Short report on Distortion Generation results.

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July 20, 2021

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1 Motivation

The gastric burden is increasing with the fact of growing population and due to the formation of cancer in the gastrointestinal tract (GI) around the world. Every year nearly 0.7 million cases of specifically gastric cancer are reported (ACS [1]). It is estimated that cancer cases in both sexes are **11,180 deaths are estimated in 2021 and 26,560 new cases in the United States alone**. The normal clinical practice includes the intestinal biopsy (tissues sample of the mucosa is taken) of GI tract. Which are then analyzed by experts (under microscope), to see if there are any cancerous or abnormal cells exist. This is an invasive method for detection of gastric abnormalities and it requires high-level of expertise. On the other hand, endoscopy is a less invasive method for screening GI tract (Kainuma et al. [2]). An endoscope is a flexible tube with a mounted camera, light source, and an accessory channel (Pennazio [3]). Moreover, an accessory channel can be used for cleansing of GI tract or inserting medical instruments. Therefore, the endoscope can also be used for the intestinal biopsy (Wallace and Keisslich [4]).

The GI tract can be categorized into several parts, starting from upper stomach parts GI tract have esophagus, stomach in middle, and duodenum as ending of stomach (upper GI tract), the jejunum, ileum (small-bowel), ending at the colon, and rectum (Carpi et al. [5]; Filip et al. [6]). Therefore, the endoscopy procedures refer to different names according to the target area of GI tract1 e.g., for esophagus referred (esophagoscopy), area of stomach and duodenum (gastroscopy), rectum and sigmoid colon (proctoscopy), sigmoid colon (sigmoidoscopy), colon (colonoscopy) for whole GI tract (laparoscopy).

The endoscopic procedure helps the physician for the detection of gastric abnormalities in their early stages. Timely detection of chronic diseases can be cured with proper treatments. Thus, the screening process can be very useful for a substantial reduction in both, death-rate as well as the cost of treatment. Specifically, the deaths occur due to different gastrointestinal cancers, which can be cured if cancer was detected in its pre-malignant stage (Hamashima et al. [7]). Still, video endoscopy is a painful procedure, it also requires both time and expertise.

In contrast with the wired endoscopy, the wireless capsule endoscopy (WCE) is a painless tool than traditionally used white light video endoscopy (VE) for examining the internal cavity of the human body (Gastelum et al. [8]; Kim et al. [9]). Normally, a VE composed of

a light source, a charged couple camera (CCD), and a video monitor (which is used to view the output of the endoscope).

1.1 Abnormalities in gastrointestinal tract

The GI tract is a crucial part of human body, it refers to stomach, small intestine and whole digestive system. The GI tract can be divided into an esophagus, stomach, small bowel and colon (Chu et al. [10]). Furthermore, the stomach has its own parts as the upper stomach, middle stomach and lower stomach (Miyahara et al. [11]). A brief introduction of the parts of a GI tract has given in Table 1.

Table 1: Anatomy of the gastrointestinal tract

Disease	**Description**
Esophagus	When we eat food, the chewed food goes into the esophagus. The esophagus is a tube-like organ that used to carry food to the stomach (Khashab et al. [12]). The entry point of food into the stomach is called gastroesophageal (GE) junction, which is located under the lungs (Owens and Appelman [13])
Stomach	The stomach is a towel-like organ that holds food (Eberlein et al. [14]). After the food arrived from esophageal the special enzymes are produced to digest the food into that stomach (Roukos et al. [15])
Small-bowel	Secretion of stomach juices and the food are mixed. Then, the food goes into the entrance of small-intestine called duodenum (Callacondo-Riva et al. [16]). The small-intestine is like a narrow tube of approximately 6 meters in length. Due to complexity and length of small intestine, the screening is a difficult and time-consuming task (Axon [17])
Colon	The last portion of GI tract, and the most prone area for having tumors and polyps. The colon cancer is the third most common disease found in the Western countries (Chu et al. [10]). The colon is consisting of several parts, ascending colon, transverse colon, descending colon and rectum (Hurlstone et al. [18])

There are many clinical conditions, including basic symptoms and mature diseases found in theGI tract. Some of these abnormalities of the digestive system are listed below.Moreover, some of them can be easily detected through a normal endoscopic procedure. However, there are some diseases in GI tract (e.g., cancer, polyps and ulcers) that do not exhibit visible signs until it approaches an advance stage (Liedlgruber and Supervisor [19]).

