main purpose of these tables is to give a rough overview of the results reported throughout literature.

Another issue concerning the comparison of methods within a publication is the statistical significance. Even if two methods deliver different classification accuracies this does not automatically imply that the difference is statistically significant. To assess the statistical significance tools to compute a p-value have been established (for example the McNemar test (Everitt, 1977)). Especially in medical literature giving evidence for statistical significance is common practice. Throughout the literature investigated within this work, however, such

information is only given in a very few cases. Due to the reasons mentioned above measuring the statistical significance across different methods is hardly possible.

5.4. Computational complexity of systems

Another issue is the computational complexity of systems proposed in literature. Specific information about the computational demand of methods is given only for a small share of diagnosis-related work (for 7 out of 91 approaches, which corresponds to about 8%). For WCE based systems complexity issues are of minor interest since these systems are usually designed to process images or videos offline (i.e. not in realtime). However, for other systems, which possibly allow realtime processing of images and videos, information about the computational demand may be of high interest. Hence, other researches may base their decision on using a proposed method or not on this information.

But it must be noted, that while complexity information is given in a very few cases only, one is usually able to at least roughly estimate the computational demand of a system if the work is based on well-known algorithms (e.g. frequency transforms, edge detection methods, statistical texture features).

Nevertheless, including at least rough estimates of the computational demand of a proposed method (separately for e.g. preprocessing, training, classification or detection) would be helpful.

6. Conclusion

In this work we give an overview of research mainly focused at the detection or classification of different pathologies of interest in endoscopy of the GI tract. We noticed that there is a rising interest in this research topic, especially throughout the last two decades. We also give an overview of different parts within the GI tract and respective pathologies of current research interest. However, interpretation of endoscopic images is always hindered by different types of degradations. This makes the development of methods coping with these degradations necessary. But as we have seen, such methods are also part of the current research in this field.

Despite the aim of diagnosis we also identified various methods which simply aim at assisting a medical expert during interpretation of endoscopic image material. These supportive systems mainly aim at reducing the time spent at investigating endoscopic videos, helping an expert to focus on images of interest only.

But we also noticed that there are some major weaknesses which hamper a proper comparison between different methods. Sorting out issues like limited and heterogeneous image databases and the missing consent on the measures used for an assessment of accuracies among systems is therefore necessary for this topic of research.

Considering the importance of CADSSs and the benefits of such systems (like saving time and therefore lowering the cost for endoscopic procedures or

improving the quality of diagnosis) the interest in CADSSs targeted at the GI tract is expected to increase even more in the future. Especially when considering the fact that for many diseases an early detection may decrease the mortality rate significantly, the need for reliable CADSSs gets even more apparent. Currently however, the majority of work found in literature is not yet applicable to clinical routine. Although in some cases rather high accuracies have been reported already, we are not aware of practically used systems. This is most probably due to the issues discussed which need to be resolved (e.g. limited image databases). Hence, there is still much research necessary – including large-scale experiments – in order to achieve this goal.

Reaching a higher level of reliability in upcoming CADSSs will also strongly depend on advances in the hardware used to acquire the underlying image material. There are still some limitations imposed by the hardware available, which leave room for improvement as well (e.g. poor image quality). But as we have shown in this work, endoscopic devices are improved more and more (in terms of patient comfort, image quality, or just to overcome current limitations).

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Appendix

In the following we provide the different queries we used to find literature targeted at computer-aided decision support in endoscopy of the GI tract. It must be noted, however, that not all results returned by these queries were related to the topic of interest. Hence, quite a few results have been ignored. On the other hand, there exists literature which, while contained in the previous sections, is returned by none of the queries below. In most cases such work has been found inside the bibliography of other work.

In addition, the queries have been executed separately for each year we considered (1988 to 2009). But since this would result in pretty redundant queries, we omit the restriction to a specific year in the queries below.

Query executed on PubMed

```
("GI tract" or "gastrointestinal" or "stomach" or "esophagus" or
"small intestine" or "colon" or "small bowel") and ("cancer" or
"carcinoma" or "Barrett's esophagus" or "polyps" or "polyp" or
"neoplasm" or "neoplasms" or "ulcer" or "ulcers" or "bleeding"
or "hemorrhage" or "helicobacter" or "gastritis" or "gastric
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mucosa" or "chrohn's" or "celiac" or "tumor" or "tumors" or
"tumour" or "tumours" or "tumorous lesions" or "tumorous lesion"
or "tumourous lesions" or "tumourous lesion") and ("colonoscopy"
or "gastroscopy" or "endoscopy" or "enteroscopy" or "WCE" or
"colon capsule" or "capsule endoscopy" or "endomicroscopy") and
("feature extraction" or "texture" or "computer-aided" or
"computer-assisted" or "automated classification") and NOT "CT"
not "tomography" not "MRI"
```

Query executed on ScienceDirect

```
(({GI tract}) or {gastrointestinal} or {stomach} or {esophagus} or
({small intestine}) or {colon} or ({small bowel})) and ({cancer}
or {carcinoma} or ({Barrett's esophagus}) or {polyps} or {polyp}
or {neoplasm} or {neoplasms} or {ulcer} or {ulcers} or {bleeding}
or {hemorrhage} or {helicobacter} or {gastritis} or ({gastric
mucosa}) or ({chrohn's}) or {celiac} or {tumor} or {tumors} or
{tumour} or {tumours} or ({tumorous lesions}) or ({tumorous lesion})
or ({tumourous lesions}) or ({tumourous lesion})) and ({colonoscopy}
or {gastroscopy} or {endoscopy} or {enteroscopy} or {WCE} or
({colon capsule}) or ({capsule endoscopy}) or {endomicroscopy}) and
(({feature extraction}) or {texture} or ({computer-aided}) or
({computer-assisted}) or ({automated classification})) and NOT {CT}
and NOT {colonography} and NOT ({computed tomography}) and NOT {MRI}
```