A new dataset of distortions on Wireless Capsule Endoscopy Images for pathological ifentification

Tan Sy NGUYEN

tansy.nguyen@math.univ-paris13.fr

LAGA, L2TI
Université Sorbonne Paris Nord

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Overview

Context

Alert

Colorectal cancer is a major health problem.

[1] Bray F, Ferlay J, Soerjomataram I, Siegel RL, Torre LA, Jemal A, "Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries", CA Cancer J Clin. 2018 Nov; 68(6):394-424.

[2] Santé Publique France, https://www.santepubliquefrance.fr/maladies-et-traumatismes/cancers/cancer-du-colon-rectum

[3] McKESSON, "Colorectal Cancer & Laboratory Screening", 2018

Context

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Colorectal cancer is a major health problem.

Example

In 2018, the Colorectal cancer (CRC) is the third (second respectively) leading cause of cancer death in the world (France, respectively).[1,2]

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Solution

Studies have shown that early detection can result in up to a **92% survival rate for stage I of cancer.**[3]

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Wireless Capsule Endoscopy

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Wireless capsule endoscopy include its **non-invasive** character and its ability to visualize proximal and distal parts of the intestine

Objectives

The main objective of the project is to develop a smart system for:

- Identify the pathological finding on wireless capsule endoscopy (WCE) images
  - Including a pre-processing module that aims at improving the quality of the acquired images
  - Develop a set of image quality enhancement solutions based on kinds of distortion

There are **many kinds of distortion** & in **different levels**

Challenges

- Some common acquisition distortions (**noise**, **blur**, **uneven illumination**, **specular reflection**) may affect the WCE based diagnosis.

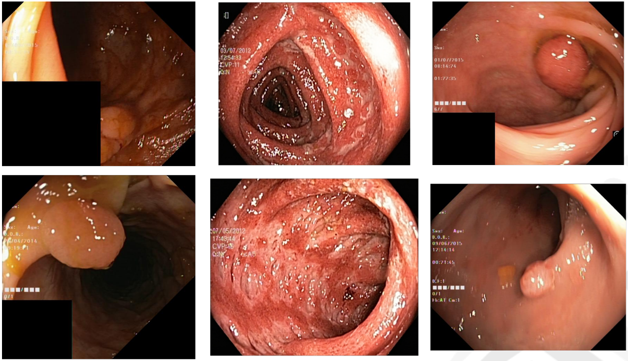

Figure 1: Illustration of some common WCE images distortions. Left column: *polyb* image with uneven illumination. Middle column: *ulcerative colitis* image with noise. Right column: *polyb* image with blur

Example

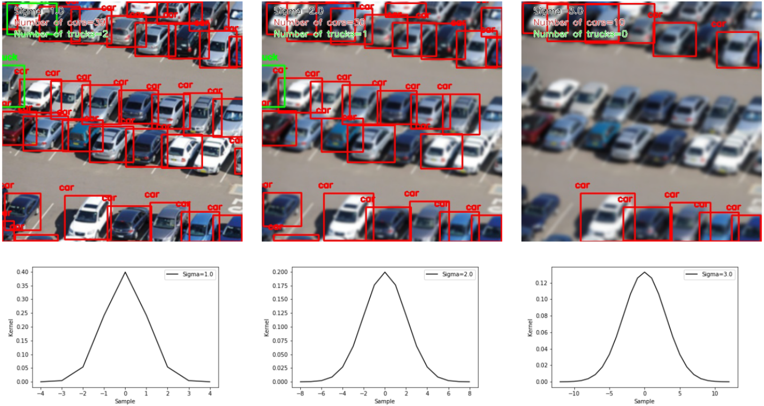

Figure 2: Degradation of the vehicle detection due to image blurring. Left column: Blurred image with kernel width $\sigma = 2.0$ detects 31 vehicles. Middle column: Blurred image with kernel width $\sigma = 1.0$ detects 41 vehicles. Right column: Blurred image with kernel width $\sigma = 3.0$ detects 10 vehicles.

Example

Figure 3: Vehicle detections for additive noise with $SNR = 1.81, 4.39, 10.24$.