1. Cancer: There are many types of cancer [e.g., adenocarcinoma (Guggenheim [20]), lymphoma (Namikawa et al. [21]), GIST (Korngold [22]), etc.]. However, most of the cancers are started from an unusual growth of cells. The older cells do not die and unusual growth of cells forms cancer. Some common symptoms of gastric cancer include early satiety, abdominal pain, nausea, vomiting, bloating, weight-loss, and

anorexia (Rogy and Bünger [23]). It is worth mentioning here, that cancer can start in any area of the GI tract.

2. Polyps: Polyps are similar to cancer, it is also an unusual mucosal growth and typically these are benign (Kato et al. [24]). On the other hand, there could be diminutive colorectal polyps, which are very dangerous if left untreated. Polyps can grow in any area of GI tract similar to cancer. However, mostly found in the colon and small-bowel (Hazewinkel et al. [25]).

3. Ulcer The ulcer is also referred to a disease caused by the acid that is produced by the stomach itself. In peptic ulcer, the gastric cells are damaged with gastric juices. Normally ulcer appears in the duodenum, small intestine or in gastric lining (Jensen et al. [26]).

4. Crohn's Disease Crohn's disease is caused due to inflammation of the lining of the gut. This is an intestinal inflammatory disease, it may also cause a severe abdominal pain. In some cases ileum (part of small intestine) is effected from this disease (Eliakim [27]).

5. Bleeding: Bleeding is another abnormality that is normally found in GI tract while screening. It may be caused by different other pathological conditions such as cancer, Crohn's disease or ulcer (Schlag et al. [28]).

6. Angiodysplasia: Angiodysplasia is an abnormality with the blood vessels in the gastrointestinal (GI) tract. The GI tract includes the mouth, esophagus, small and large intestines, stomach, and anus. This condition causes swollen or enlarged blood vessels, as well as the formation of bleeding lesions in the colon and stomach (Sotiropoulou [29]).

1.2 Distortion in WCE

Today, medical endoscopy is a widely used procedure to inspect the inner cavities of the human body. As a consequence different medical fields exist for which automated decision-support systems based on endoscopic images have been developed [19]. But since images taken with endoscopes often suffer from various kinds of degradations, a pre-processing of the images is often necessary in order to make them useful for an automated analysis [30] (to cope with e.g. sensor noise, focus and motion blur, and specular reflections [19]).

In [31] the impact of distortion correction on the classification accuracy regarding celiac disease images has been investigated. Gschwandtner et al. showed that applying distortion correction as a pre-processing step to the endoscopic images is a absolutely important stage to increase the classification accuracy. However, to the best of our knowledge up to now there are only a few studies available, which investigate the impact of various distortions and distortion correction on the accuracy of automated classification systems for endoscopic images. Many papers focus on a mono-distortion and propose a certain pre-processing stage for all images while there are many kinds of distortion which can occur in one observed test case [32, 33, 34].

Therefore, in order to improve performance of existing pre-processing stage, image quality assessment (IQA) metrics is an unavoidable tool. However, with the quick advancement of

IQA research, the booming of open IQA databases calls for associated comprehensive and accurate visual attention dataset. Table 3 gives an overview of some existing datasets of images and videos for IQA.

Table 3: IQA dataset

Dataset	**Description**
IVC	database consists of 10 pristine images, and 235 distorted images, including four types of distortions (JPEG, JPEG2000, locally adaptive resolution coding, blurring). Quality score ratings (1 to 5) are provided in the form of MOS.
LIVE IQA	has two releases, Release 1 and Release 2. Laboratory for Image and Video Engineering (University of Texas at Austin) conducted an extensive experiment to obtain scores from human subjects for a number of images distorted with different distortion types. Release 2 has more distortion types—JPEG (169 images), JPEG2000 (175 images), Gaussian blur (145 images,White noise (145 images), bit errors in JPEG2000 bit stream (145 images). The subjective quality scores in this database are DMOS (DifferentialMOS), ranging from 0 to 100.
A57 Database	has 3 pristine images, and 54 distorted images, including six types of distortions (JPEG, JPEG2000, JPEG2000 with dynamic contrast-based quantization, quantization of the LH subbands of DWT, additive Gaussian white noise, Gaussian blurring). Quality score ratings (0 to 1) are provided in the form of DMOS
Toyoma Database	consists of 14 pristine images, and 168 distorted images, including two types of distortions (JPEG, JPEG2000). Quality score ratings (1 to 5) are provided in the form of MOS.
TID2008	contains 25 reference images and 1,700 distorted images (25 reference images x 17 types of distortions x 4 levels of distortions images. The MOS was obtained from the results of 838 experiments carried out by observers from three countries. 838 observers have performed 256,428 comparisons of visual quality of distorted images or 512,856 evaluations of relative visual quality in image pairs. Higher value of MOS (0 - minimal, 9 - maximal, MSE of each score is 0.019) corresponds to higher visual quality of the image. A file enclosed "mos.txt" contains the Mean Opinion Score for each distorted image.
CSIQ	database consists of 30 original images, each distorted using one of six types of distortions, each at four to five different levels of distortion. The images were subjectively rated based on a linear displacement of the images across four calibrated monitors placed side-by-side with equal viewing distance to the observer. The database contains 5,000 subjective ratings from 35 different

