

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

Tan Sy NGUYEN

tansy.nguyen@math.univ-paris13.fr

LAGA, L2TI
Université Sorbonne Paris Nord

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Overview

1 Objectives

- Context
- Wireless Capsule Endoscopy
 - Challenges
 - Solutions

2 Existing datasets

- Existing GI datasets
- HyperKvasir dataset

3 Our work

- Method
- Results

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**

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



Challenges

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

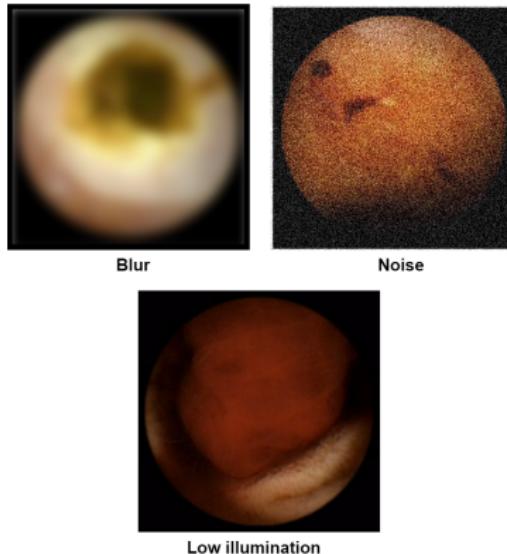


Figure 1: Illustration of some common WCE images distortions

Algorithm

```
input : distorted_image
output: enhanced_image
1 types_distortion = classifier (distorted_image);
2 for type in types_distortion do
3   | enhanced_image  $\leftarrow$  enhancertype (distorted_image)
4 end
5 return enhanced_image
```

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Requirement:

Create the classifier and enhancer_{type}

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Create the classifier and enhancer_{type} by using learning - based method



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Requirement:

Create the classifier and enhancer_{type} by using learning - based method

Creating a dataset is the most important thing to do



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 and few 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
EI 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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They are rather small, and often limited to polyps. Several of these have also lately become unavailable.



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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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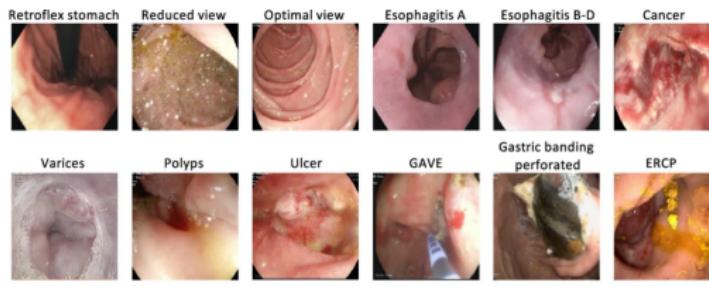
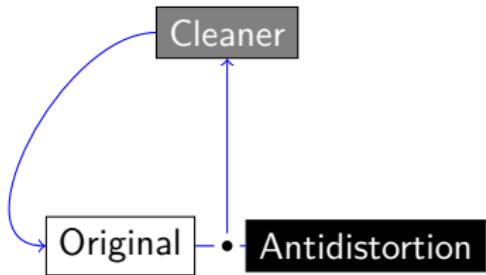


Figure 2: Image examples of the various labeled classes for images and/or videos.

