Image Based Quality Assurance of Inkjet Printed Electronics and Coated Screen Printed Electronics

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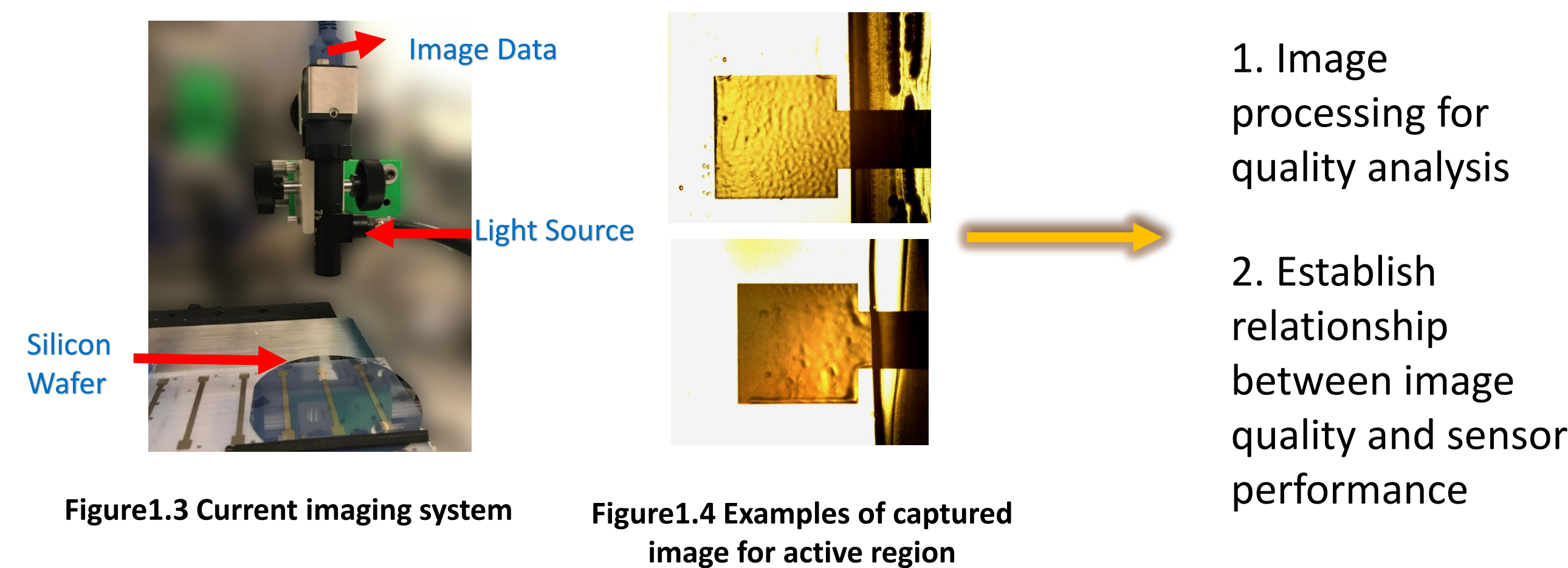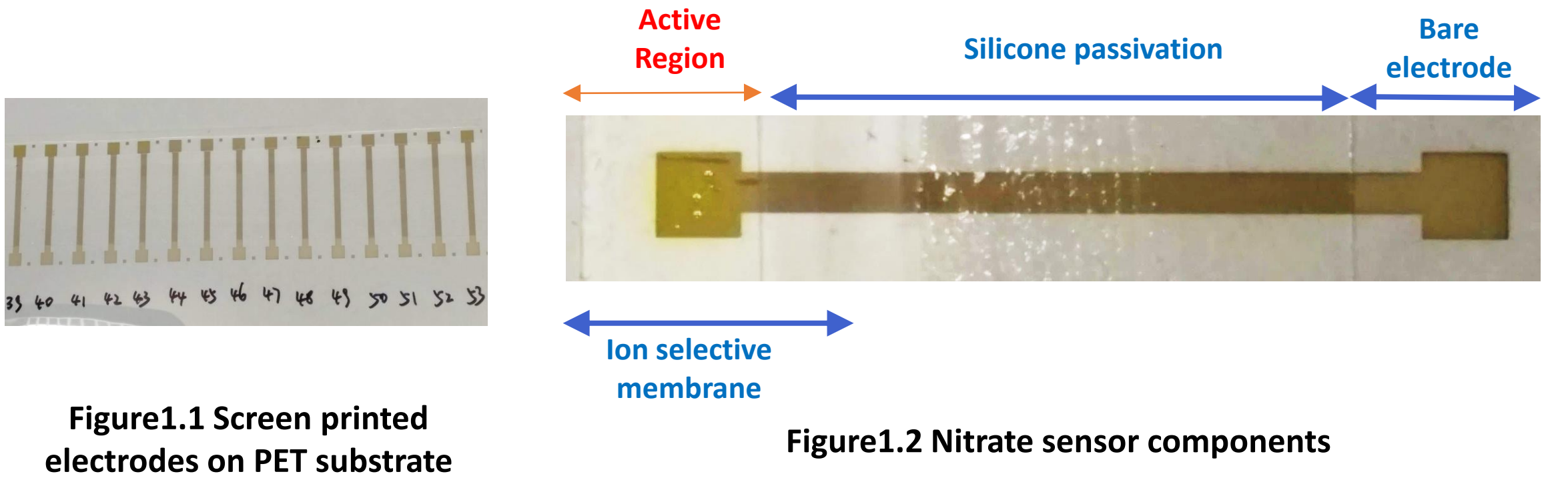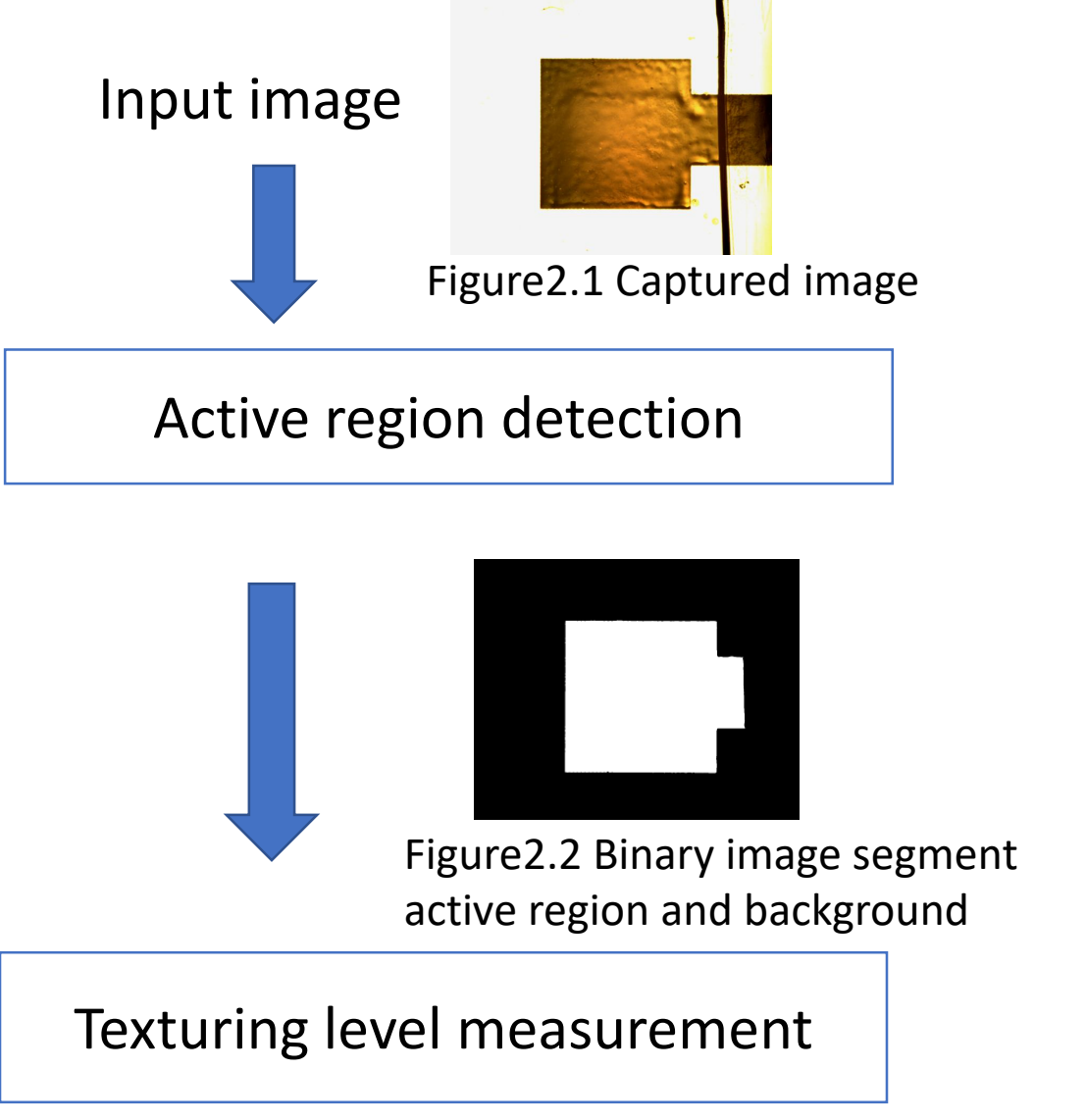## I. Motivation