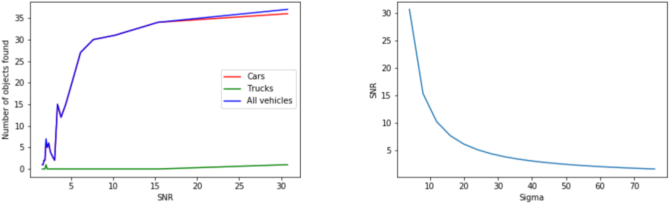

Figure 4: Number of cars detected as a function of the Gaussian noise added with a signal to noise $SNR = 1.62, ..., 30.76$. Right: SNR as a function of $\sigma = 4, 8, ..., 80$.

Example

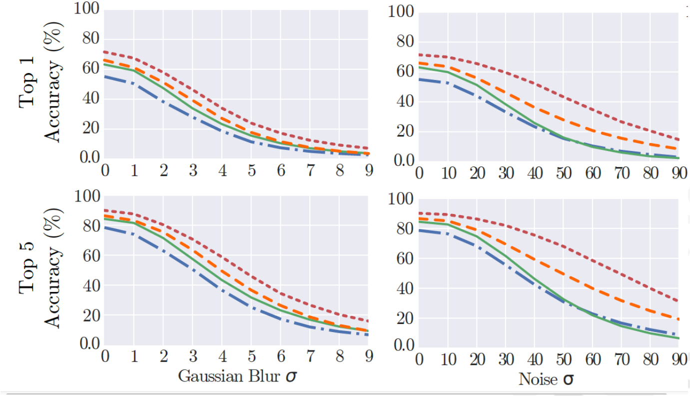

Figure 5: Top-1 and Top-5 Accuracy rates under different quality distortions. The networks are very sensitive to changes in blur and noise

Method

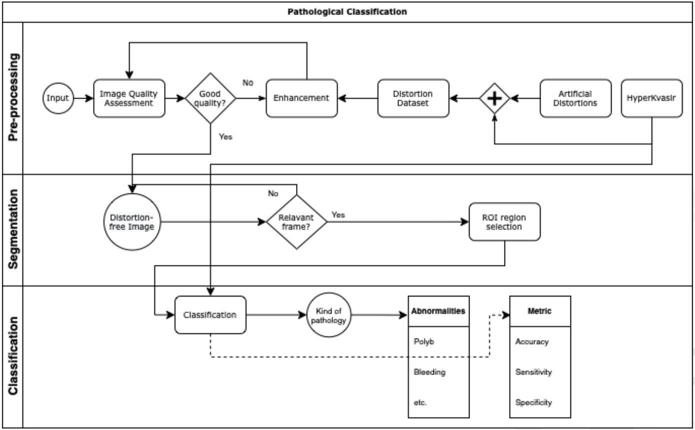

Figure 6: Flow chart of the pathological classification process

Existing datasets

Table 1: An overview of existing GI datasets.

Dataset	Findings	Size
CVC-356 [1]	Polyps	356 images
CVC-ClinicDB (also named CVC-612) [2]	Polyps	612 images
CVC-VideoClinicDB (also named CVC-12k) [1]	Polyps	11954 images
CVC-ColonDB [1]	Polyps	380 images
Endoscopy Artifact detection 2019 [3]	Endoscopic Artifacts	5,138 images
ASU-Mayo polyp database [4]	Polyps	18,781 images
ETIS-Larib Polyp DB [5]	Polyps	196 images
KID [6]	Angiectasia, bleeding, inflammations, polyps	2371 images and 47 videos
GIANA 2017 [7]	Polyps & Angiodysplasia	3462 images and 38 videos
GIANA 2018 [8]	Polyps & Small bowel lesions	8262 images and 38 videos
GASTROLAB [9]	GI lesions	Some 100s of images andfew videos
WEO Clinical Endoscopy Atlas [10]	GI lesions	152 images
GI Lesions in Regular Colonoscopy Data Set [11]	GI lesions	76 images
Atlas of Gastrointestinal Endoscope [12]	GI lesions	1295 images
El salvador atlas of gastrointestinal video endoscopy [13]	GI lesions	5071 video clips
Kvasir [14]	Polyps, esophagitis, ulcerative colitis, Z-line,pylorus cecum, dyed polyp, dyed resection margins, stool	8000 images
Kvasir-SEG [15]	Polyps	1000 images
Nerthus [16]	Stool - categorization of bowel cleanliness	21 videos

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Using **HyperKvasir** [17] dataset

HyperKvasir dataset

Table 2: Overview of the data records in the HyperKvasir dataset.

