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DLR

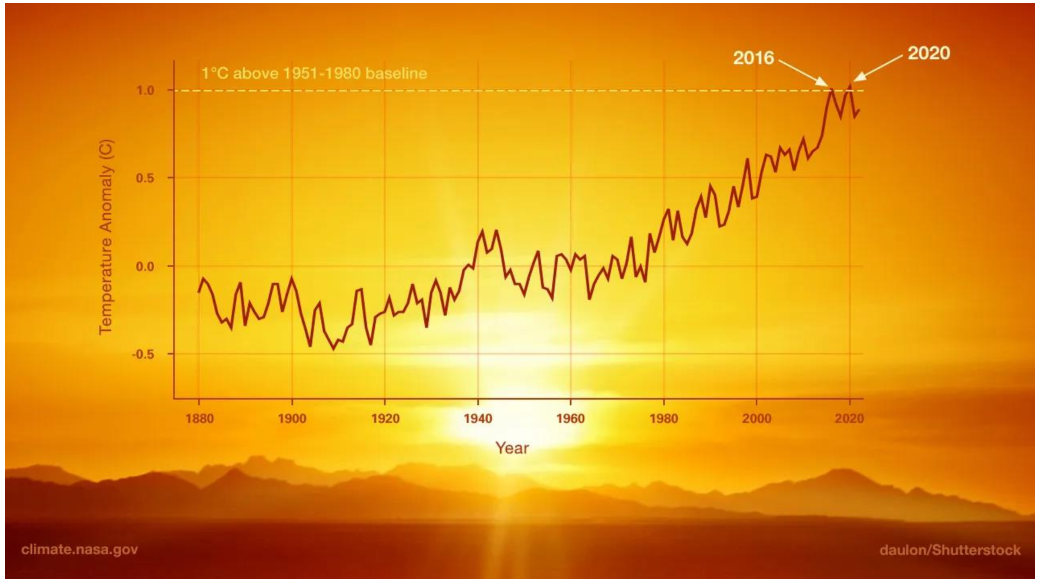
MICROSCOPIC IMAGE SUPER-RESOLUTION FOR CARBON FIBER REINFORCED POLYMER SAMPLES

Bhupender Bindal, 20 August 2024

Introduction

Source: unsplash

Global warming



Source: science.nasa.gov

Introduction: Motivation

Source: Airbus

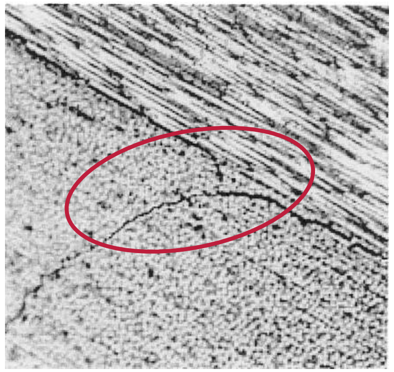
- Zero CO2 emission in aviation by 2035
- Alternative fuel: Liquid hydrogen

Lightweight and Cost-efficient tanks for storing liquid hydrogen

Source: aviationweek

LH2 tank

Microcracks development on thermal cycling



Source: Timmerman2002

Visual inspection & material and process improvement

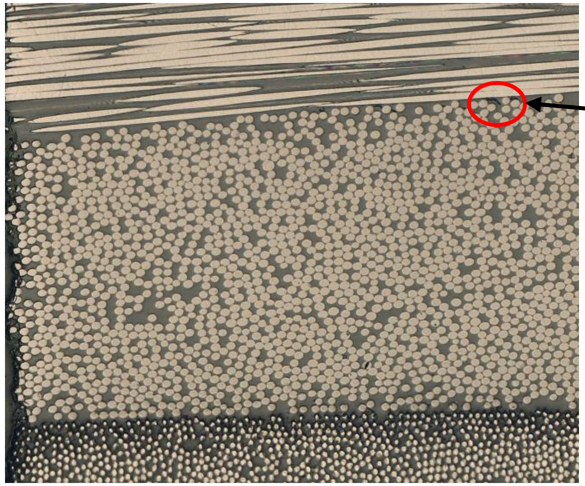
- Develop better composites so that they serve their purpose without failure
- How: One way is to evaluate the properties of composite parts from their microscopic images
- In our project, we aim to study microscopic images of carbon fibre-reinforced polymer samples

Introduction: Motivation

- **Current methodology:**
  - acquisition of a High-Resolution image of the sample
  - inspect for minute details like micro-cracks

Source: aviationweek

Source: Keyence



Microcrack

LH2 tank

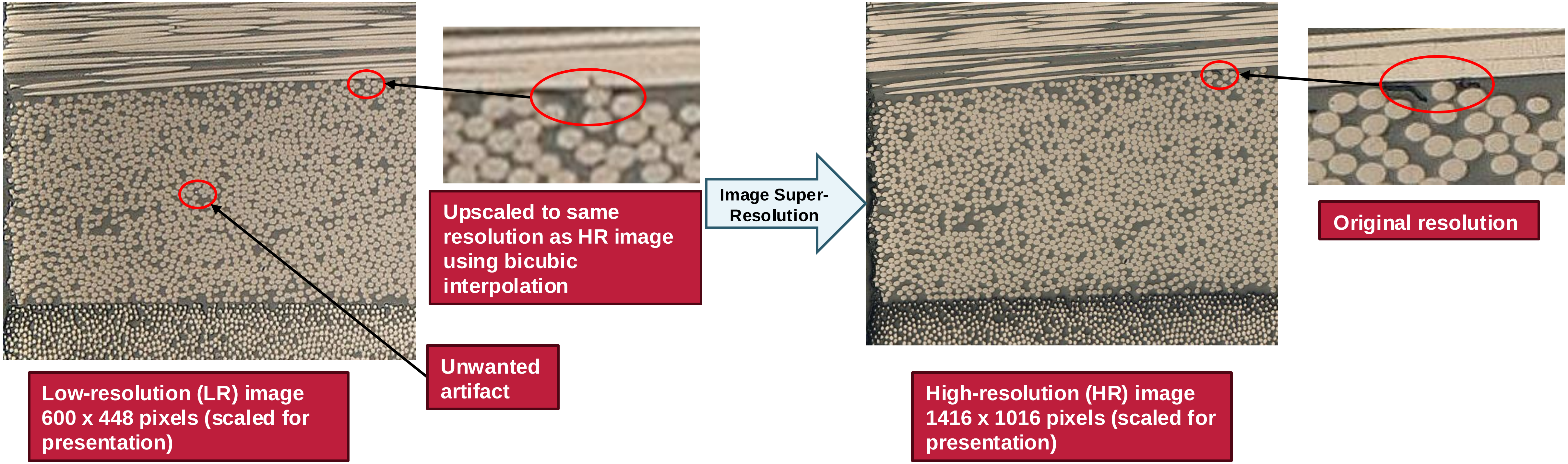
Acquire HR image of sample

Visual inspection

- **Problem:**
  - This process is time-consuming, more than one hour for a single sample high-resolution image acquisition

Introduction: Motivation

- **Proposed approach:** Obtain a high-resolution image from an acquired low-resolution image, which is called Image Super-Resolution (SR), with the following advantages:
  - Reduce acquisition time and operational costs
  - No need to upgrade the equipment



Introduction

Scope of this Masterarbeit:

a) Overview of different methods developed in the field of image SR
b) Application of representative model from different categories
c) Assess the performance of these methods with special attention to the reconstruction of small details

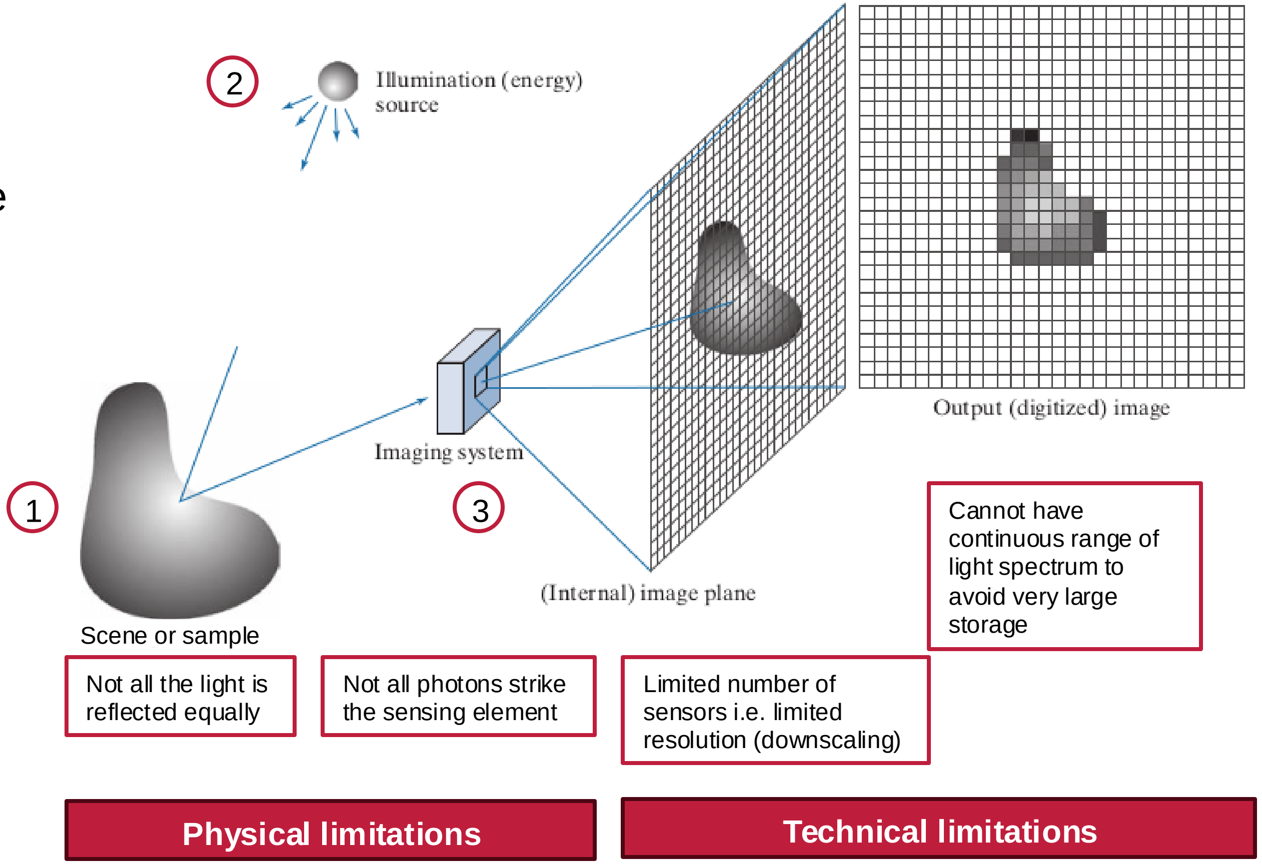
Introduction

The organisation of the presentation:

