Robust Calibration Marker Detection in Powder Bed Images from Laser Beam Melting Processes

TF-010464

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Taipei
Taiwan

Institute of
Imaging and
Computer Vision

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What is Laser Beam Melting (LBM)?

"3D printing" with metal powder

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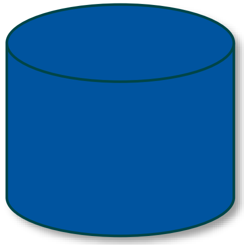

Design (3D)

What is Laser Beam Melting (LBM)?

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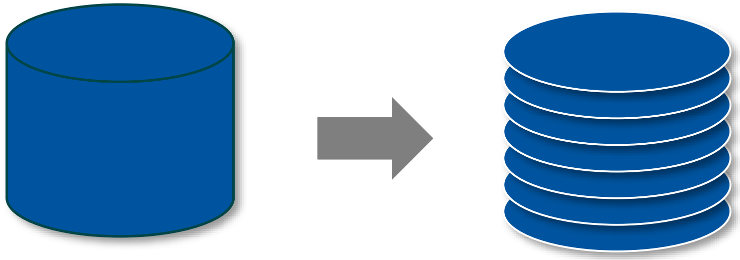

Design (3D) Slices (2D + 1D)

- Layer-based, iterative

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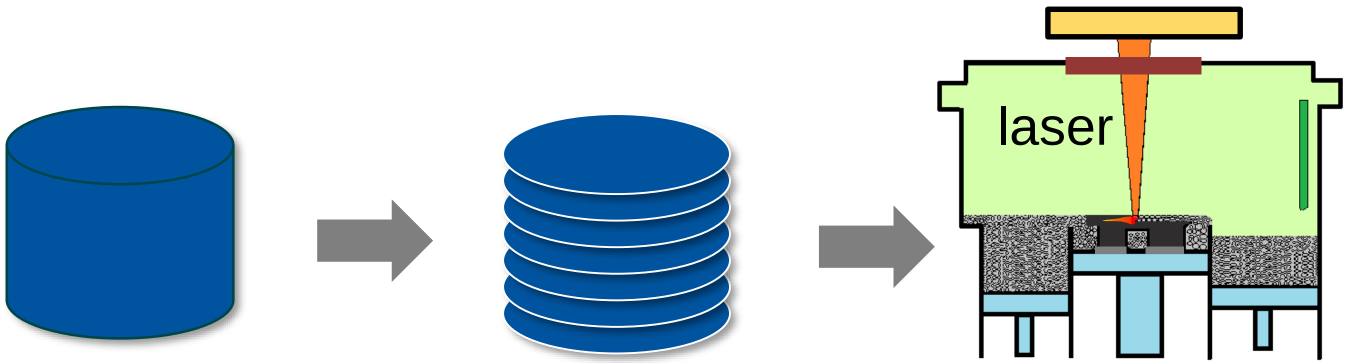

Design (3D)　　Slices (2D + 1D)　　Build Layers

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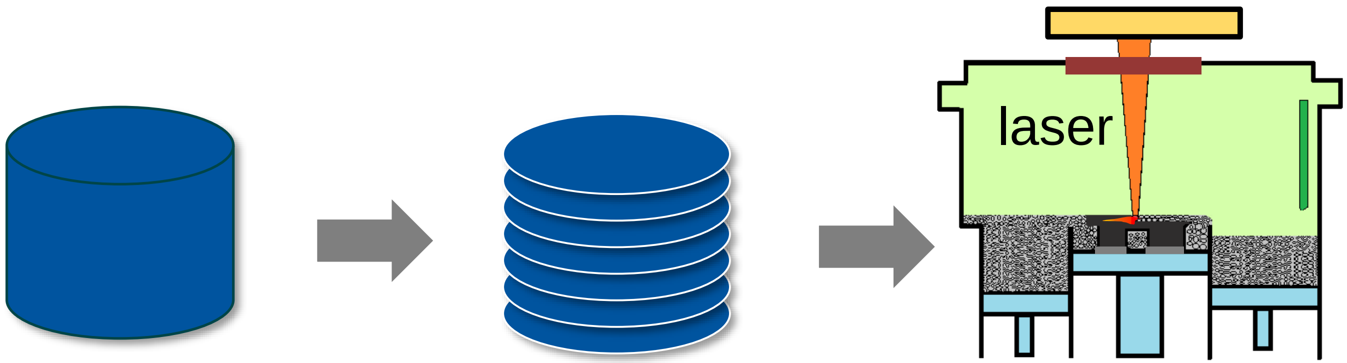
“3D printing” with metal powder