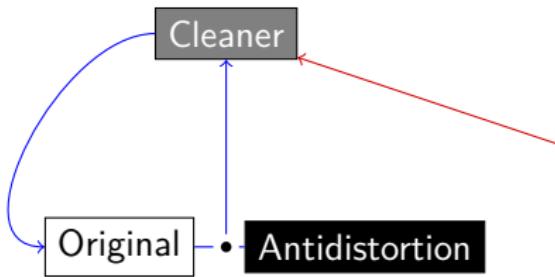
Our work



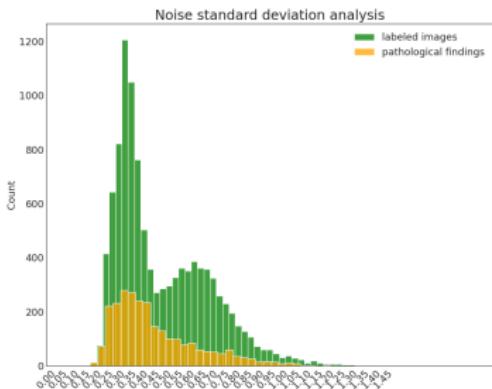
a) *Clean the image*

Step 1 Cleaning the existing distortion in HyperKvasir dataset

Our work

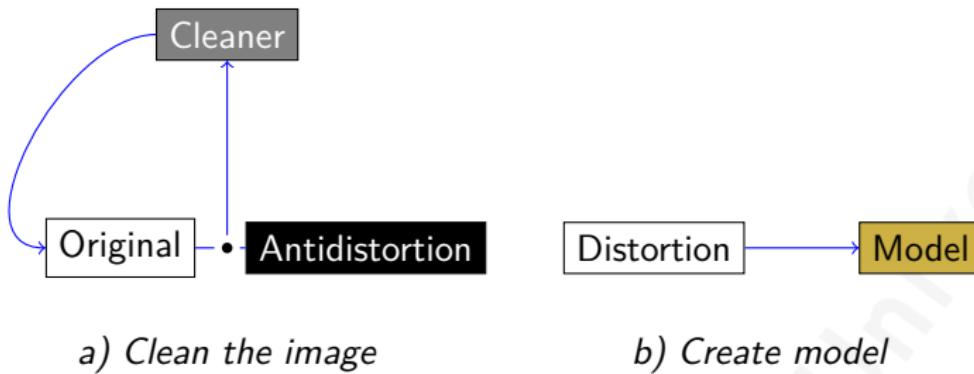


a) *Clean the image*



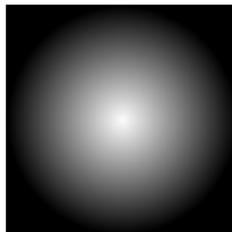
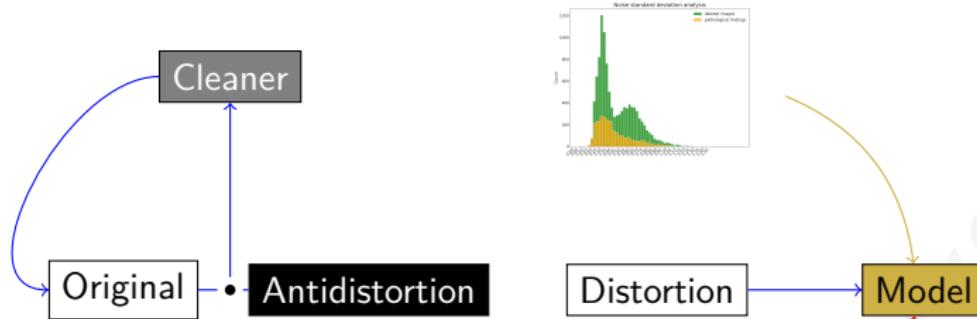
Step 1 Cleaning the existing distortion in HyperKvasir dataset