1. Digital image acquisition process
2. Problem formulation
3. Approaches for solution
4. Simple methods
5. Advanced methods
6. Dataset
7. Results
8. Discussion
9. Conclusion

1. Digital image acquisition process

- We want true representation of the scene or sample
- But our imaging systems have physical and technical limitations
- We get an approximate representation of the scene with some artifacts
- Hence, we want to minimise the artifacts by using the imaging system to its best capabilities or process the digital image that reduces the artifacts



Source: Digital Image Processing, Gonzales and Woods

2. Problem formulation

We need a model:

- Image degradation modelling → Forward problem
- Super resolution (SR) →Inverse problem and its Ill-posedness

2. Problem formulation: Image degradation modelling

LR image is generally modelled as the output of HR image by degradation model:

Blurring operator or degradation kernel

Forward problem: $y = (x \ast k) \downarrow_s + n$

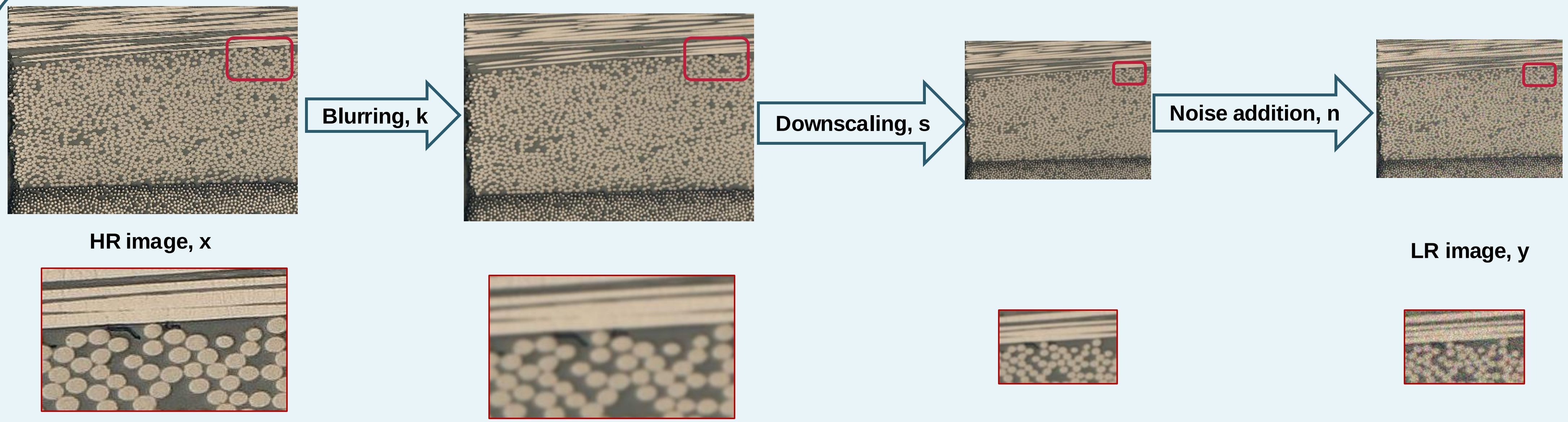
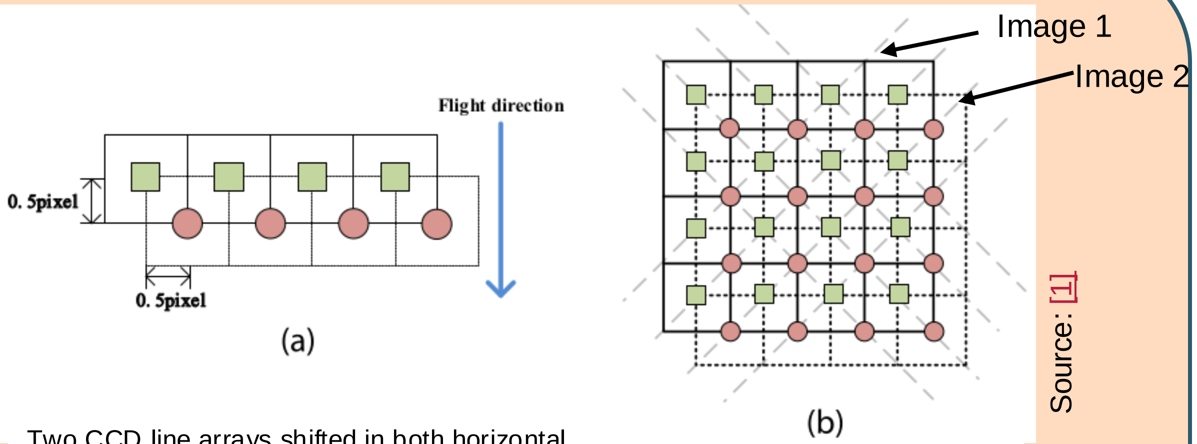


Image degradation modelling

2. Problem formulation: Image SR as Inverse problem

- Obtaining/recovering high-resolution (HR) image from one or several of its low-resolution (LR) versions.
- Two types:
  - Multi-frame image super-resolution (MISR): fusing the complementary information in a series of correlated images of the same scene [8]
  - Single image super-resolution (SISR): generates HR image from a single LR image
  - In this project, we deal with SISR

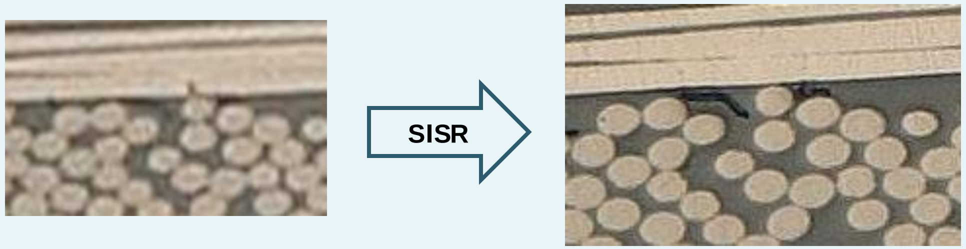


Source: [1]

Two CCD line arrays shifted in both horizontal and Vertical directions

Two images with sub-pixel shift

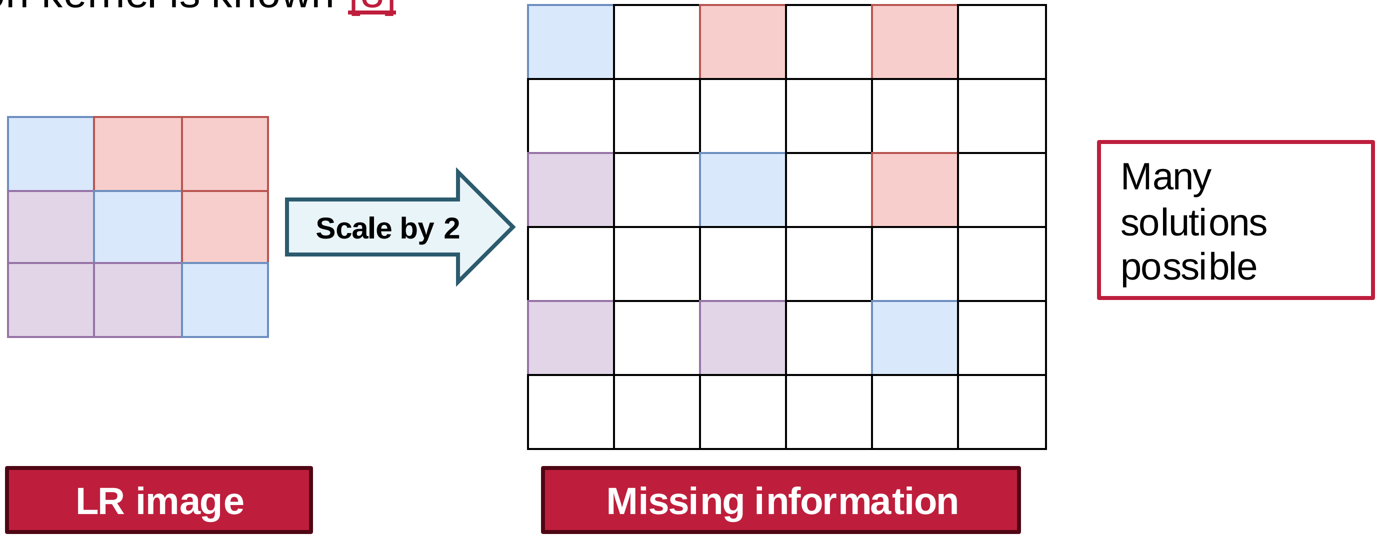
Multi-frame image super-resolution (MISR)



Single image super-resolution (SISR)

2. Problem formulation: Inverse problem and its ill-posedness

- Given LR image, find HR image: Inverse problem
- Reconstructing or predicting lost information
- ill-posed even if the degradation kernel is known [3]