Design (3D) Slices (2D + 1D) Build Layers

- Layer-based, iterative
- Laser melts metal powder according to layer geometry

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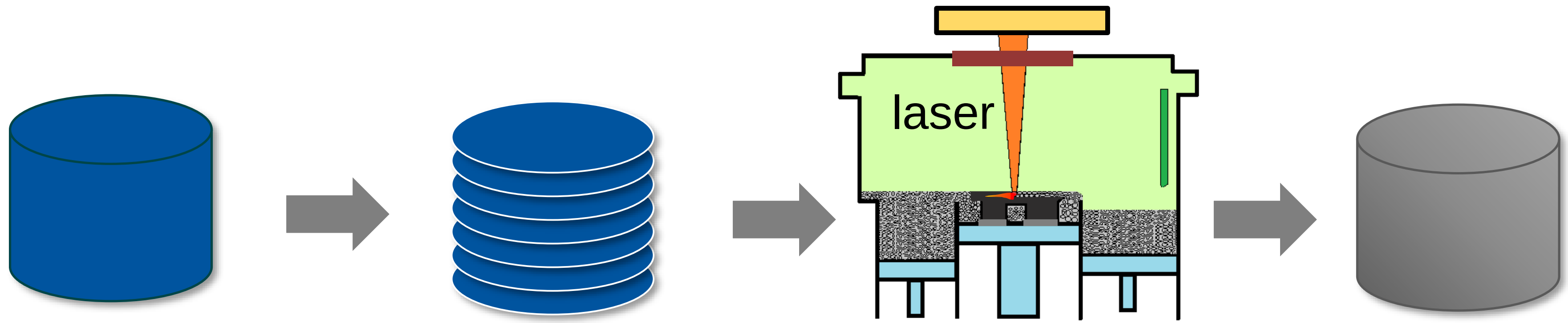
“3D printing” with metal powder



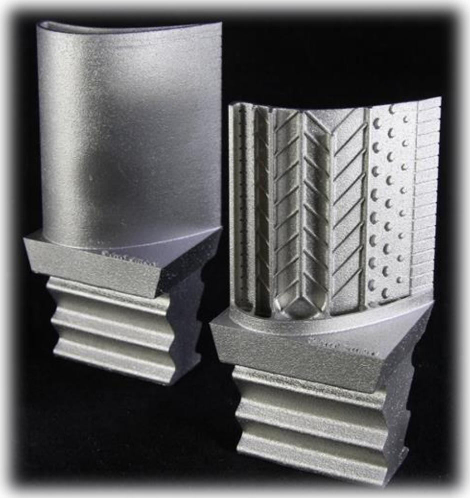
Design (3D)
Slices (2D + 1D)
Build Layers
Part

- Layer-based, iterative
- Laser melts metal powder according to layer geometry

Laser Beam Melting – „3D Printing with Metal“

hip implant
[www.slm-solutions.com]

injection nozzle
[www.eos.info]



turbine blade (demo)
[RTC Duisburg]

spiders
[RTC Duisburg]

impeller
[RTC Duisburg]

Motivation

Visual Inspection of Produced Layers

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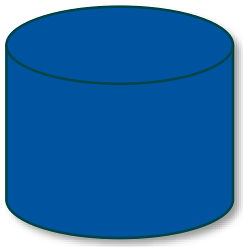

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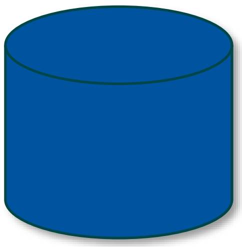

Detect flaws

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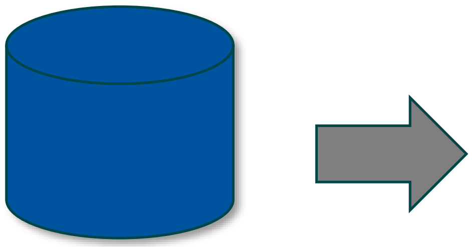

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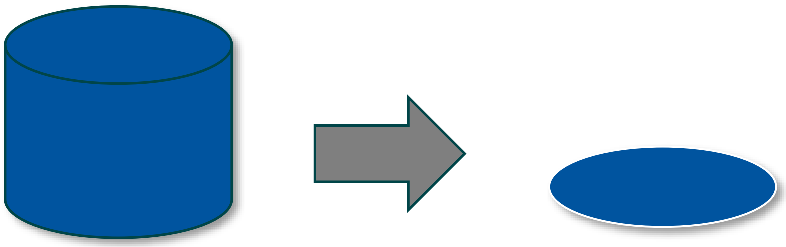