Our work



Step 2 Creating the model to generate the new artificial distortions

Our work



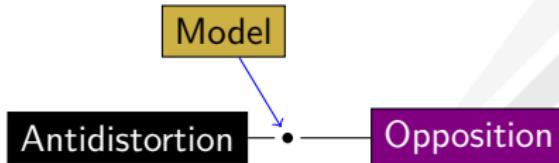
Our work

Step 3 Add the new artificial distortions to the antidistorted images



a) Clean the image

b) Create model



c) Add artificial distortion



Results

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



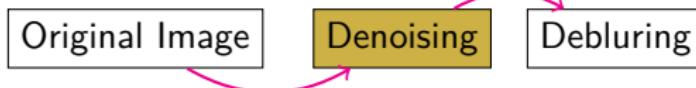
Results

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



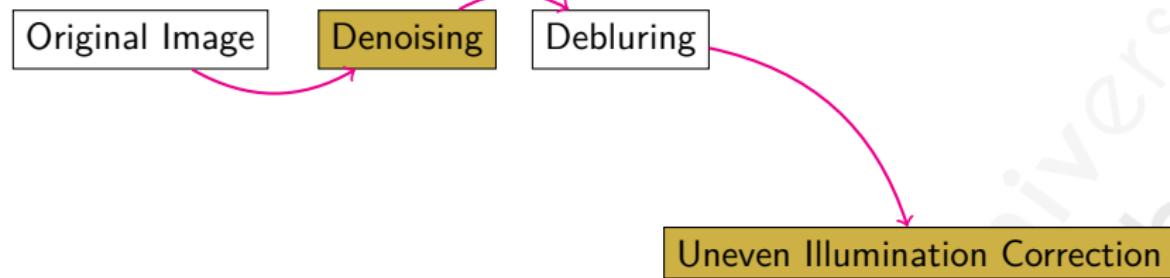
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Stage 1: we have to clean the existing distortion in the HyperKvasir dataset.