Data Record	# Files	Description
Labeled images	10,662 images	23 classes of findings
Segmented Images	1,000 images	Segmentation masks for polyp findings
Unlabeled Images	99,417 images	Unlabeled
Videos	374 videos	30 different classes

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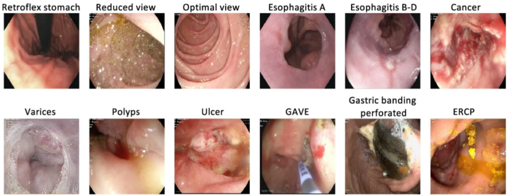
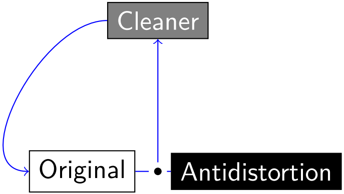


Figure 7: Image examples of the various labeled classes for images and/or videos.

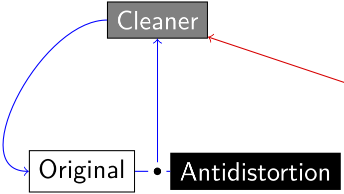
Ourwork



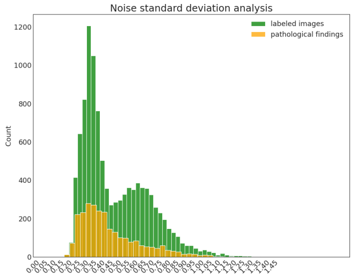
a) Clean the image

Step 1 Cleaning the existing distortion in HyperKvasir dataset

Ourwork



a) Clean the image



Step 1 Cleaning the existing distortion in HyperKvasir dataset

Ourwork

a) Clean the image   *b) Create model*

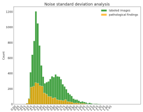
Step 2 Creating the model to generate the new artificial distortions

Ourwork

Cleaner

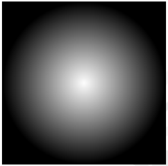
Original — Antidistortion

a) *Clean the image*



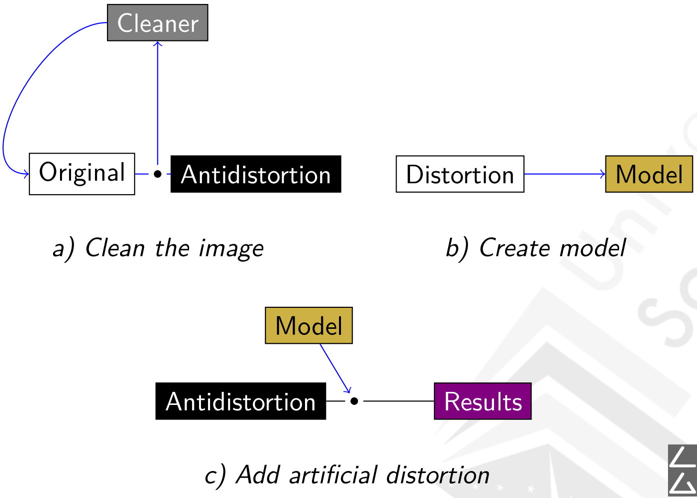
Distortion → Model

b) *Create model*



Ourwork

Step 3 Add the new artificial distortions to the antidistorted images



Results

Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.

Results

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Original Image → Denoising

Results

Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.

Original Image → **Denoising** → Debluring

Results

Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.

Original Image → Denoising → Debluring → Uneven Illumination Correction

Results

Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.

Original Image

Denoising

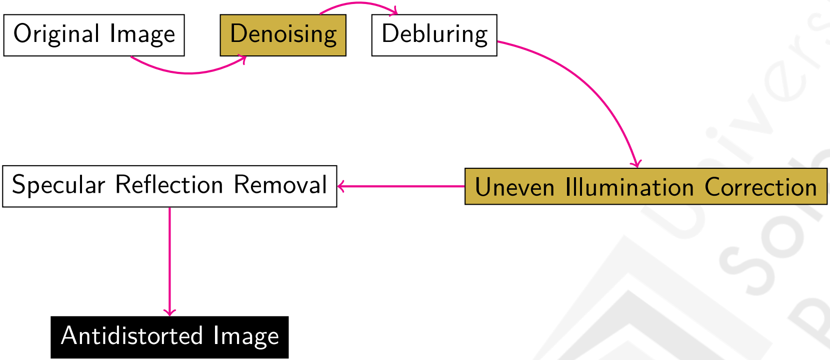
Debluring

Uneven Illumination Correction

Specular Reflection Removal

Results

Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.