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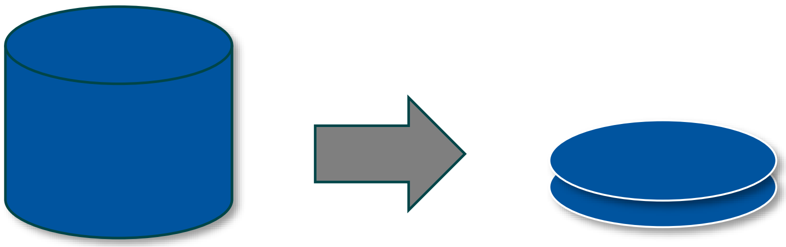

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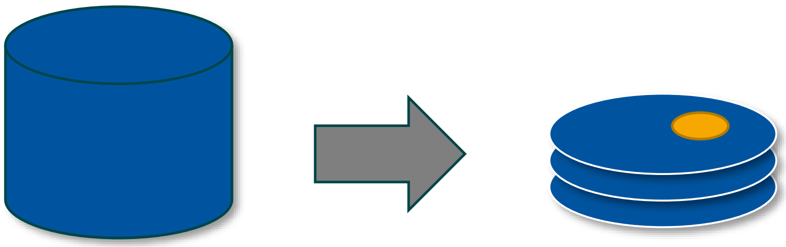

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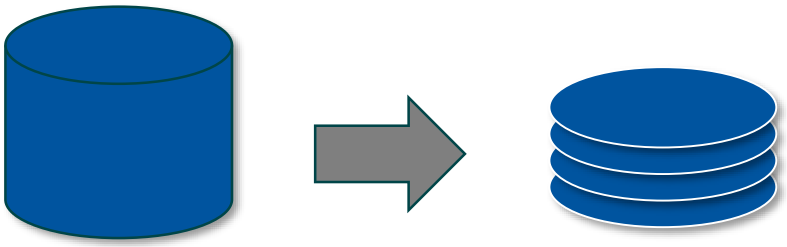

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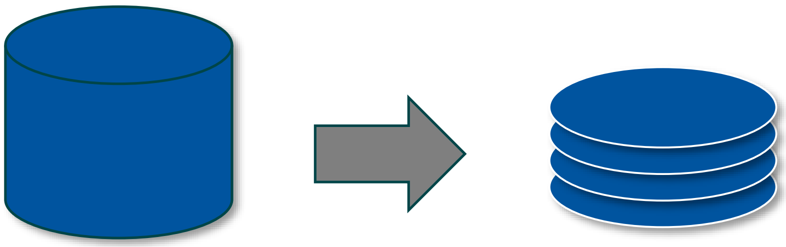
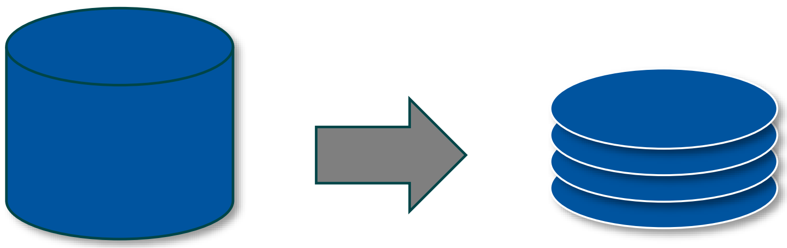


Detect flaws

➢ Acquire images of powder bed and melt result

Motivation

Visual Inspection of Produced Layers



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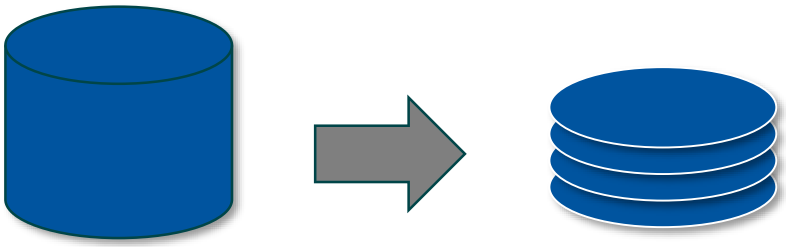