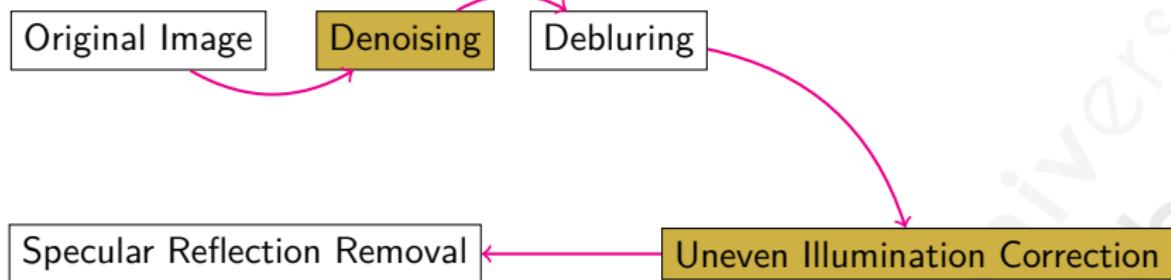
Results

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



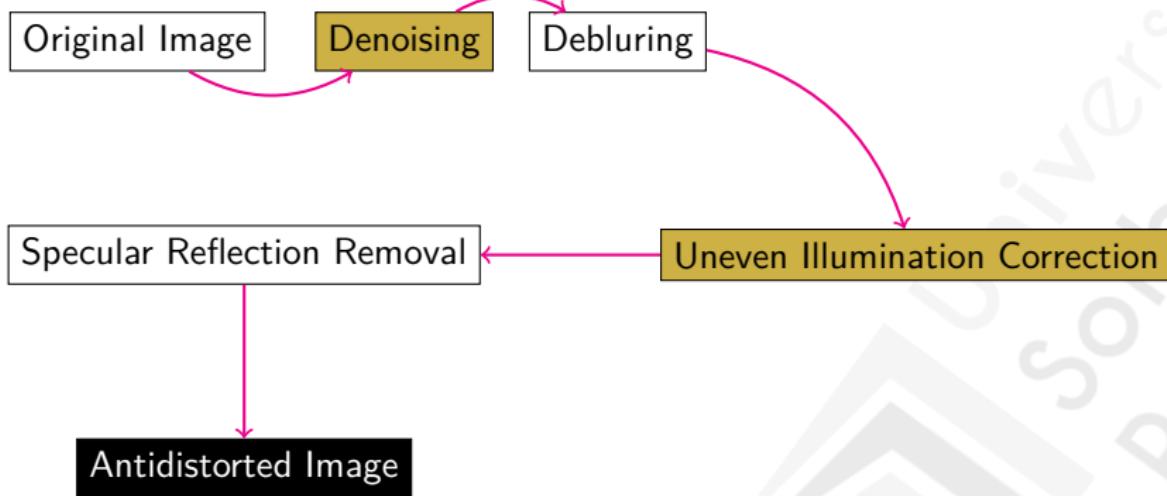
Results

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



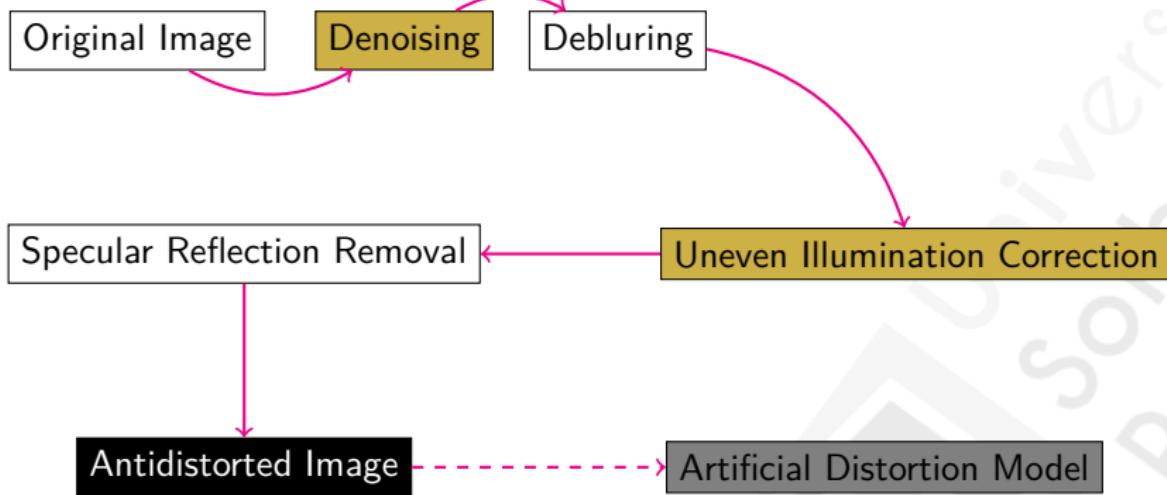
Results

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



Results

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Results

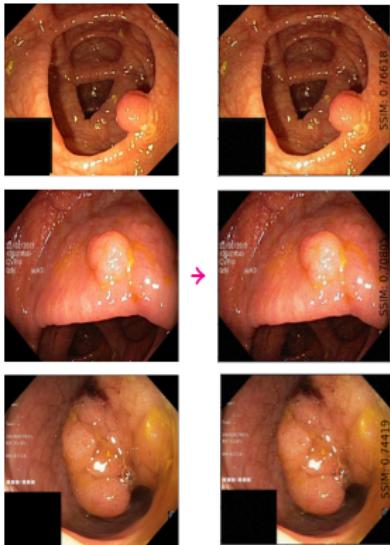
■ Noise



a) *Original*

Results

■ Noise

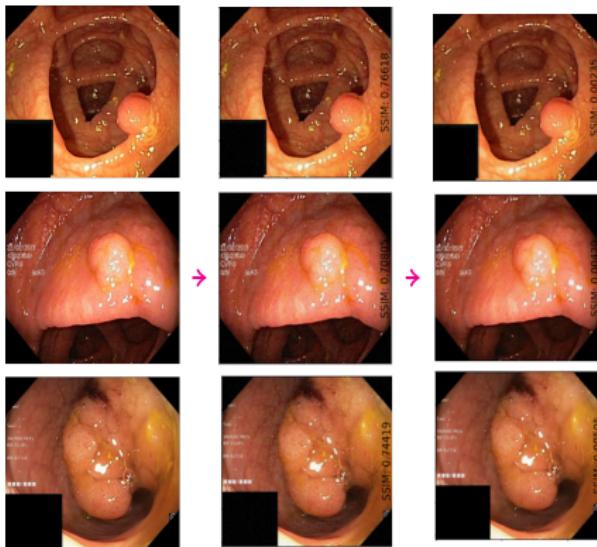


a) Original

b) Noisy

Results

■ Noise



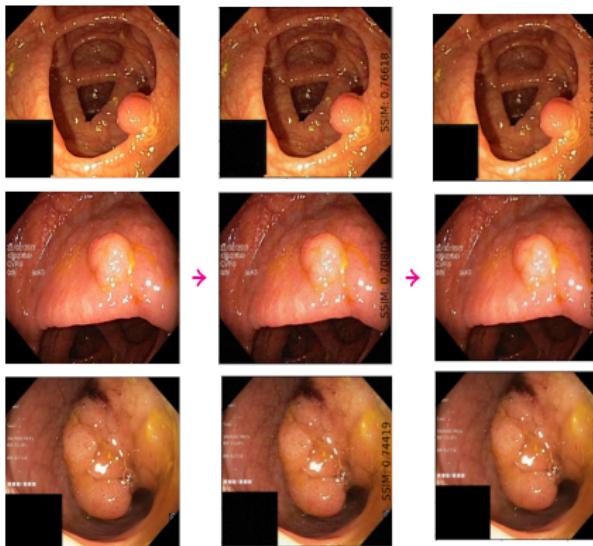
a) Original