Establish relationship between image quality (as measured in captured image) and functional properties of sensor.

Figure1.1 Screen printed electrodes on PET substrate

Figure1.2 Nitrate sensor components

Figure1.3 Current imaging system

Figure1.4 Examples of captured image for active region

1. Image processing for quality analysis

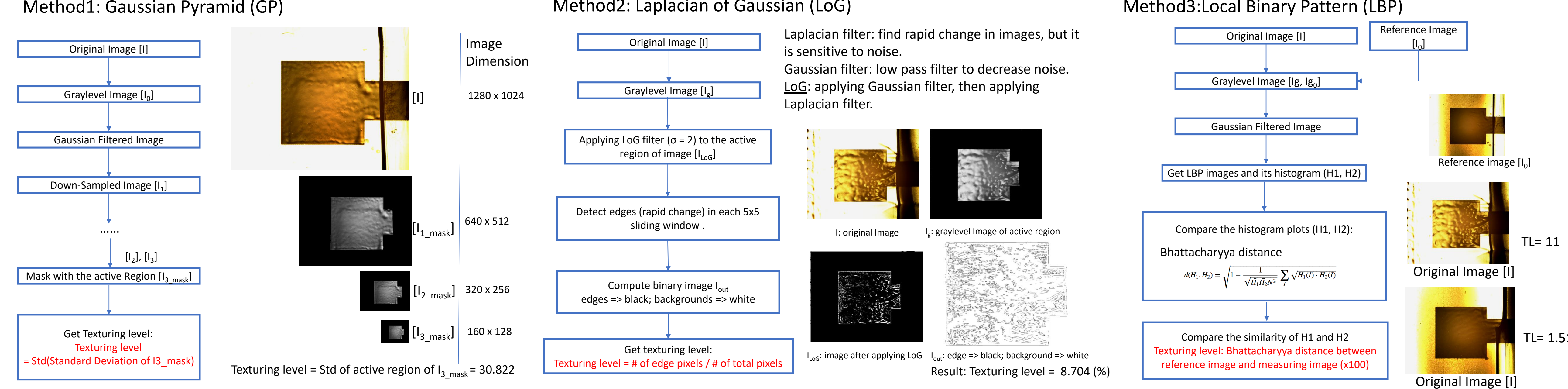2. Establish relationship between image quality and sensor performance

II. Image Quality Analysis

Overview of image quality analysis

Input image

Figure2.1 Captured image

Active region detection

Figure2.2 Binary image segment active region and background

Texturing level measurement

Detection of active region:
- Use image processing including Sobel filter, Otsu's method and morphological transformation to identify the active region in captured image.
- Show the segmentation result in binary image as figure2.2.