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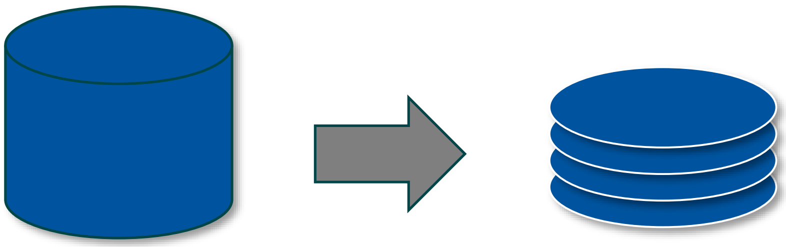
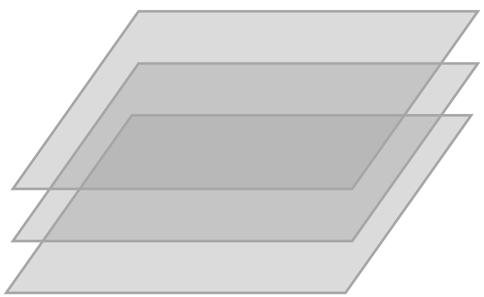
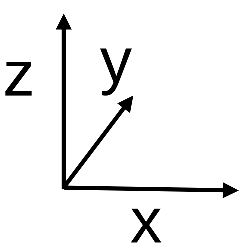
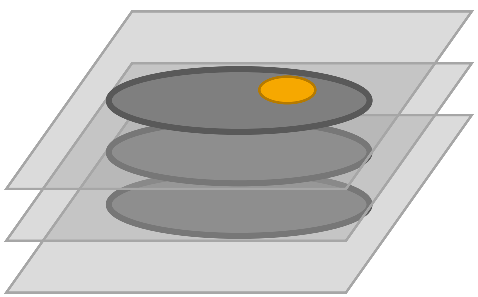






before laser exposure



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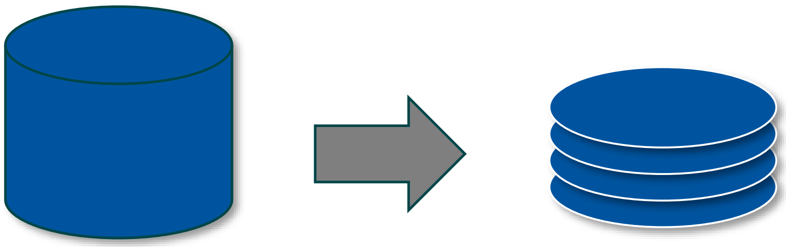