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

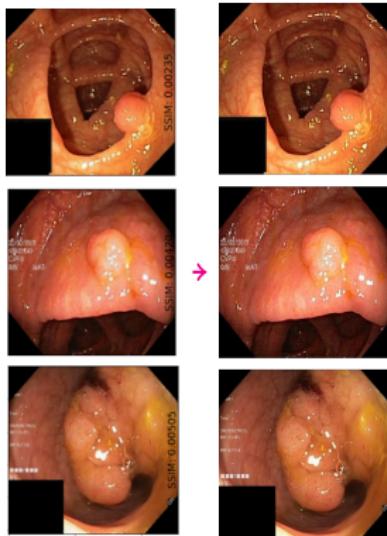
■ Blur



a) Denoised b) Deblurred

Results

■ Blur



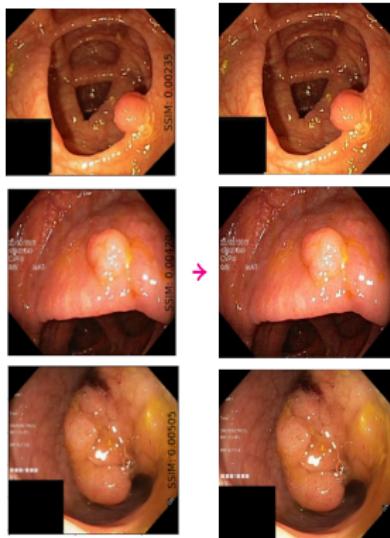
a) Denoised b) Deblurred

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

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

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

Results

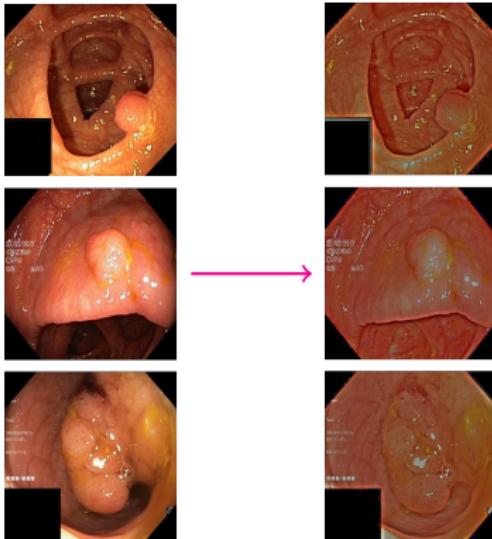
■ Uneven Illumination



a) Deblurred

Results

■ Uneven Illumination

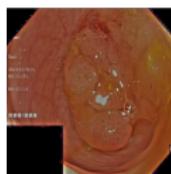
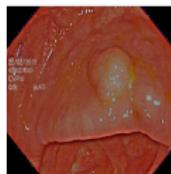
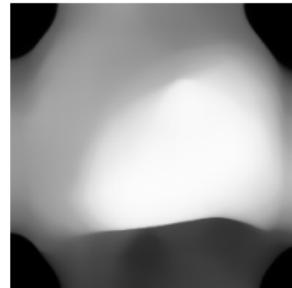
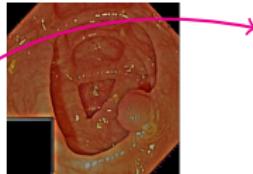