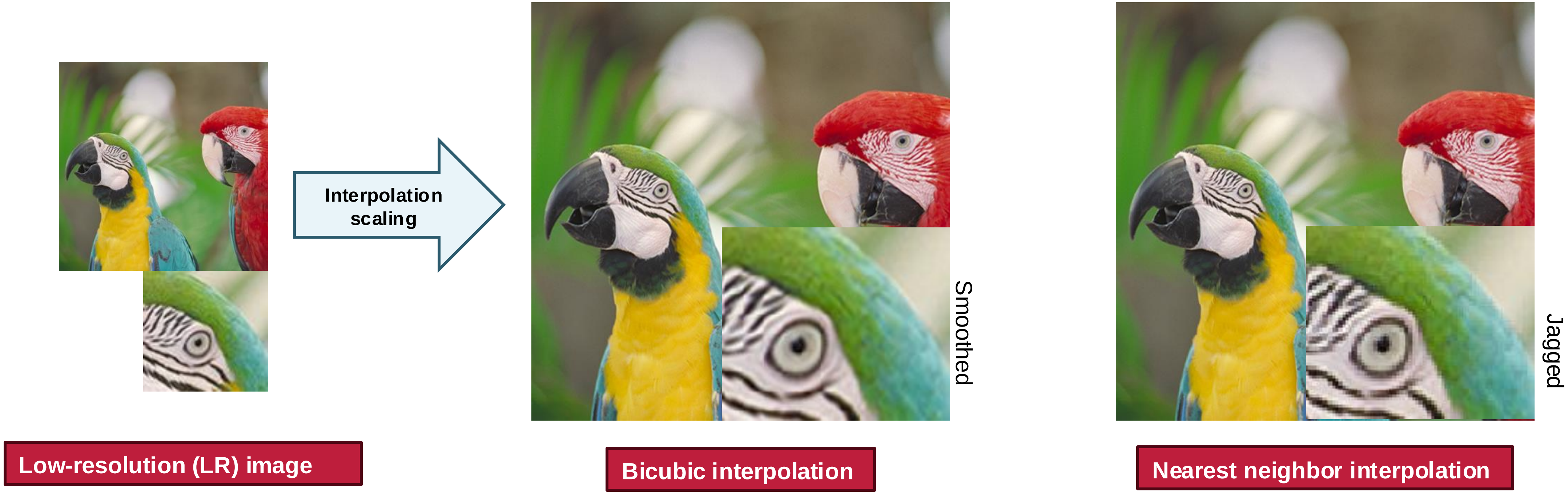
3. Approaches for solution

1. Simple methods, which **use less extra information**
   - Example: interpolation based methods
   - makes generic and simpler assumptions
   - have limited capability

2. Advanced SR methods which are here called so due to:
   - complex in terms of the model for super-resolution
   - use of external dataset

4. Simple methods: Interpolation based methods

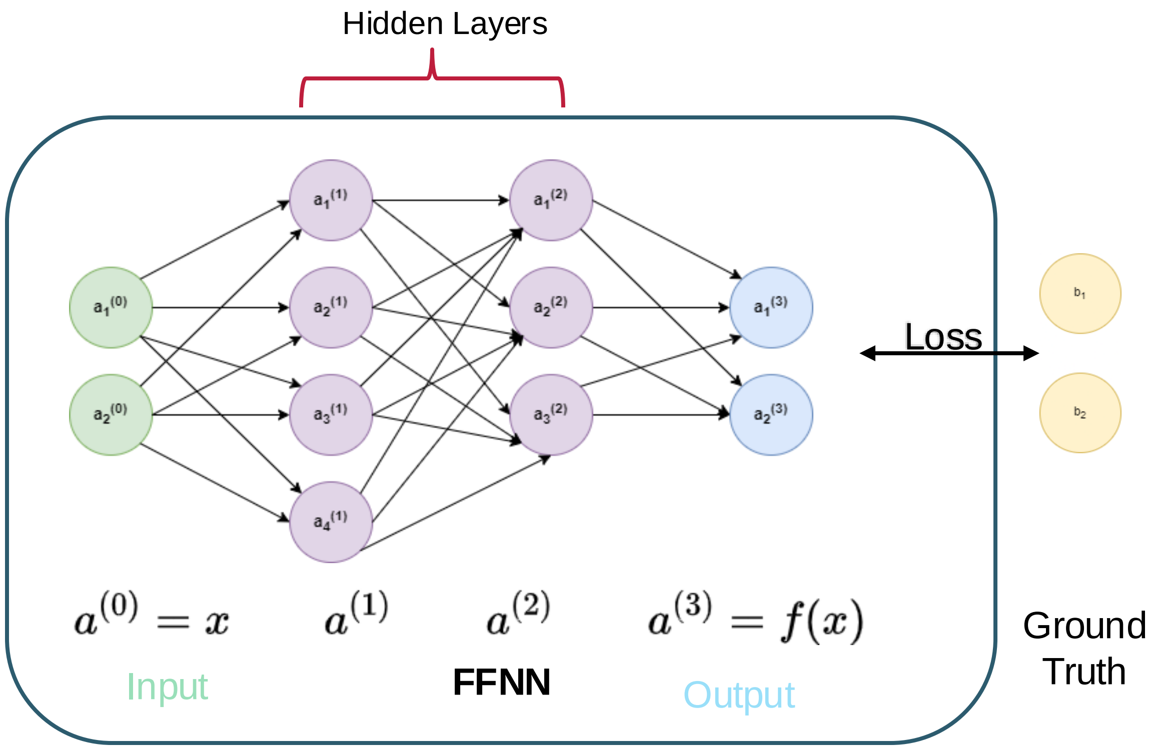
- Works on the idea of polynomial interpolation or values of the neighboring pixels
- Interpolation-based methods are simple in application but generate smooth images with ringing and jagged artifacts [11]



- These methods use no or less external information to recover lost details or missing information [12]
- Can serve as a minimal baseline for SR

Neural Networks

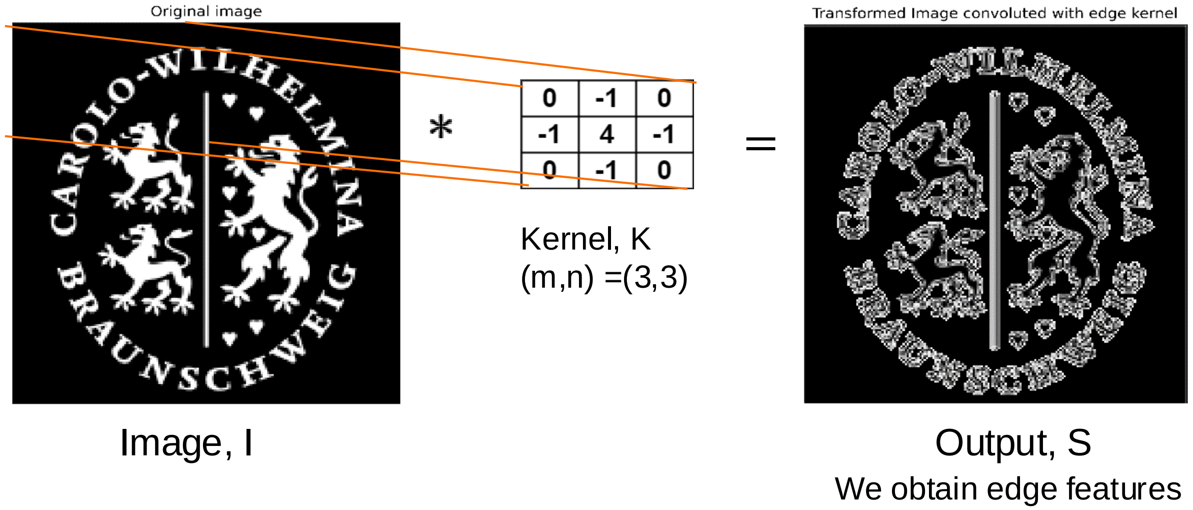
- **Why neural networks are so popular? :** It can automatically identify data-specific information given sufficient data
- **Simplest type:** Feed Forward Neural Network (FFNN) ~ a composition of many individual non-linear functions



$$a^{(l)} = \underbrace{f^{(l)}}_{\text{Non-linear Activation}}(\underbrace{W^{(l)}a^{(l-1)} + b^{(l)}}_{\text{Affine linear transformation}}), \quad for \quad \underbrace{l}_{\text{Layer}} \in \{1,2,3\}$$

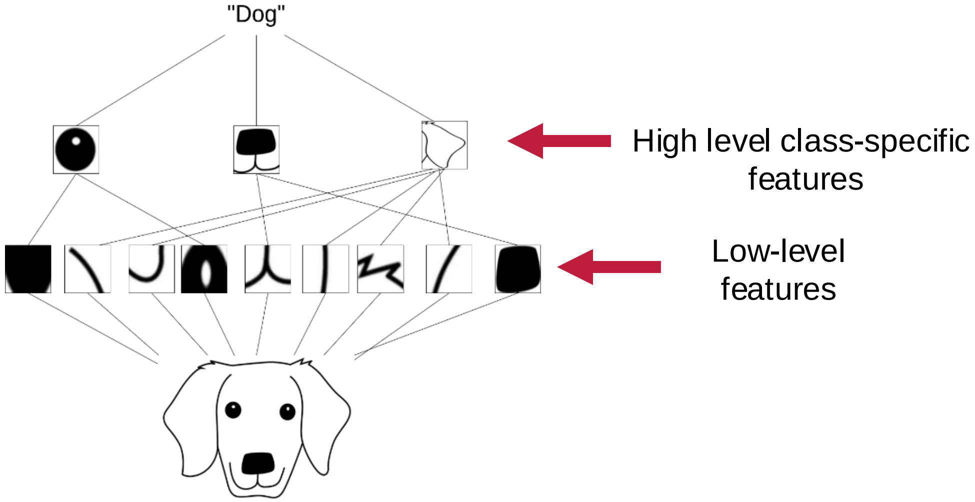
Convolutional Neural Networks

- Convolutional Neural Network (CNN) is a type of FFNN that processes multi-dimensional array data
- **How does it process multi-dimensional data?:** Convolution operation



In a CNN:

- Each convolutional layer consists of many such kernels
- Entries of each kernel are **learnable** parameters of the network
- Extracted features are composed in subsequent layers



Advanced methods

5. Advanced methods: Single image super-resolution

Principle	Pros
- internal statistics or properties of natural images provide cross-scale information - Example: ZSSR + KernelGAN	- Does not require external datasets - Individual image specific degradation learning

Assumption	Cons
- patches of a single image tend to recur within and across different scales of this image	Assumption may fail, especially for natural images with diverse contents (e.g., animals) or monotonous scenes (e.g., sky)