Measurement of texturing level:
- Set up a model and get numerical representations for different texturing.
- Three methods are developed to describe the texturing levels.

Three methods to represent texturing level (TL) of active region in sensor images

Method1: Gaussian Pyramid (GP)

Original Image [I]

Graylevel Image [I_g]

Gaussian Filtered Image

Down-Sampled Image [I_1]

....

[I_2], [I_3]

Mask with the active Region [I_{1_mask}]

Get Texturing level:
Texturing level = Std(Standard Deviation of I3_mask)

Image Dimension

1280 x 1024 [I]

640 x 512 [I_{1_mask}]

320 x 256 [I_{2_mask}]

160 x 128 [I_{3_mask}]

Texturing level = Std of active region of I_{3_mask} = 30.822

Method2: Laplacian of Gaussian (LoG)

Original Image [I]

Graylevel Image [I_g]

Applying LoG filter (σ = 2) to the active region of image [I_{LoG}]

Detect edges (rapid change) in each 5x5 sliding window.

Compute binary image I_{out} edges => black; backgrounds => white

Get texturing level:
Texturing level = # of edge pixels / # of total pixels

Laplacian filter: find rapid change in images, but it is sensitive to noise.
Gaussian filter: low pass filter to decrease noise.
LoG: applying Gaussian filter, then applying Laplacian filter.

I: original Image I_g: graylevel image of active region

I_{LoG}: image after applying LoG I_{out}: edge => black; background => white

Result: Texturing level = 8.704 (%)

Method3:Local Binary Pattern (LBP)

Original Image [I]   Reference Image [I_b]

Graylevel Image [I_g, I_{gb}]

Gaussian Filtered Image

Get LBP images and its histogram (H1, H2)

Compare the histogram plots (H1, H2):
Bhattacharyya distance

$$d(H_1, H_2) = \sqrt{1 - \frac{1}{\sqrt{\bar{H_1}\bar{H_2}N^2}} \sum_I \sqrt{H_1(I) \cdot H_2(I)}}$$

Compare the similarity of H1 and H2
Texturing level: Bhattacharyya distance between reference image and measuring image (x100)

Reference image [I_b]