a) Deblurred

b) Uneven Illumination Correction

Results

■ Uneven Illumination

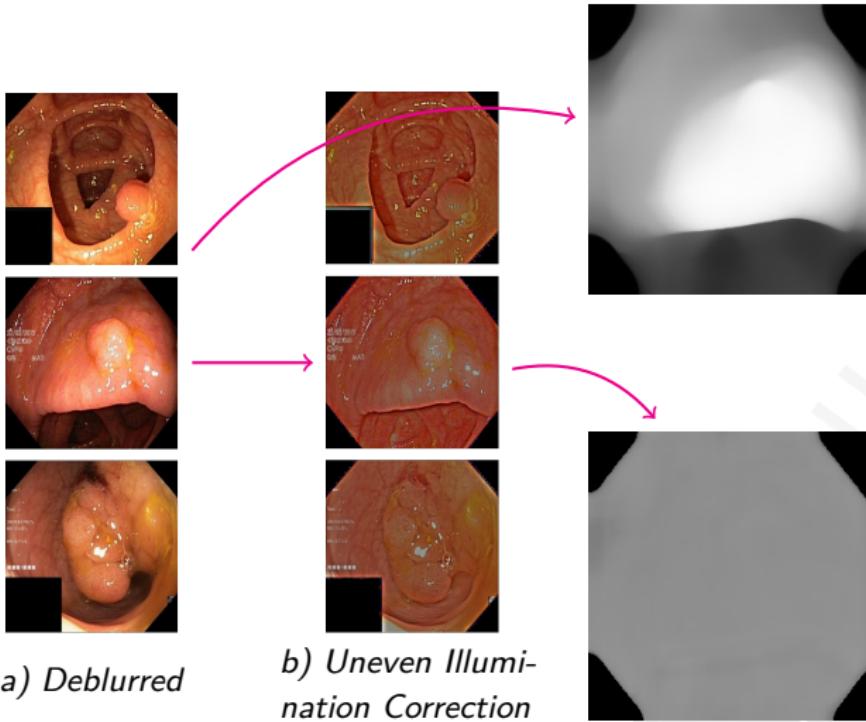


a) Deblurred

b) Uneven Illumination Correction

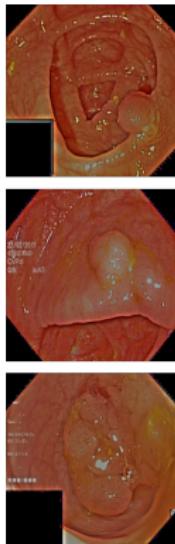
Results

■ Uneven Illumination



Results

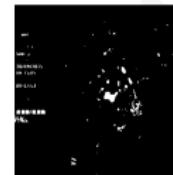
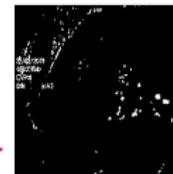
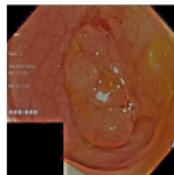
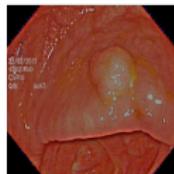
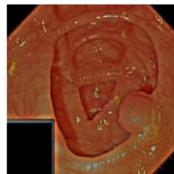
■ Specular Reflection