IVC-LAR	database contains 8 pristine images (4 natural images and 4 art images), and 120 distorted images, consisting of three types of distortions (JPEG, JPEG2000, locally adaptive resolution coding). Quality score ratings (1 to 5) are provided in the form of MOS.
IRSQ	consists of 57 reference images grouped into four attributes, specfically face and people, clear foreground object, natural scenery, and geometric structure. Moreover, ten different retargeting methods (cropping, seam carving, scaling, shift-map editing, scale and stretch, etc.) are applied to generate retargeted images. In total, 171 test images can be found in this database
TID2013	contains 25 reference images and 3,000 distorted images (25 reference images x 24 types of distortions x 5 levels of distortions). MOS (Mean Opinion Score) is provided as subjective score, ranging from 0 to 9.
KADID-10k	consists of 81 pristine images and 10, 125 distorted images derived from the pristine images considering 25 different distortion types at 5 intensity levels (10, 125 = 81x25x5). In contrast, KADIS-700k contains 140, 000 pristine images and distorted images were derived using 25 different distortion types at 5 intensity levels but MOS values are not given in this database.
CID2013	database contains 474 images with authentic distortions captured by 79 imaging devices, such as mobile phones, digital still cameras, and digital single-lens reflex cameras.

However, deep learning methods for classification are infamous for being data hungry. For problems in natural image analysis, this is often solved by mining massive numbers photos from social media and having non-experts perform annotations through crowdsourcing. For medical problems, this data is often harder to acquire and labeling requires expensive experts, meaning it takes longer for deep learning methods to find their way to medical image analysis. As a result, many of the algorithms for classification are prototyped on natural data and subsequently adjusted to medical problems. We can clearly see that those mentioned IQA datasets are natural image which challenge the real-life endoscopic imaging classification task. Therefore, our motivation is creating a new endoscopic dataset which contains different level of different types of distortion.

2 Additive white Gaussian noise (AWGN)

The various type noises affecting various types of images are Gaussian Noise, Poisson Noise, Impulse Noise and Quantization noise. While manifestation of any type of noise in various images is an entirely random stochastic process, the Additive White Gaussian Noise is the most prevalent noise in images as it occurs during acquisition and transmission through analogy circuitry which is pretty much the basic operation required for computerised operation [35].

Additive white Gaussian noise (AWGN) is a basic noise model used in information theory

to mimic the effect of many random processes that occur in nature. Digital imaging is widely used in applications such as medical, biometrics, multimedia,...etc. In many cases, images are transmitted through Internet from one point to another. During image acquisition and transmission, factors such as moving objects, sensor quality, and channel interferences may result in additive noise. Parameters such as noise mean and variance provide noise characteristics of AWGN. Image independent noise can often be described by an additive noise model, where the recorded image $f(i, j)$ is the sum of the true image $s(i, j)$ and the noise $n(i, j)$:

$$f(i, j) = s(i, j) + n(i, j) \tag{1}$$

The noise $n(i, j)$ is often zero-mean and described by its variance σ_n^2. The impact of the noise on the image is often described by the signal to noise ratio (SNR), which is given by:

$$SNR = \frac{\sigma_s}{\sigma_n} = \sqrt{\frac{\sigma_f^2}{\sigma_n^2} - 1} \tag{2}$$

where σ_s^2 and σ_f^2 are the variances of the true image and the recorded image, respectively. The image after being applied AWGN noise will be clipped to maintain the proper image data range. Therefore, the output will be on the range [0, 1].