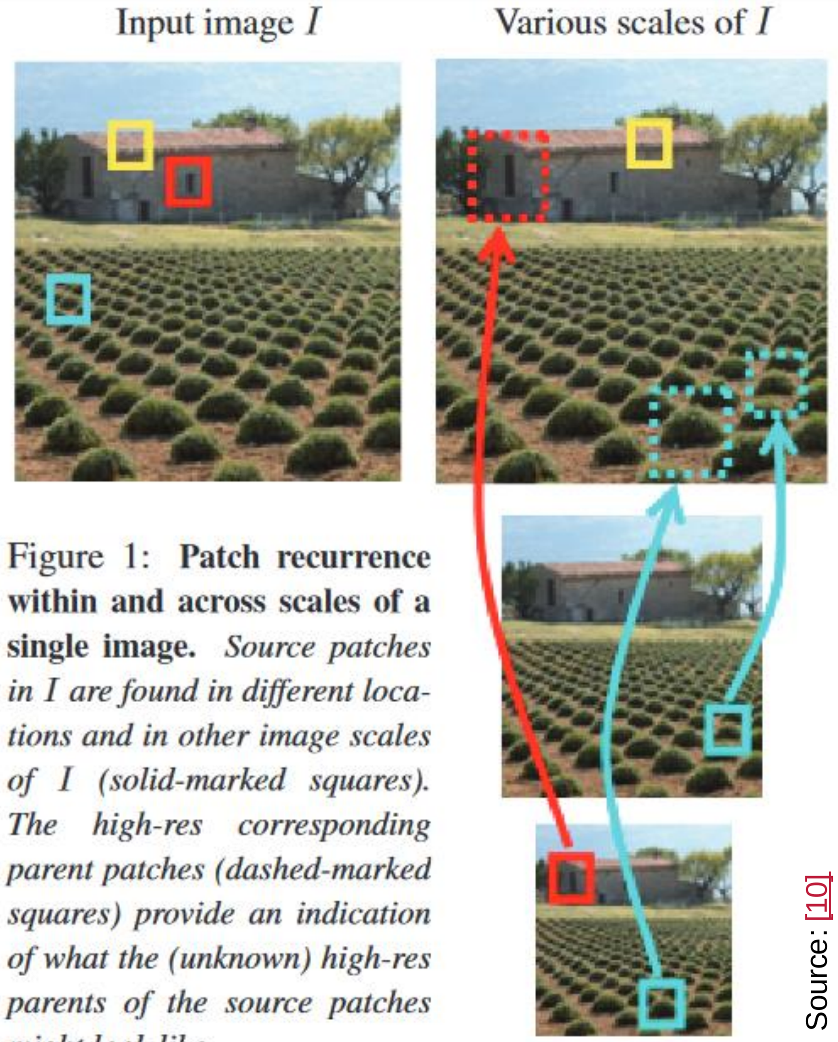


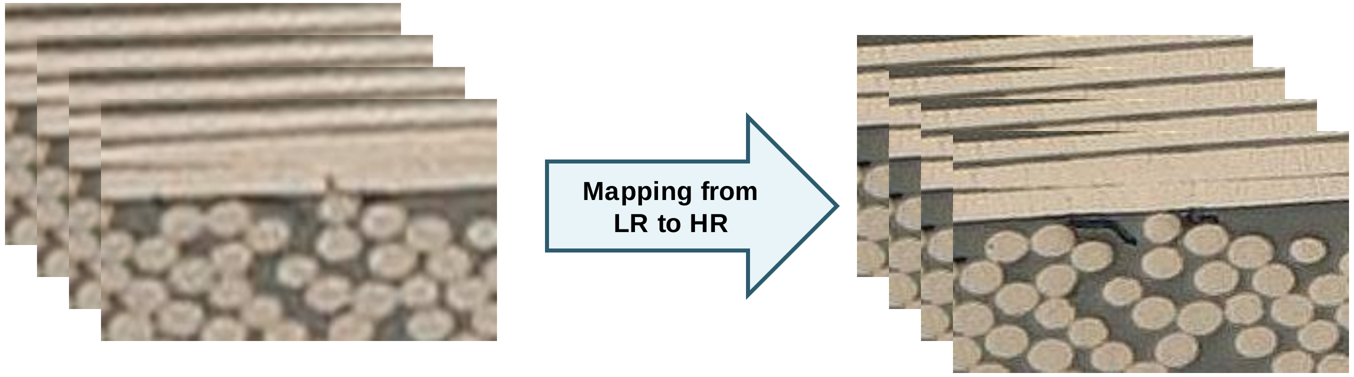
Figure 1: **Patch recurrence within and across scales of a single image.** *Source patches in I are found in different locations and in other image scales of I (solid-marked squares). The high-res corresponding parent patches (dashed-marked squares) provide an indication of what the (unknown) high-res parents of the source patches might look like.*

Source: [10]

5. Advanced methods: Example based

Principle

- Utilizes database of paired-images to fill or hallucinate missing details
- Examples: patch-based and supervised deep learning methods



Assumption

Degradation kernel remains fixed for the all the images in the domain

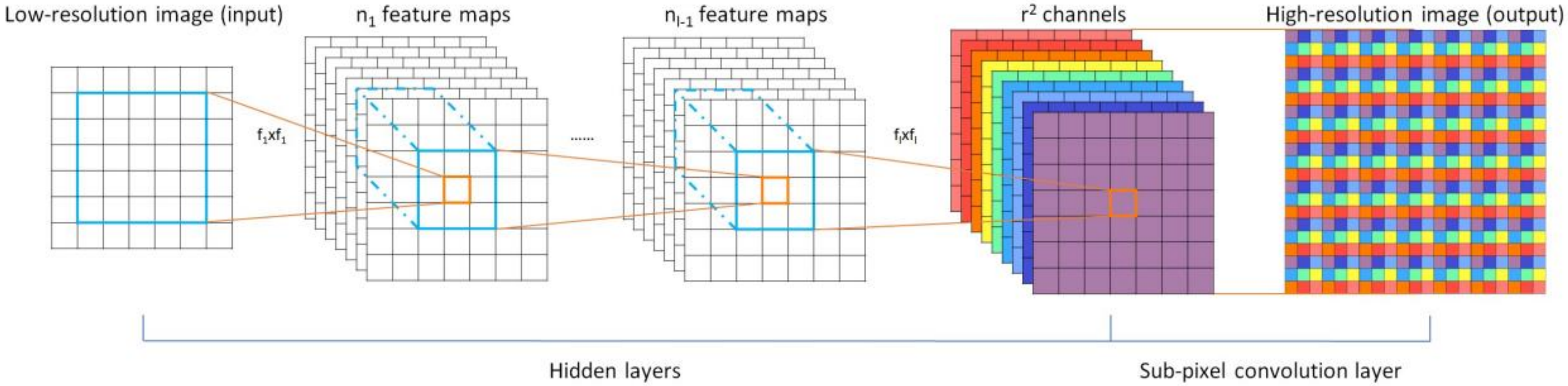
Pros

Overcomes ill-posedness utilising large database of paired images

Cons

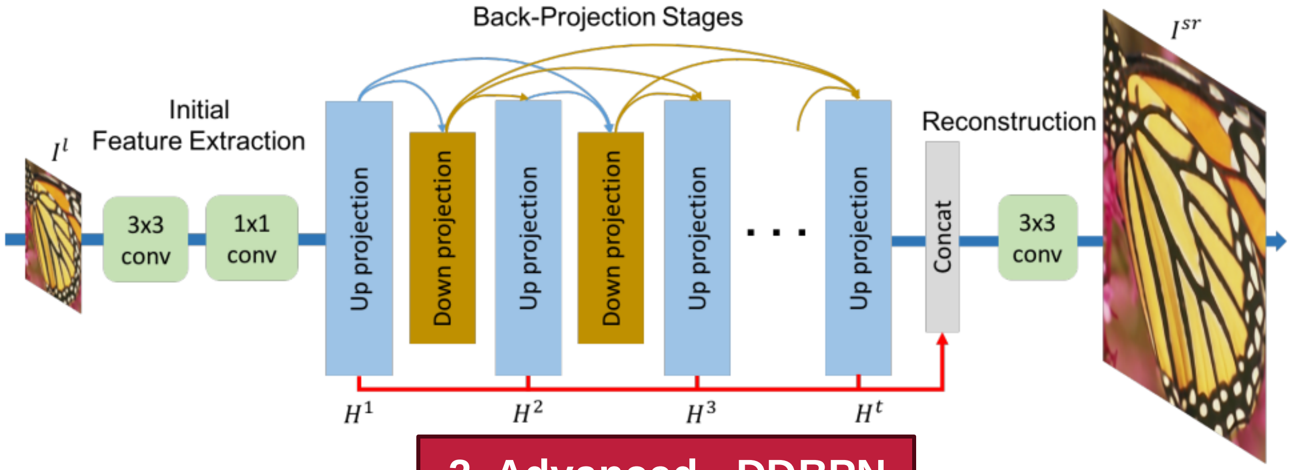
- Fails on unknown degradation than that of LR-HR paired dataset
- Dependency on the available data

5. Advanced methods: Example based



Source: [13]

1. Simpler - SRCNN



Source: [14]

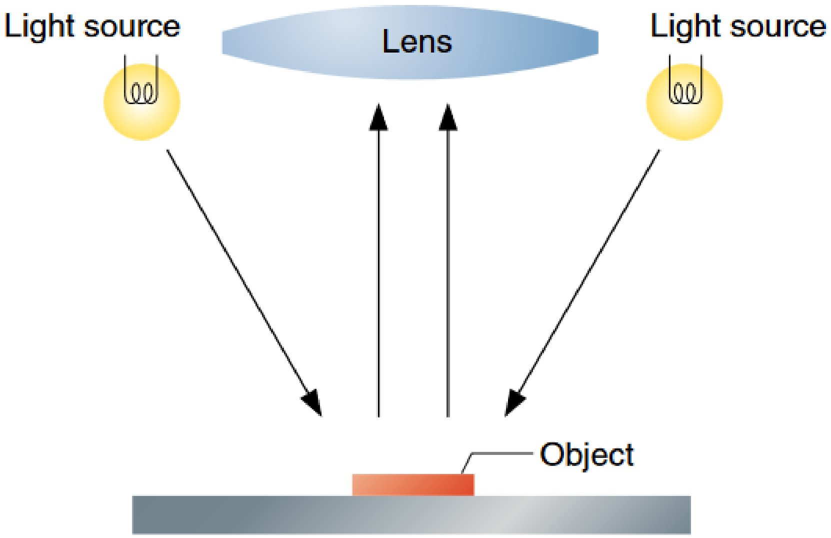
2. Advanced - DDBPN

6. Dataset

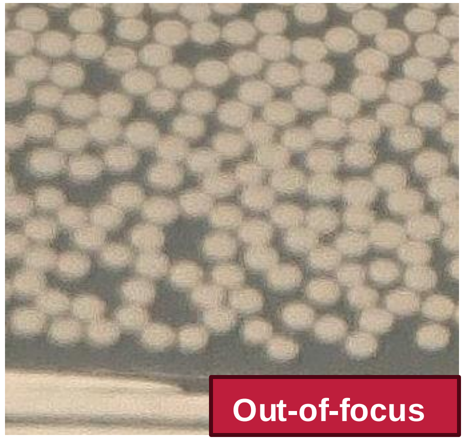
- Understanding of data is most important for any data based method
- Transforming original and predicting missing or new pixels