Results

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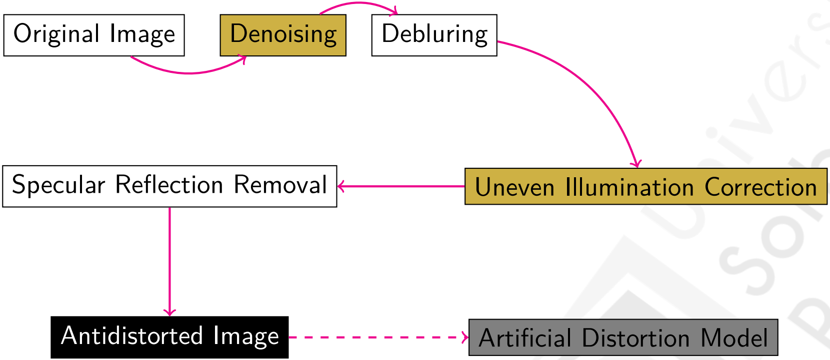
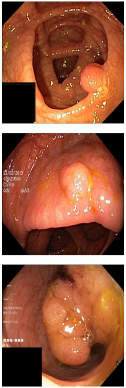


Results

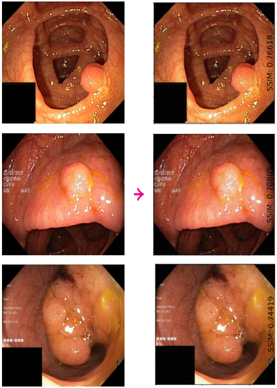
- Noise



a) Original

Results

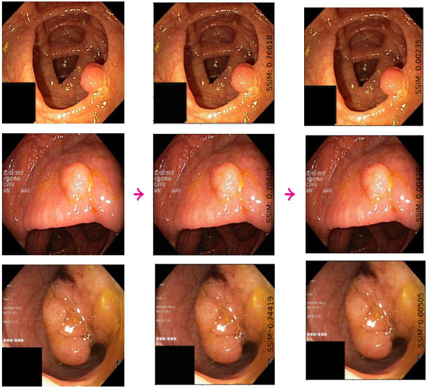
- Noise



a) Original   *b) Noisy*

Results

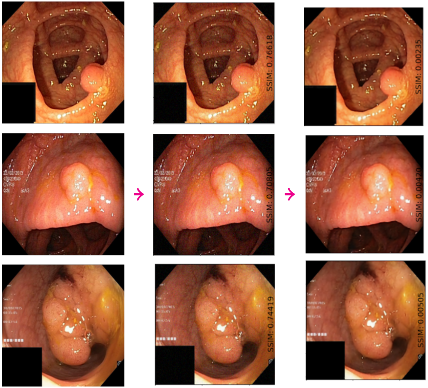
- Noise



a) Original *b) Noisy* *c) Denoised*

Results

- Noise



a) Original *b) Noisy* *c) Denoised*

		Noisy-image	C-BM3D	NM-Mean	CAE
σ_n	0.25	0.8095	0.7364	0.9068	**0.9158**
	0.3	0.7561	0.7275	0.8884	**0.9097**
	0.35	0.7084	0.7106	0.8752	**0.9033**
	0.4	0.6615	0.7039	0.8614	**0.8991**
	0.6	0.5102	0.6517	0.8222	**0.8766**
	0.65	0.4810	0.6428	0.8132	**0.8681**
	0.7	0.4508	0.6389	0.8051	**0.8661**

d) Comparison using mean SSIM for different level where $n \sim N(0, \sigma_n^2)$

Results

- Noise

Table 3: Comparison using mean SSIM for different level where $n \sim N(0, \sigma_n^2)$

	σ_n						
	0.25	0.3	0.35	0.4	0.6	0.65	0.7
Noisy-image	0.8095	0.7561	0.7084	0.6615	0.5102	0.4810	0.4508
C-BM3D	0.7364	0.7275	0.7106	0.7039	0.6517	0.6428	0.6389
NM-Mean	0.9068	0.8884	0.8752	0.8614	0.8222	0.8132	0.8051
CAE	**0.9158**	**0.9097**	**0.9033**	**0.8991**	**0.8766**	**0.8681**	**0.8661**