2.0.1 Result

The result of image applied AWGN is present in Fig. 1

2.1 Blur

Because WCE acquires images during a slow squirm process and transmits them from inside of the body by a wireless transmitter, the received images are often blurred due primarily to the complicated environment of the intestine and intrinsic restrictions of the equipment in terms of image acquisition and transmission. This in turn imposes difficulties for accurate and effective diagnosis. Capsule endoscopes are usually equipped with fisheye lenses that have small depths of field. Blurred images may be obtained due to fast camera motions with low frame rates and the use of the wrong lens focus. These reasons caused two types of possible occurred blur (Motion blur and Defocus blur)

2.1.1 Motion blur

The degradation process of blurred image can be approximately simulated as a liner degradation system, and the blurred image caused by the relative motion between camera and scene can be described as a two-dimensional convolution model in the linear space translation, which is modeled as:

$$g(x, y) = f(x, y) * g(x, y) + n(x, y) \tag{3}$$

where $g(x, y)$, $f(x, y)$ represent the blurred and original image respectively, $h(x, y)$ is the PSF (Point Spread Function) function or blur kernel, and $n(x, y)$ refers to the additive noise. The notation "*" represents the convolution operator.

(a) Input testing image

(b) $\sigma = 0.0005$

(c) $\sigma = 0.001$

(d) $\sigma = 0.005$

(e) $\sigma = 0.01$

Figure 1: Input (a) and output (b)-(e) images showing the effect of AWGN distortion created by the above theory. Note that we can change the level of noise.

From (3), we can see that the keypoint of deblurring is to determine the PSF function $g(x, y)$. Assuming that the scene objects move uniformly relative to the camera, we can

deduce that the gray values of any points in the blurred image are related to the gray values of their corresponding adjacent points in the original image, and the PSF for motion blurring can be expressed as [36]:

$$h(x,y) = \begin{cases} \frac{1}{l}, & \text{if } 0 \leq |x| \leq l\cos\theta, |y| = l\sin\theta \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where l is the length of blur, and θ represents the angle of blur.

2.1.2 Defocus blur

The idea to create the defocus blur is the same to motion blur but I used a different type of filter. Concretely, I created a Gaussian Kernel. After that, Gaussian Blur is done by convolving an image with a above normalized box filter.

$$G_0(x,y) = Ae^{\frac{-(x-\mu_x)^2}{2\sigma_x^2} + \frac{-(y-\mu_y)^2}{2\sigma_y^2}} \tag{5}$$

where μ is the mean (the peak) and σ^2 represents the variance (per each of the variables x and y)

For the normal distribution, the values less than one standard deviation away from the mean account for 68.27% of the set; while two standard deviations from the mean account for 95.45%; and three standard deviations account for 99.73%. Therefore, the rule of thumb for

Figure 2: Standard deviation and coverage

Gaussian filter design is to choose the filter size to be about 3 times the standard deviation (sigma value) in each direction, for a total filter size of approximately 6σ rounded to an odd integer value. Because the filter size has been an odd number so I have created a filter whose size:

$$w = \lceil 6\sigma \rceil \tag{6}$$

where the Gaussian filter's size is $w \times w$

2.1.3 Results

Motion blur(Fig. 3) **Defocus blur**(Fig. 4)

(a) $l = 5, \theta = 0$

(b) $l = 10, \theta = 0$

(c) $l = 15, \theta = 0$

(d) $l = 20, \theta = 0$

Figure 3: Output images showing the effect of motion blur created by the above theory with $\theta = 0$. Note that we can change the level and the direction of motion.

2.2 Uneven illumination

In WCE, it is clear to know that the lighting modules consist of a bundle of flexible glass fibers that can each have a diameter as small as 30 microns. They provide shadowless illumination because their output angle exactly matches the 120-degree imaging angle of a camera. When making hundreds of thousands of single-use endoscopes, it becomes extremely time-consuming and expensive to handle and install glass optical fibers for each instrument. Therefore, LEDs and plastic fibers became a new solution. However, they typically have output angles that are greater or less than before imaging angle of the camera, which can produce uneven lighting or shadows that degrade image quality. Especially thin endoscopes such as bronchoscopes, rhinoscopes, and cystoscopes have very little space for illumination, leading to extremely limited outer diameters for light guides. It made us to be careful with this type of distortion.

VALUE (OR BRIGHTNESS) in HSV color space will be used to adjust to illumination of original image. To be clearer, **VALUE (OR BRIGHTNESS)** works in conjunction

(a) $\sigma = 0.75$

(b) $\sigma = 1$

(c) $\sigma = 2$

(d) $\sigma = 3$

Figure 4: Output images showing the effect of defocus blur created by the above theory. Note that we can change the level of blur

with saturation and describes the brightness or intensity of the color, from 0 to 100 percent, where 0 is completely black, and 100 is the brightest and reveals the most color.