Data acquisition process
- Images at 200x and 500x magnification of samples
- Efficacy of SR: comparison with image at 500x

Variation in the CFRP data
- Surrounding or ambient Light
- Manual positioning of the sample
- Presence of dirt and out-of-focus regions



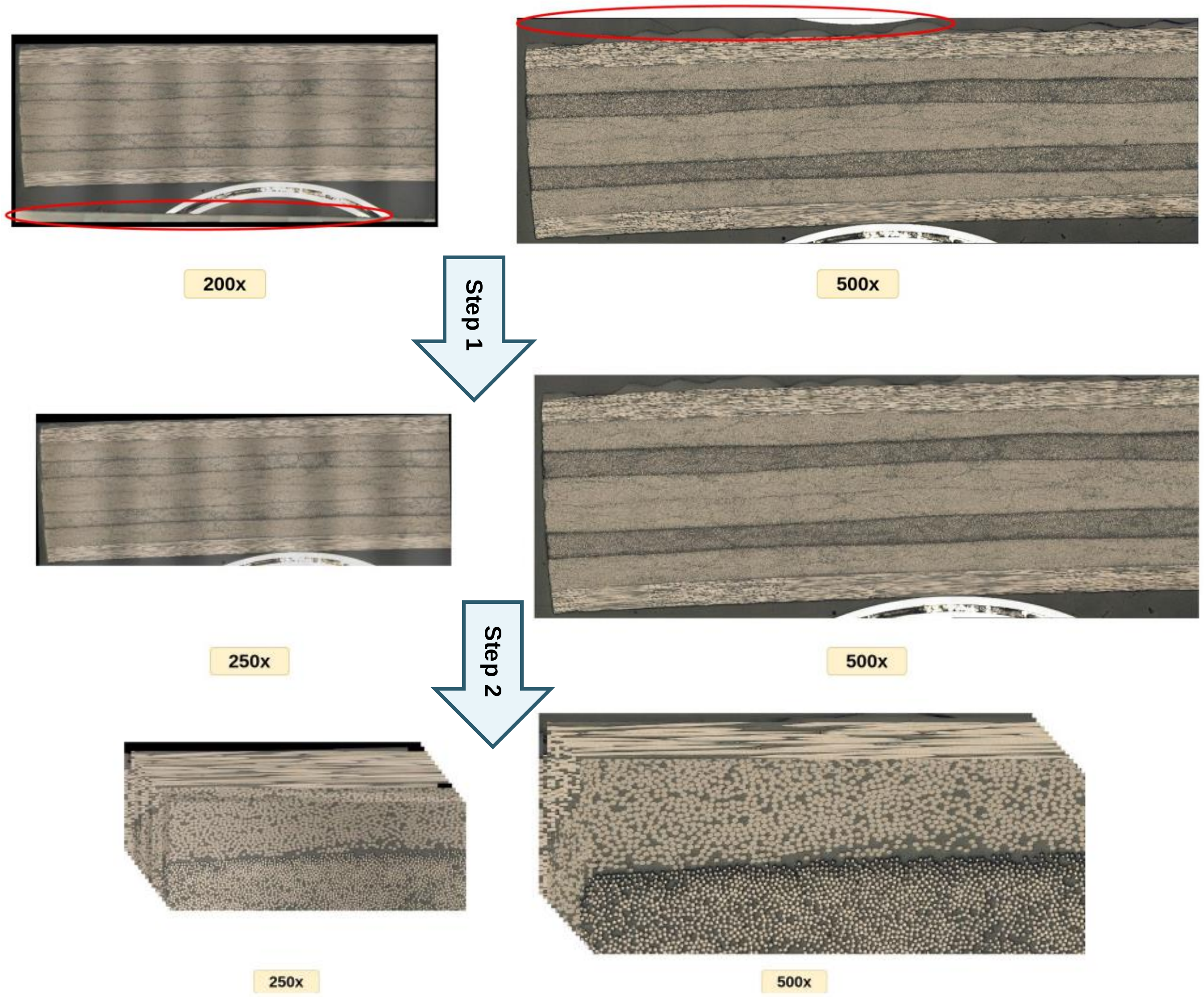
Source: Keyence



6. Dataset: Data processing

Necessity of data processing:

- Learning of a mapping-function requires same content
- 200x to 500x requires 2.5 scaling, causing decimal sizes → scale LR to half-size of HR
- Image quality assessment requires aligned images
- HR image has more than 10^9 or 1 billion pixels → cannot be used for deep learning on nominal systems → split in smaller parts



6. Dataset: Metrics for assessing SR image quality

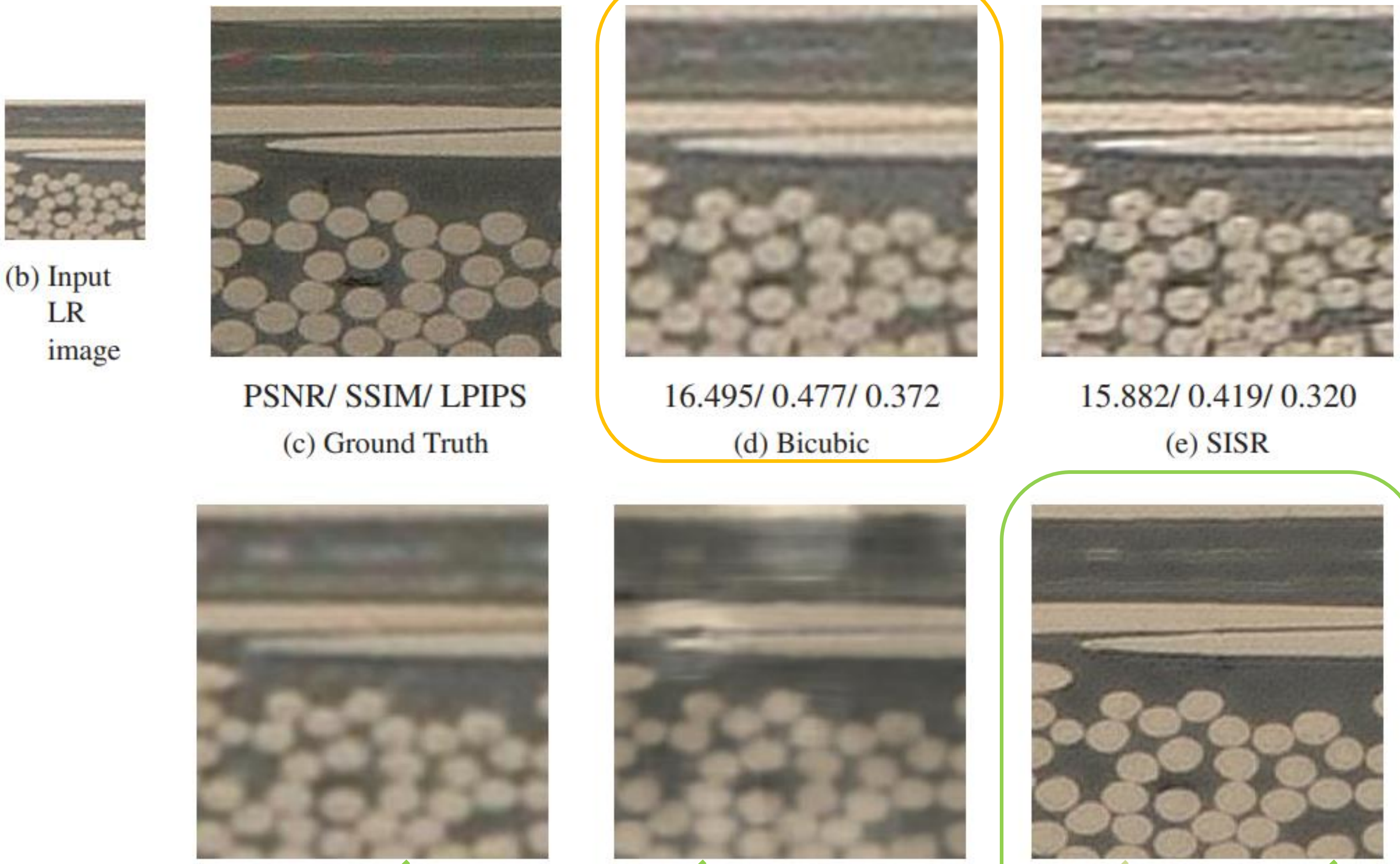
Metrics	Objective			Subjective
	PSNR ↑	SSIM ↑	LPIPS ↓	
Idea of similarity	Pixel-wise	Statistical values from pixels	Features like edges, structures	Human judgement
Value for identical images (worst to best)	0 to Infinite	0 to 1	1 to 0	Not to Yes

Ground Truth
PSNR/ SSIM/ LPIPS

Image 1
15.395/ 0.38/ 0.664

Image 2
11.764/ 0.698/ 0.192

7. Results: comparing methods



(b) Input LR image

PSNR/ SSIM/ LPIPS
(c) Ground Truth

16.495/ 0.477/ 0.372
(d) Bicubic

15.882/ 0.419/ 0.320
(e) SISR

19.443/ 0.496/ 0.468
(f) SRCNN (L2 loss)

19.981/ 0.485/ 0.401
(g) D-DBPN (L2 loss)