a) Uneven Illumination Correction

Results

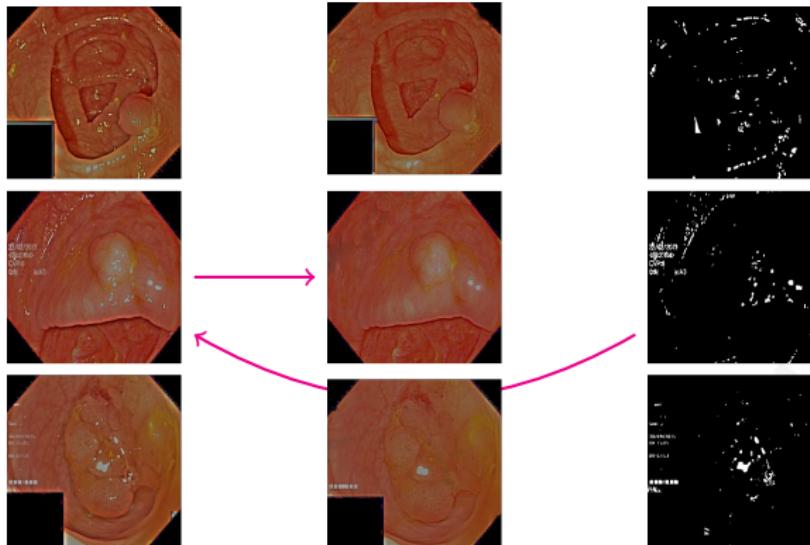
■ Specular Reflection



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



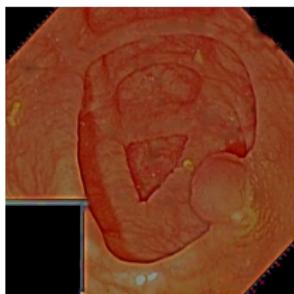
Results

Stage 2: We add the artificial distortion to the image



Results

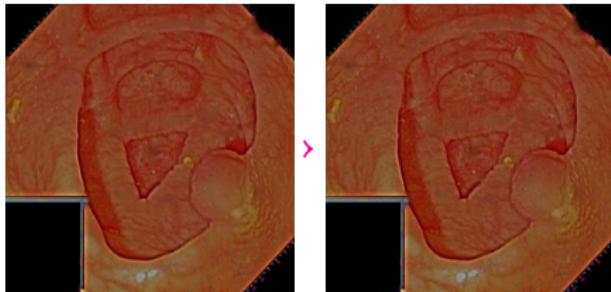
- Noise



*a) Antidistorted
Image*

Results

■ Noise

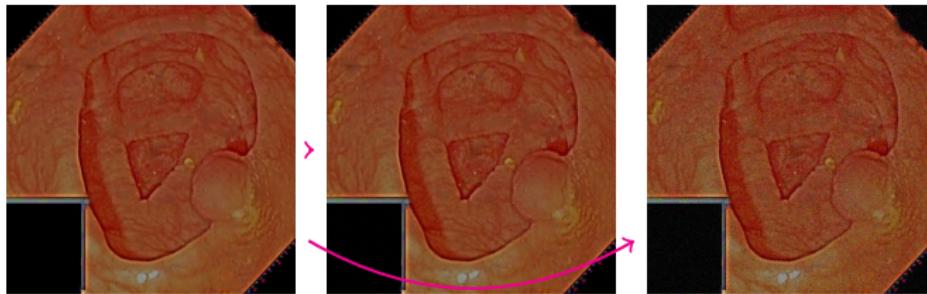


a) Antidistorted
Image

b) Noised im-
age with Gaus-
sian Noise
 $n \sim N(0, \sigma_n^2 =$
 $(0.0005)^2)$