Original Image [I]   TL= 11

Original Image [I]   TL= 1.51

Comparison of results with three methods

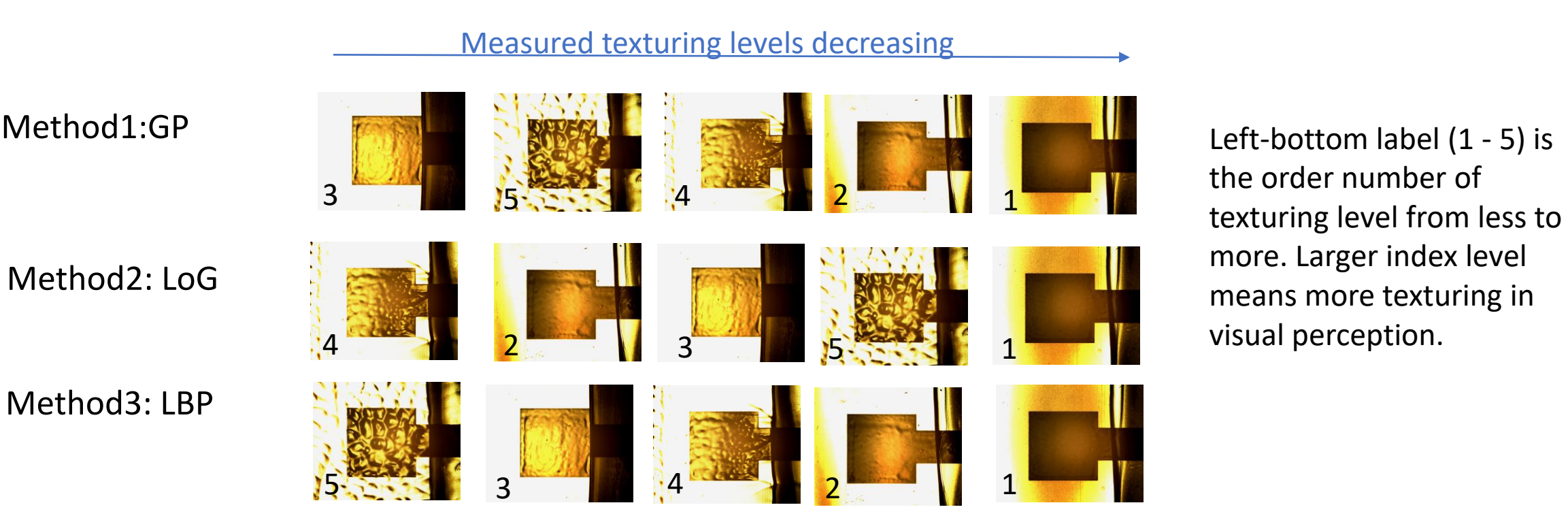