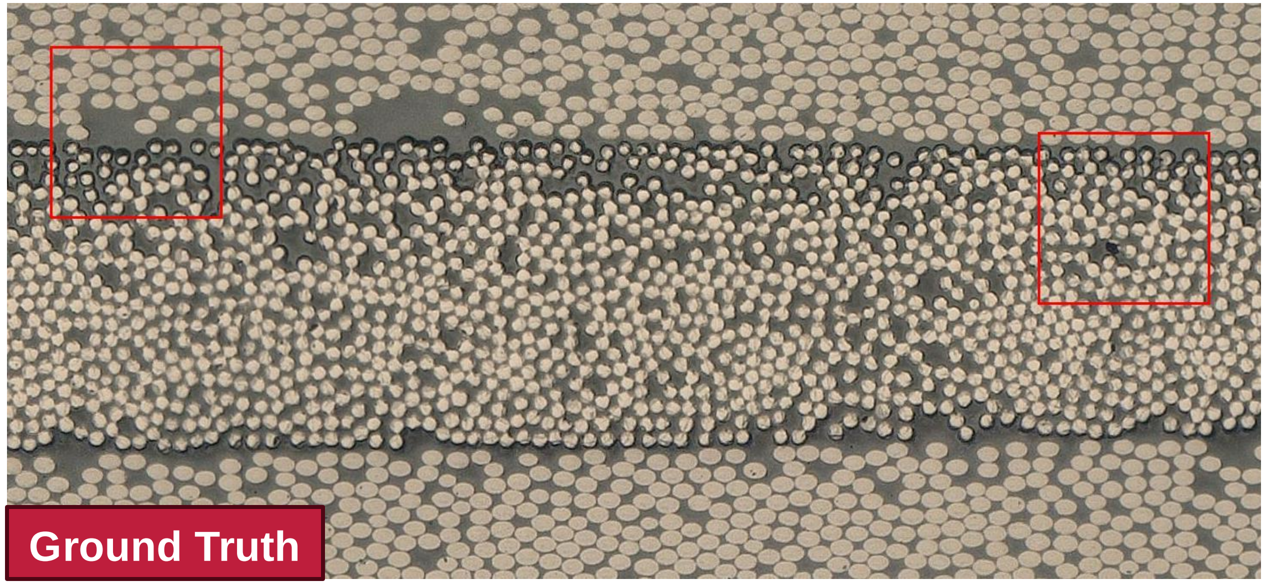
19.123/ 0.384/ 0.099
(h) D-DBPN (CoBi loss)

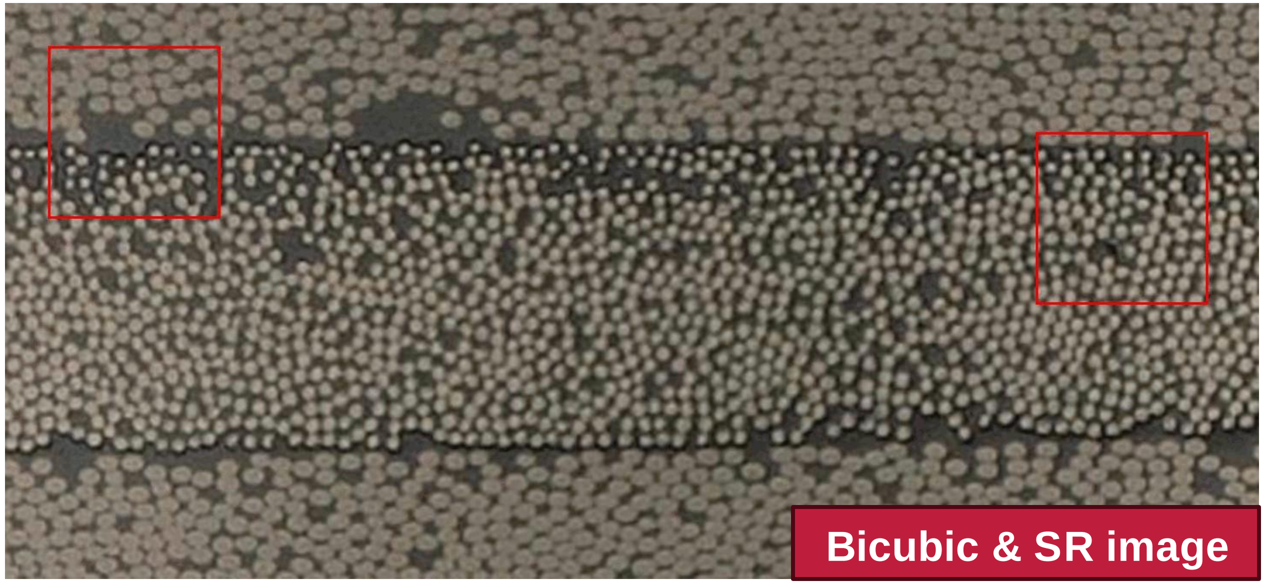
Bicubic interpolated image ~ information in LR image

7. Results: Metrics

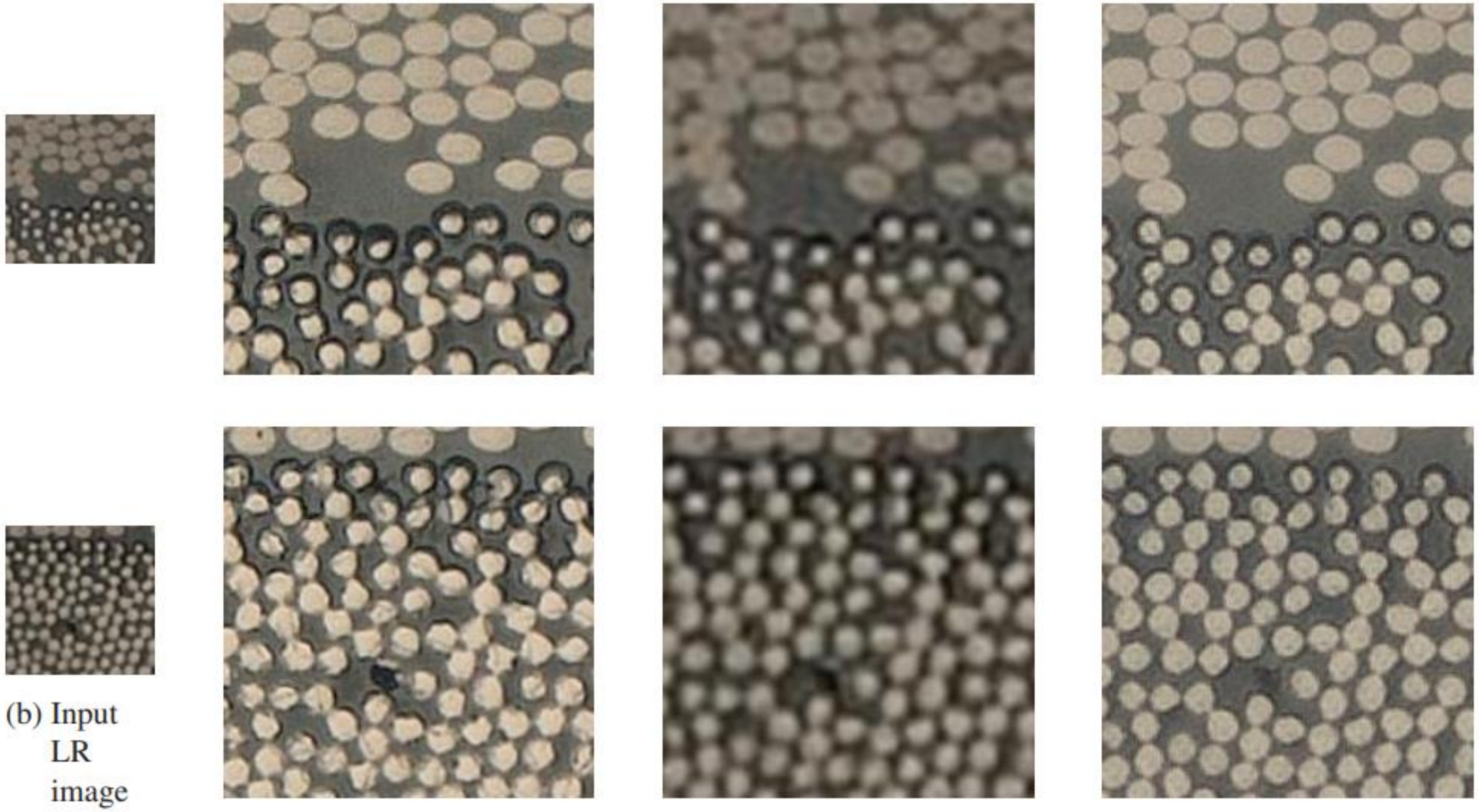
Method	CFRP data		
	PSNR↑	SSIM↑	LPIPS↓
Bicubic	18.083	0.495	0.448
SISR	17.663	0.473	0.362
SRCNN (L2 loss)	19.228	0.488	0.527
D-DBPN (L2 loss)	17.111	0.475	0.463
D-DBPN (CoBi loss)	18.168	0.378	0.141