Table 4: Comparison using mean PSNR for different level where $n \sim N(0, \sigma_n^2)$

	σ_n						
	0.25	0.3	0.35	0.4	0.6	0.65	0.7
Noisy-image	32.89	31.44	30.34	29.32	26.37	25.85	25.22
C-BM3D	27.51	27.52	27.47	27.47	27.28	27.21	27.16
NM-Mean	**35.81**	**34.74**	**34.12**	**33.48**	**31.85**	**31.51**	31.14
CAE	32.28	32.56	32.70	32.38	31.42	31.18	**31.43**

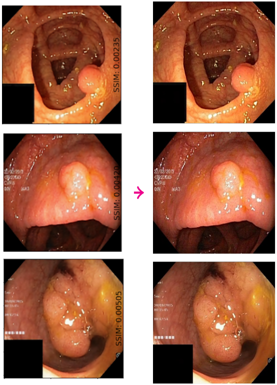
Results

- Blur

a) Denoised

Results

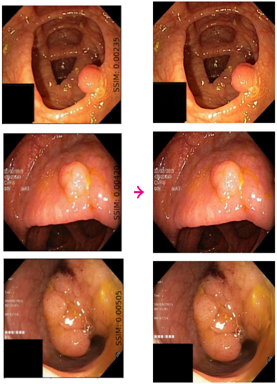
- Blur



a) Denoised *b) Deblurred*

Results

- Blur



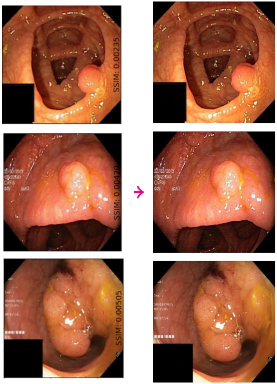
a) Denoised *b) Deblurred*

$$index = var(\mathcal{L}(f(x, y)))$$

*Apply the **variance of the Laplacian**[18] method to your own photos to detect the amount of blurring.*

Results

- Blur



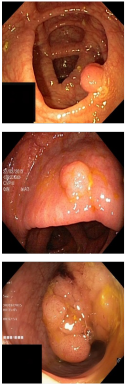
a) Denoised *b) Deblurred*

	Denoised-image	Deblured- mage
First exp	378	501
Second exp	321	428
Third exp	224	367

Table 5: The variance Laplacian Index before and after deblurring.