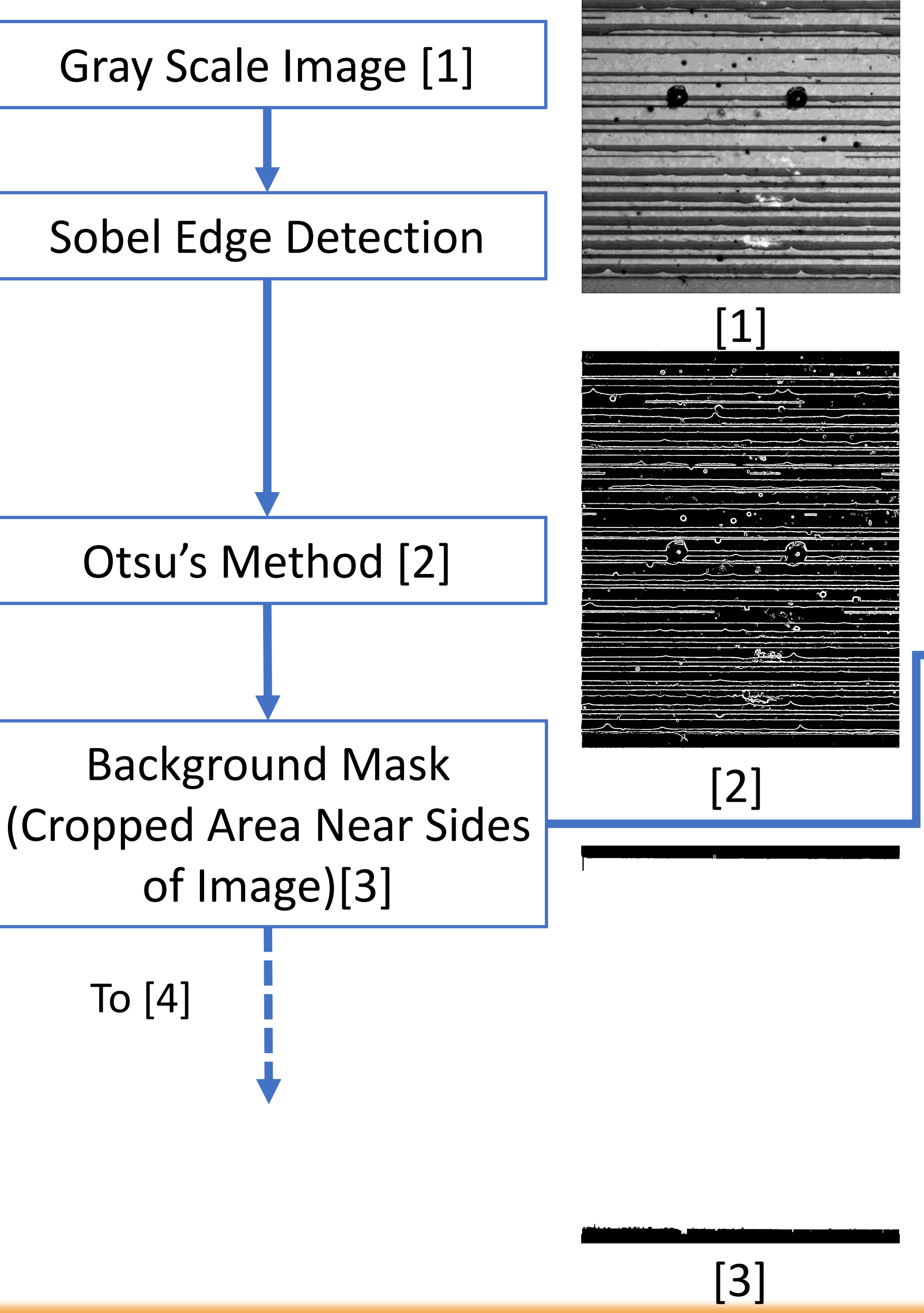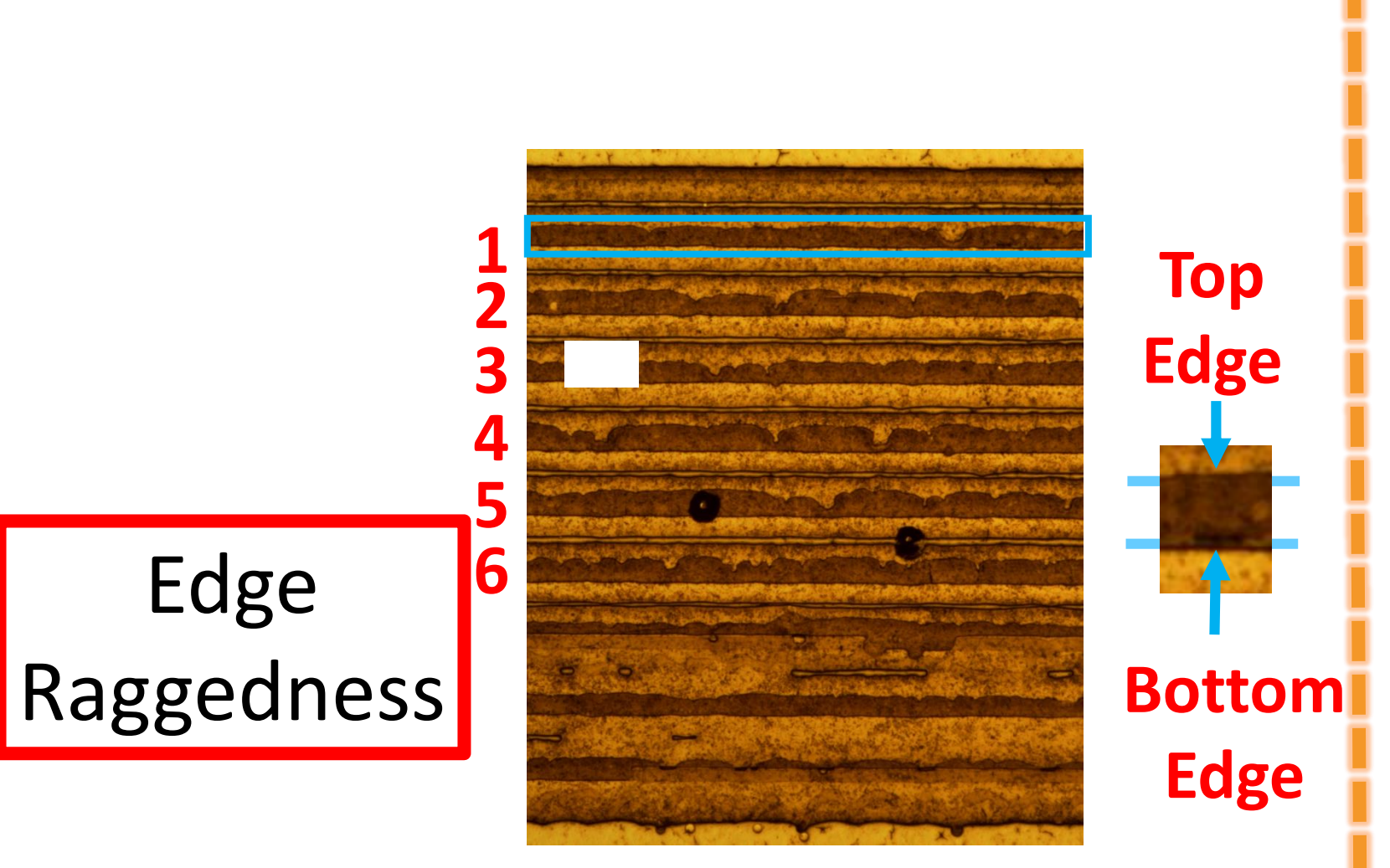Measured texturing levels decreasing