Results

■ Noise



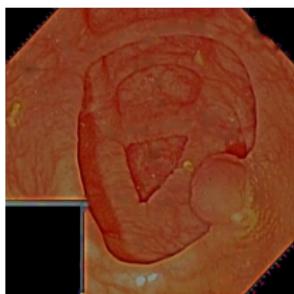
a) Antidistorted Image

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

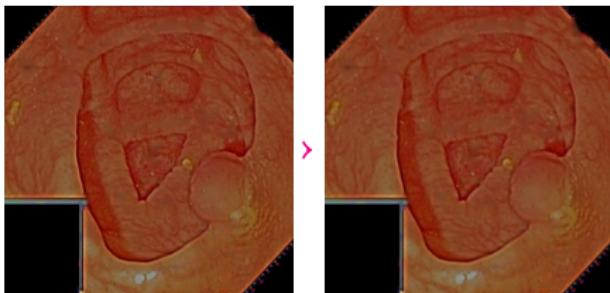
- Blur



a) Antidistorted
Image

Results

■ Blur

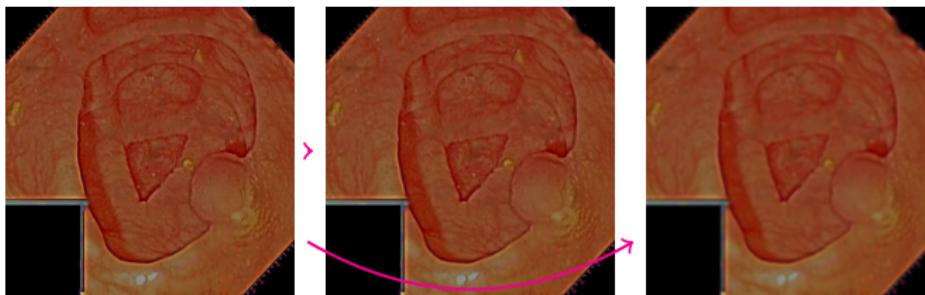


a) Antidistorted
Image

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

Results

■ Blur



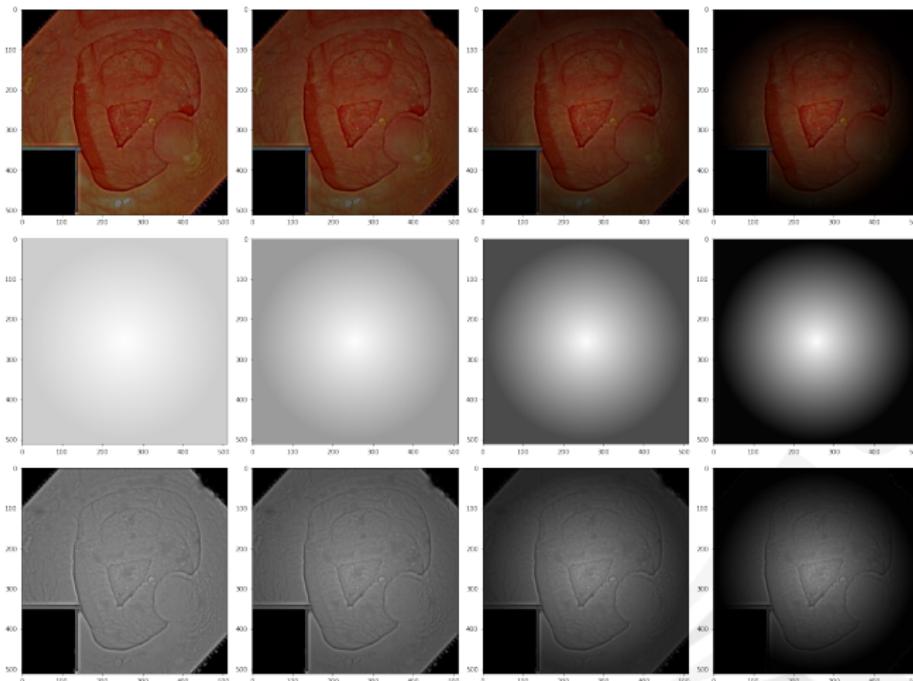
a) Antidistorted
Image

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

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

Results

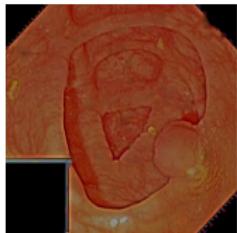
■ Uneven Illumination



Artificial Uneven Illumination process

Results

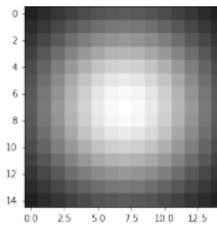
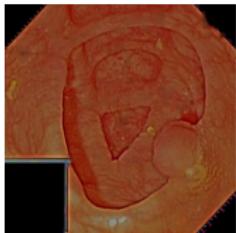
- Specular Reflection



*a) Antidistorted
Images*

Results

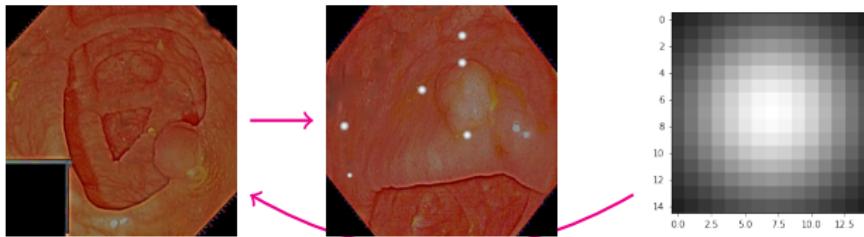
■ Specular Reflection



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