7. Results: Test on aligned LR-HR





7. Results: Test on aligned LR-HR

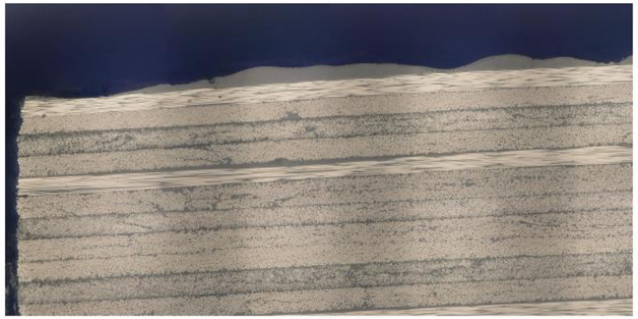


(b) Input LR image

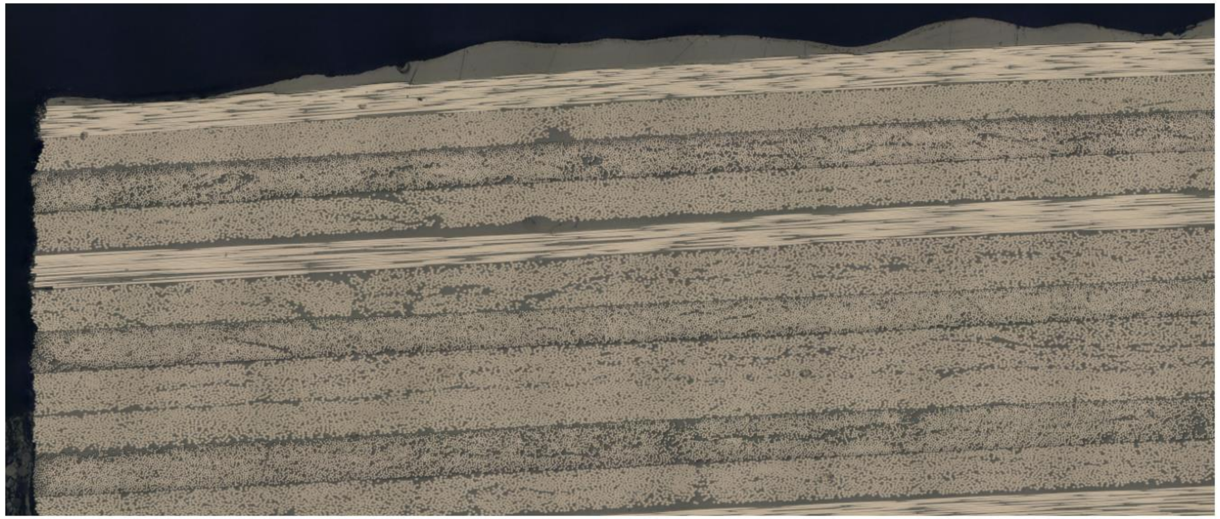
PSNR/ SSIM/ LPIPS | 15.156/ 0.502/ 0.473 | 19.275/ 0.486/ 0.097

(c) Ground Truth | (d) Bicubic | (e) D-DBPN (CoBi loss)