Method1:GP

Method2: LoG

Method3: LBP

Figure2.1 Arrange results of texturing levels after applying three different method as decreasing order.

Left-bottom label (1 - 5) is the order number of texturing level from less to more. Larger index level means more texturing in visual perception.

Method1 GP (Gaussian pyramid with normalization): It uses multi-scale representation of texturing level. The texturing level in active region can be shown in different scale space. Sometimes the variant illuminance effects our result.

Method2 LoG (Laplacian of Gaussian): Applying Laplacian of gaussian filter is a way to find rapid change in an image. Variant illuminance does not effect result. It describes the edges in active region.

Method3 LBP (Local binary pattern): LBP algorithm is always used to describe the texturing in an image. The results are robust with variant illuminance and rotation. It describes local texturing in active region.

III. Morphological Analysis

Gray Scale Image [1]

Sobel Edge Detection

Otsu's Method [2]

Background Mask (Cropped Area Near Sides of Image)[3]

To [4]

From [3]

Otsu's Method (With Background Mask) [4]

K-Means Clustering (With Background Mask and Inversed [4]) [5]

Final Segmentation [6]

[1]

[2]

[3]

Image Segmentation

[4]

[5]

Original Image
1016 dpi, 10pl, w/ 3% Ammonium Carbamate [6]

Single Layer
Double Layer
No Ink

Edge Raggedness

Top Edge

Bottom Edge

Edge Position	Top Edge Edge Roughness (μm)	Bottom Edge Edge Roughness (μm)
1	15.63	4.46
2	17.16	3.90
3	20.79	3.83
4	27.12	4.16
5	27.01	4.59
6	27.02	5.93
Average	22.46	4.50

$$Edge\ Roughness = \sqrt{\frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} [Fitted\ line(i,j) - Data\ (i,j)]^2},$$

where $m = image\ width$, $n = image\ length$, $(i,j) = Pixel\ Position$

IV. Cross Validation

Microscope imaging of printed device
•Morphology

Performance of printed device
•Conductivity

Microscope Imaging

?

Performance

Various printing variables including cartridge drop size, printing resolution, viscosity of silver ink.

Training Set

Test Set

1.Training (Model Fitting) → Model

Same Model

2. Testing Microscope imaging Data → Model

Performance Prediction

Performance Data → Model Accuracy