To simulate this kind of distortion, a scheme has been established as follow:

1. Convert the original image from RGB color space to HSV color space.
2. A circular-gradient mask will be generated which represent the uneven illumination distortion.
3. In HSV color space, channel V will be extracted and applied above mask.
4. Convert the distorted image back to RGB channel.

The most important step is step 2. We have to create the mask as close as possible to a real image. Because if the light source is not straight to the view direction, the illumination mask will be changed to present correctly the shadow sign.

According to your requirements, I have used Lab color space as well as maintain the RGB color space to generate the result. The result of 3 color spaces are compared to get the most suitable one.

2.2.1 Results

I would like to show two different result which present us the 2 different shadow shape for uneven illumination in 4 levels of Illumination gradient. The level of distortion is calculated as the difference between the highest illumination (in the middle of the light source) and the lowest illumination (in the border of light sigh).

$$\Delta_I = I_{center} - I_{border} \tag{7}$$

(a) $\Delta_I = 50$

(b) $\Delta_I = 100$

(c) $\Delta_I = 180$

(d) $\Delta_I = 250$

Figure 5: Output with 'circle' images showing the effect of uneven illumination created by the above theory and the light source is in the center of image. Note that we can change the direction, position and illumination level of distortion.

(a) Position = top-left

(b) Position = center

(c) Position = bottom-right

Figure 6: Output with 'circle' images showing the effect of uneven illumination created by the above theory regarding to the light source position.

3 Specular Reflection - SR

Endoscopic images often contain specular light reflections, also called highlights, on the wet tissue surface. They are caused by the inherent frontal illumination and are very distracting for the observer. In Hyper-Kvasir dataset, there is existed SR, so, it is necessary to detect and remove the existed specular reflection before adding the our own artificial SR.

3.1 Detection

The specular detection is the subject in different medical applications have investigated by many researchers. In some cases, the thresholding algorithms show the effectiveness of detecting specular regions [37, 38]. On the other hand, Zimmerman-Moreno et al. proposed to use probabilistic segmentation on hue and saturation components for detection specular regions [39]. Each of these methods has strong and weak points. The main disadvantages of the known methods come from the fact that most of them are unable to detect large specular

reflection regions and are more suitable for the small high intense specular highlights. To cover these problem, I see that using a kernel or mask as a filter to detect SR pixels present in image can be a possible solution. This kernel is referred as structuring element (SE).

In previous work, Lange [40] extracted green component of an image to get high glare to background ratio and treated it as a feature image. Morphological top hat filters are used to detect SR pixels from extracted feature image. Watershed segmentation is used to find the complete boundary of glare region. The method suffers from drawback of accurate selection of structuring element in morphological processing. Sun and Sang [41] also suggested using kernel as a filter on image. Xue et al. [42] followed similar approach to use structuring element in top hat transform on intensity image (I) of cervigrams. Because our work is not proposing a new method for specular reflection, I have used top-hat filter following by Otsu thresholding [42] to detect the SR due to its simplify (Fig. 7-8).

Figure 7: SR detection scheme

3.2 Inpainting

Image inpainting is a computer vision technique that has a broad definition. It is a process that restores damaged or lost part of an image, insert an object into or remove an object from an image as the human eye could not understand it. Most articles in this field can be classified into one of the two categories:

- Algorithmic approaches
- Learning approaches

3.2.1 Algorithmic Approaches

Different techniques of image processing are used for image inpainting. In the following, the recent and essential procedures would be described. Predicting missing pixels in an image are

(a) Original image

(b) SR mask

Figure 8: Otsu mask which is extracted using TOP-HAT filter and otsu threshold.

very depended on neighboring pixels. Accordingly, M.Akbari et al. [43] proposed a method for selecting the best patch around a pixel, which leads to better prediction. By choosing this, the computational time reduced, and the output result is reasonable.

Interpolation is one of the image processing techniques that could predict pixels between pixels. In [44], M. Motmaen et al. utilize one and two-dimensional bicubic spline interpolation in multiple directions to predict missing pixels.

3.2.2 Learning approaches

Deep Neural Networks (DNN) have recently received much attention because of their capabilities in different applications with large datasets. Image inpainting is one of the applications that benefit from these neural networks. In most recent articles in this field, different types of DNN with different views are implemented [45, 46, 47]. Because the advantage of naturality of DL-based result, I decided to use one state-of-the-art DL based method named: CRA [48] due to its time consumption and performance.

3.2.3 Result

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Figure 9: The overall pipeline of the method: (top) CRA mechanism, (bottom) the architecture of the generator.

(a) Original image

(b) Impainted image

Figure 10: Impainting result using CRA method.

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