Results

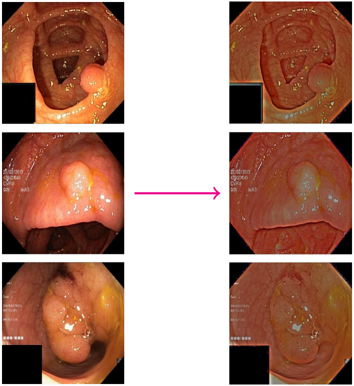
- Uneven Illumination



a) Deblurred

Results

- Uneven Illumination

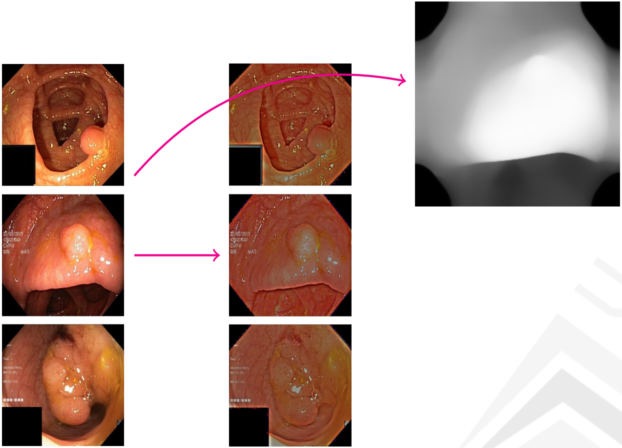


a) Deblurred

b) Uneven Illumination Correction

Results

- Uneven Illumination

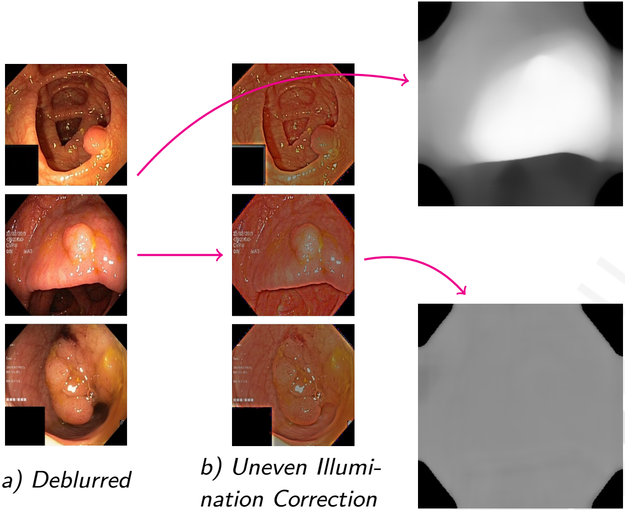


a) Deblurred

b) Uneven Illumination Correction

Results

- Uneven Illumination

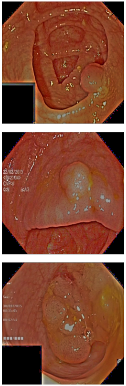


a) Deblurred

b) Uneven Illumination Correction

Results

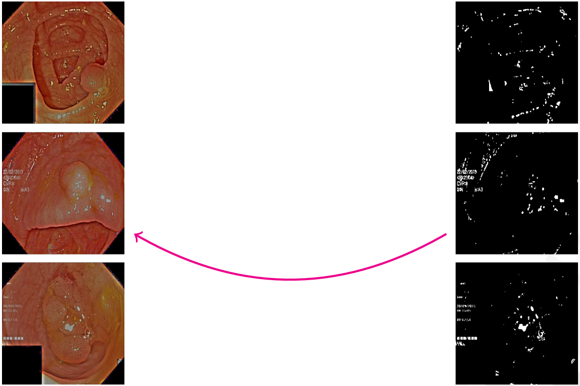
- Specular Reflection



a) Uneven Illumination Correction

Results

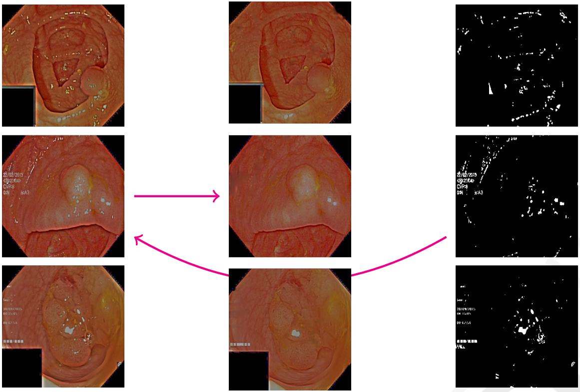
- Specular Reflection



a) Uneven Illumination Correction

Results

- Specular Reflection



a) Uneven Illumination Correction

b) Specular Reflection Inpainting

Results

Stage 2: We add the artificial distortion to the image

Antidistorted Image

Results

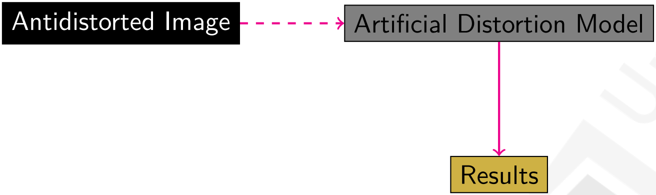
Stage 2: We add the artificial distortion to the image