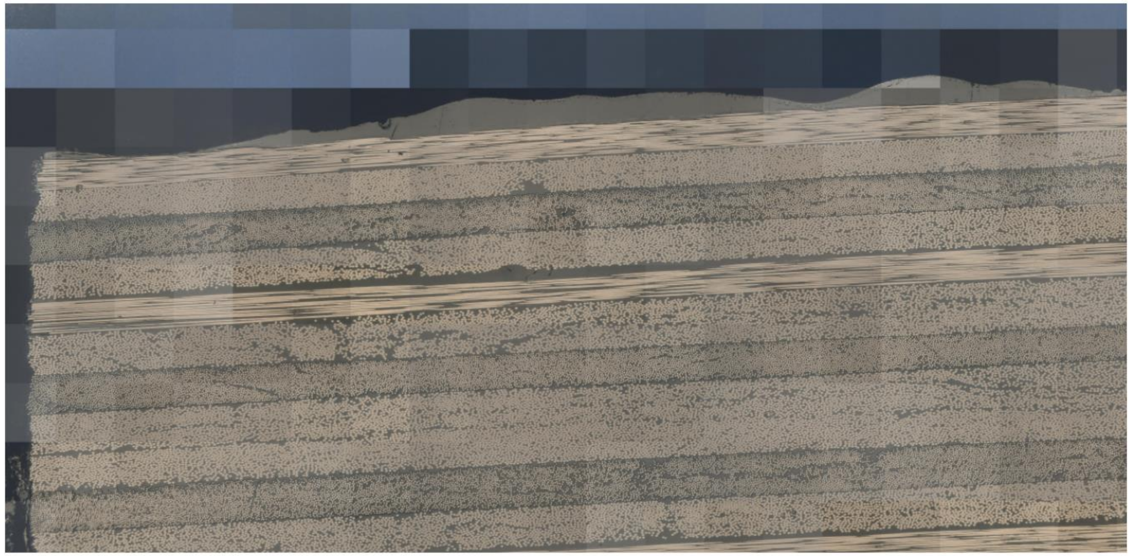
7. Results: Test on Full-size image



(a) LR input at 200x

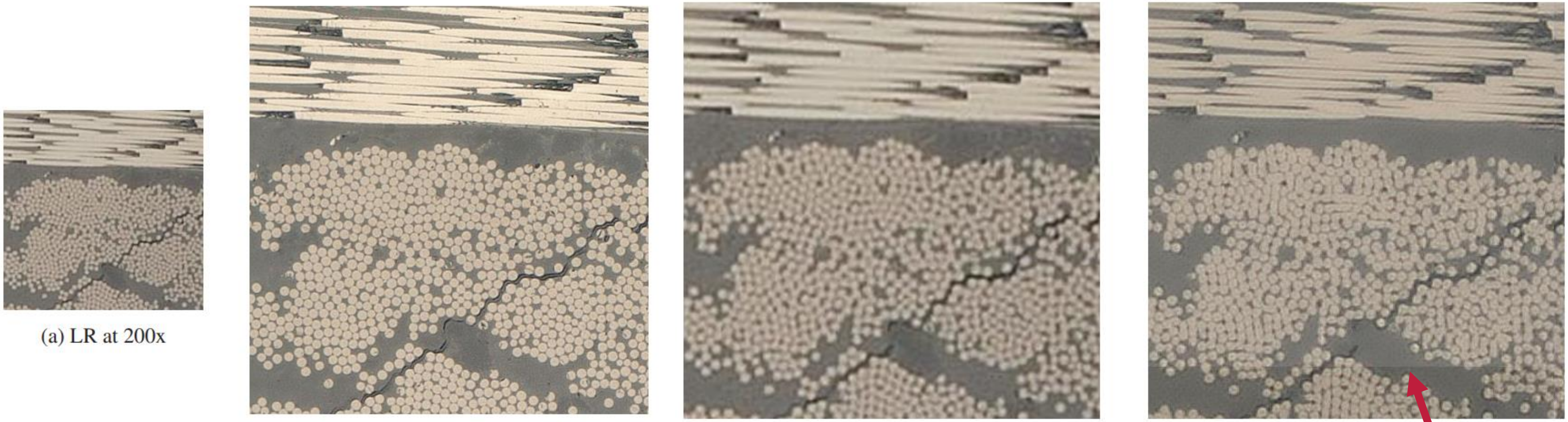


(b) Ground Truth at 500x



(c) SR image with D-DBPN (CoBi loss) model at 400x

7. Results: Test on Full-size image



(a) LR at 200x

(b) Ground Truth at 500x

(c) Bicubic image at 400x

(d) SR image at 400x

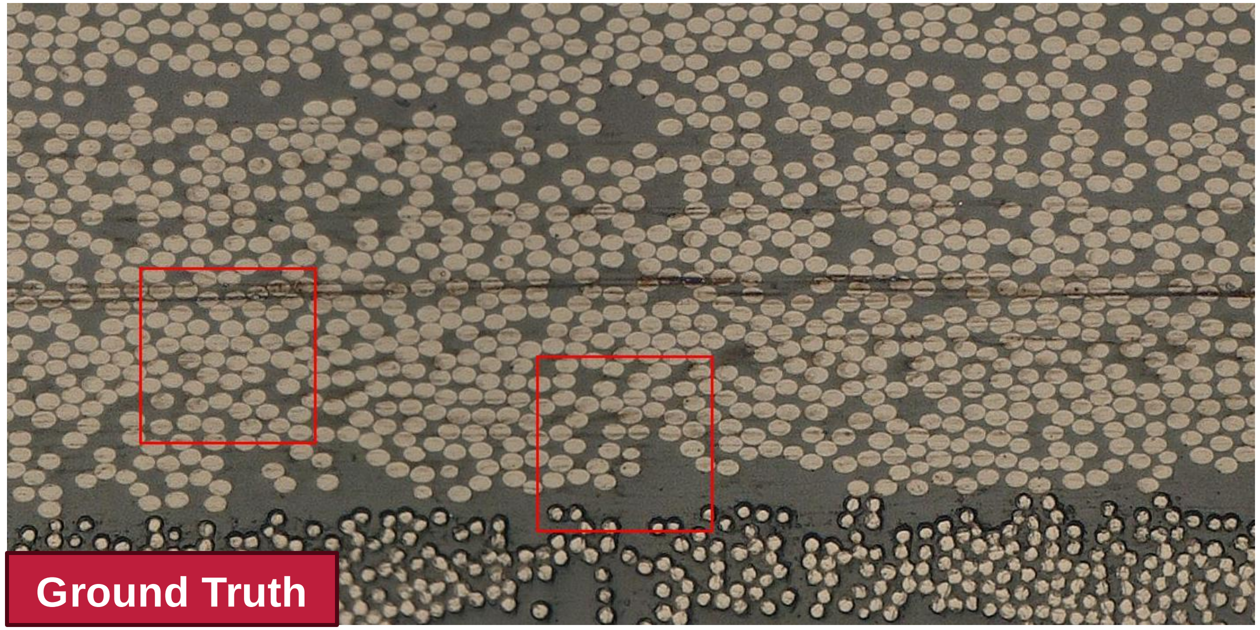
Patch line

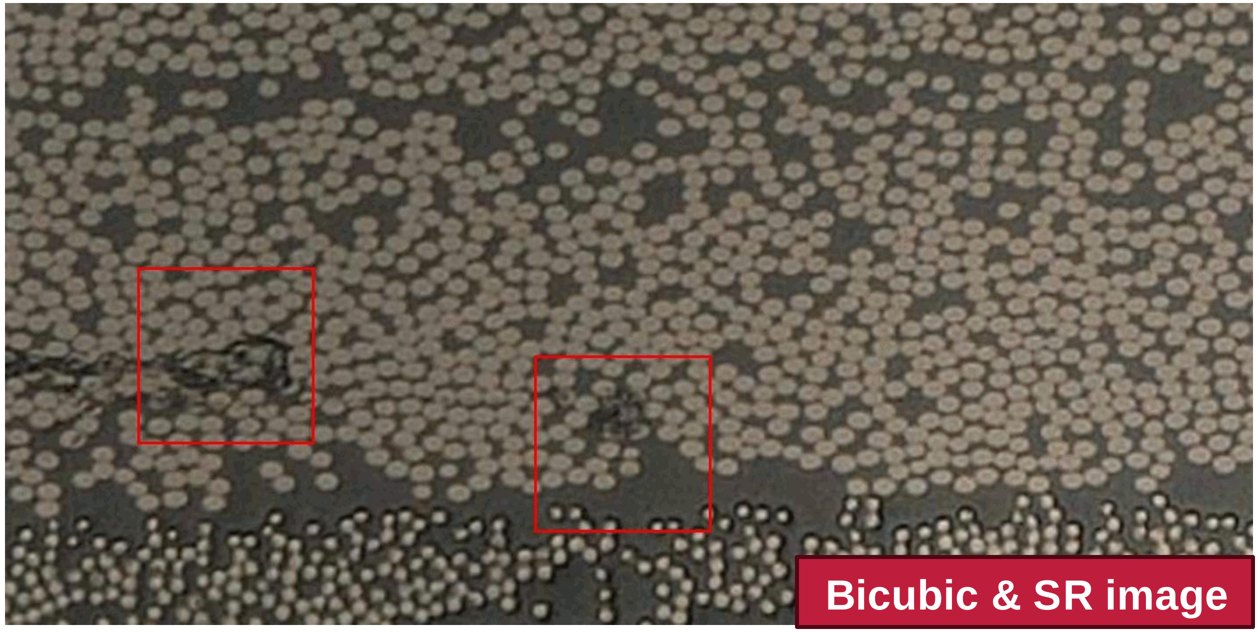
Observing effect of patch lines

7. Results: Time comparison

	LR image	HR image	SR of LR image
Size (pixels x pixels)	29,432 x 6,640	73,580 x 16,600	58,864 x 13,280
Time (in minutes)	12	70	26, Total = 12+26 = 38 minutes

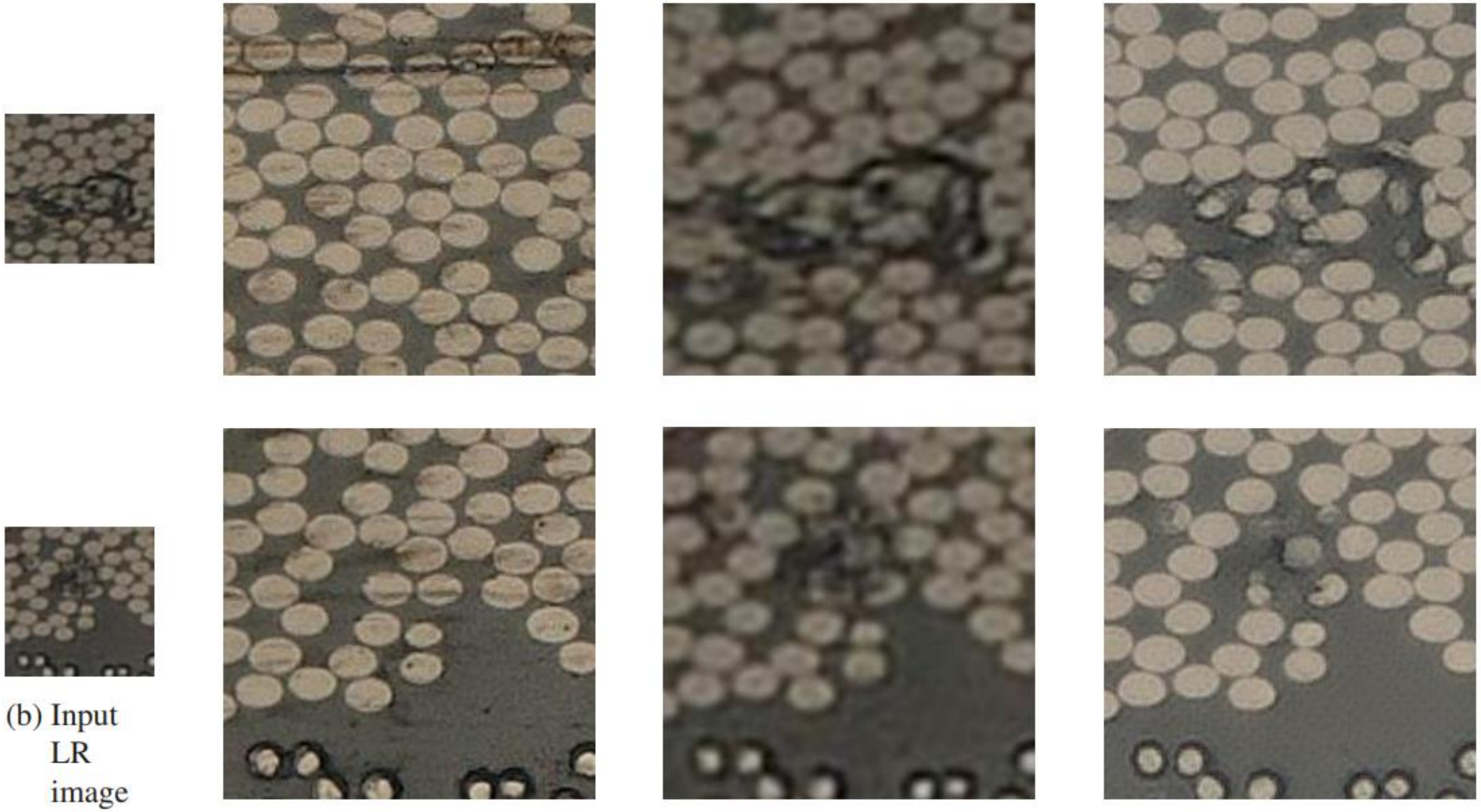
Discussion: Dependence on features in low-resolution image





Effect of dirt in the input LR image

Discussion: Dependence on features in low-resolution image

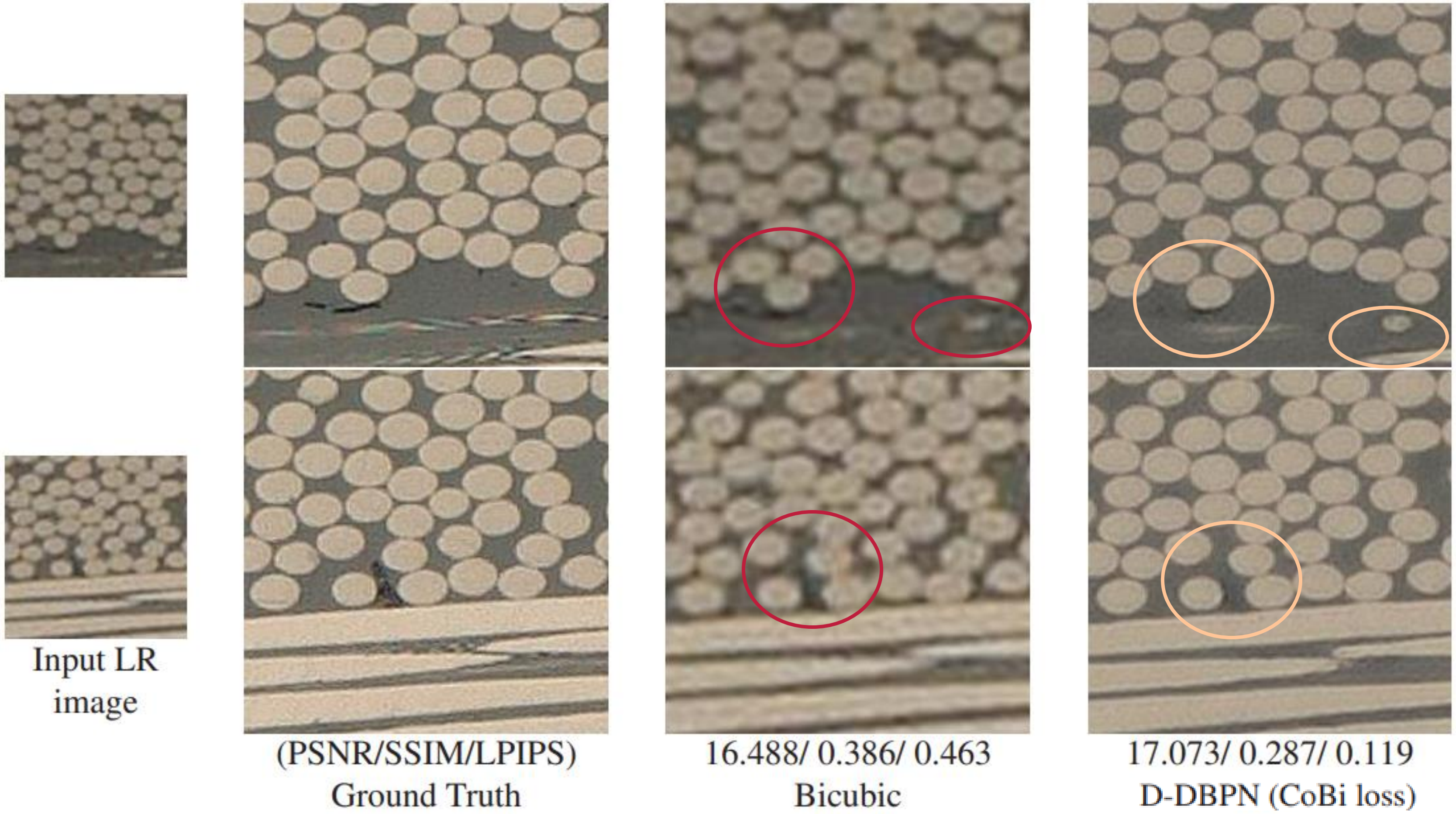


(b) Input LR image

PSNR/ SSIM/ LPIPS	19.509/ 0.512/ 0.442	18.446/ 0.467/ 0.099
(c) Ground Truth	(d) Bicubic	(e) D-DBPN (CoBi loss)

Effect of dirt in the input LR image

Discussion: Dependence on features in low-resolution image



Limitation: Paint-brush stroke effect for unclear & small feature

SR of extremely small feature

Conclusion

Criteria	Does it work?	Scope for improvement
Image quality	Yes, except for minute cracks	▪ Data improvement ▪ Tuning with crack specific data ▪ Enhancing the output ▪ A different model
Time	Yes, aprrox 45 % less time	▪ A smaller model specifically tuned for data

Thank you!!





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DLR Team, Stade

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