Antidistorted Image

Artificial Distortion Model

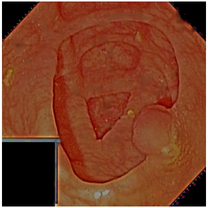
Results

Stage 2: We add the artificial distortion to the image



Results

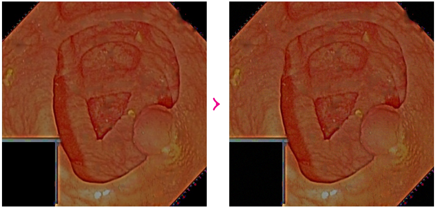
- Noise



a) Antidistorted Image

Results

- Noise

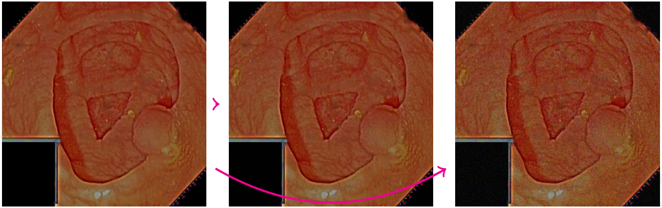


a) Antidistorted Image

b) Noised image with Gaussian Noise $n \sim N(0, \sigma_n^2 = (0.0005)^2)$

Results

- Noise



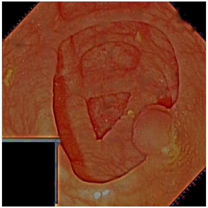
a) *Antidistorted Image*

b) *Noised image with Gaussian Noise* $n \sim N(0, \sigma_n^2 = (0.0005)^2)$

c) *Noised image with Gaussian Noise* $n \sim N(0, \sigma_n^2 = (0.005)^2)$

Results

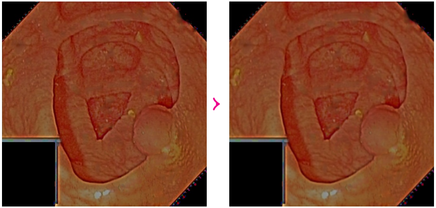
- Blur



a) Antidistorted Image

Results

- Blur

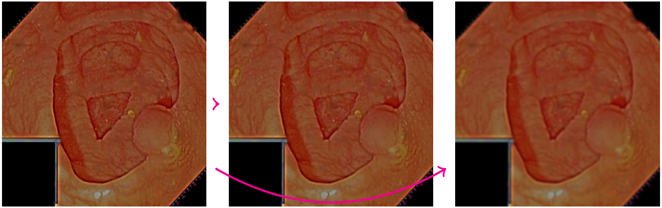


a) Antidistorted Image

b) Blured image with Defocus Blur $b \sim N(0, \sigma_b^2 = (0.75)^2)$

Results

- Blur



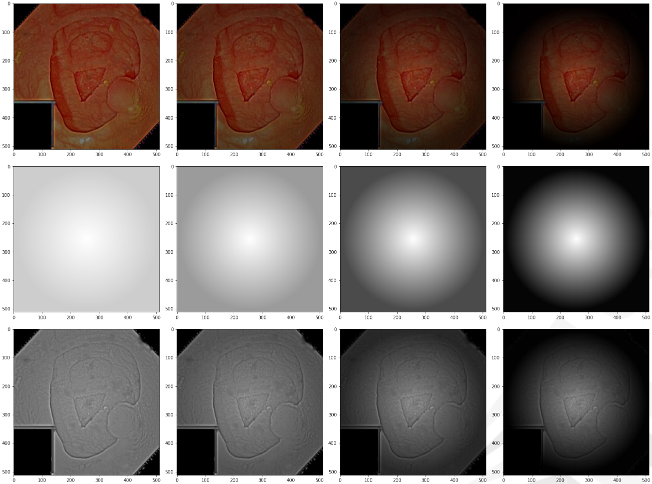
a) Antidistorted Image

b) Blured image with Defocus Blur $b \sim N(0, \sigma_b^2 = (0.75)^2)$

c) Blured image with Defocus Blur $b \sim N(0, \sigma_b^2 = (2)^2)$

Results

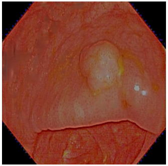
- Uneven Illumination



Artificial Uneven Illumination process

Results

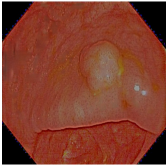
- Specular Reflection

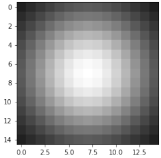


a) Antidistorted Images

Results

- Specular Reflection

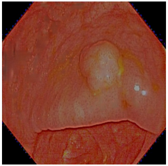


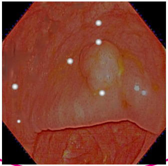


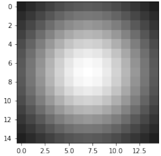
a) Antidistorted Images

Results

- Specular Reflection







a) Antidistorted Images

b) Artificial Specular Reflection Image

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Thank you for watching!

Contact:

tansy.nguyen@math.univ-paris13.fr