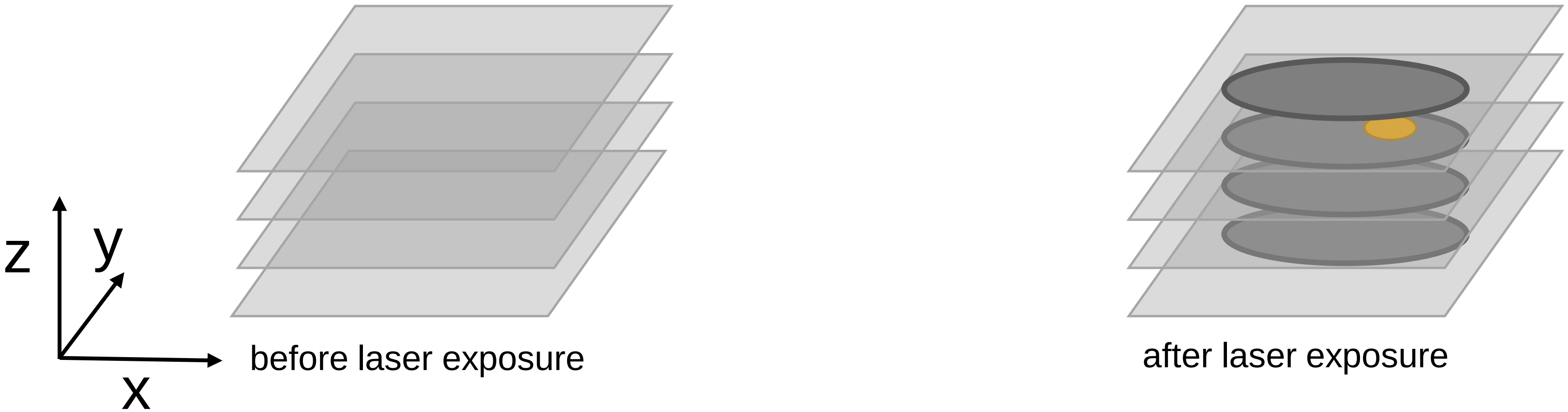

Detect flaws

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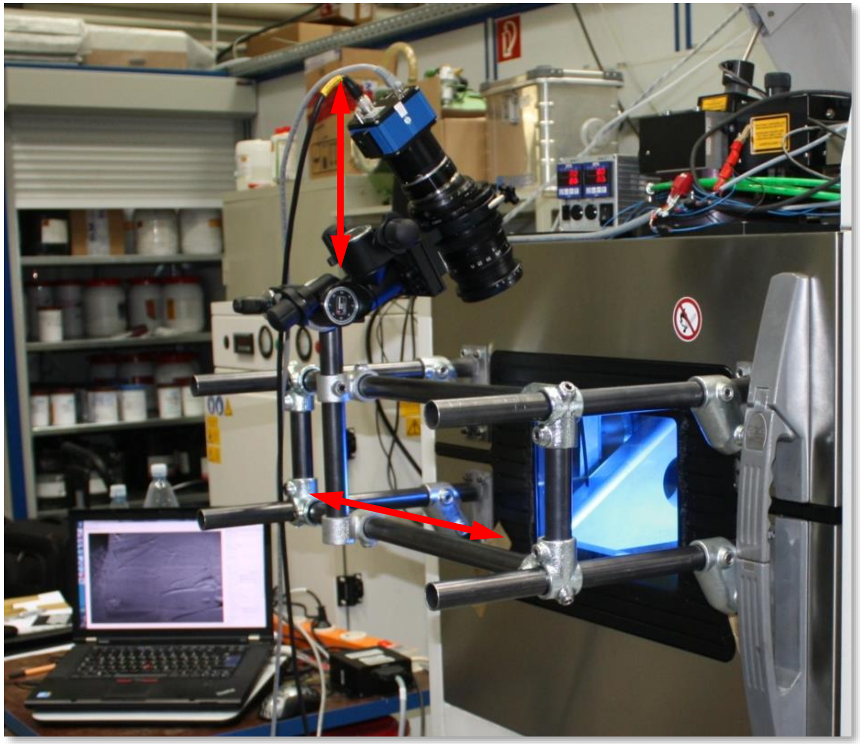
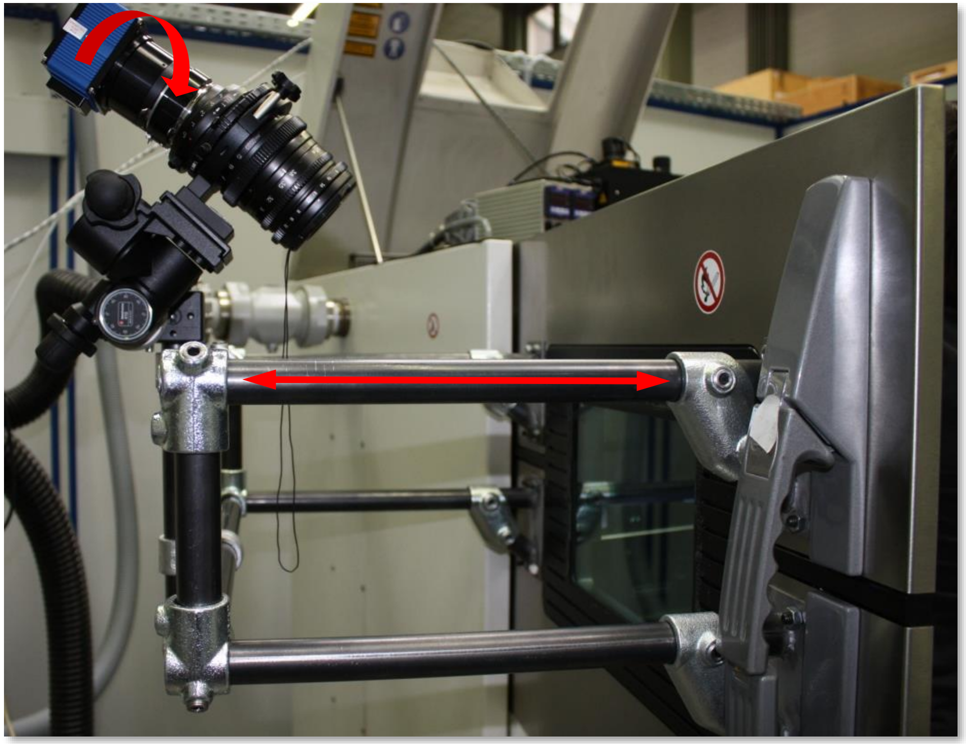
Layer Image Acquisition





zur Jacobsmühlen, J.; Kleszczynski, S.; Schneider, D. & Witt, G.
High Resolution Imaging for Inspection of Laser Beam Melting Systems
IEEE International Instrumentation and Measurement Technology Conference (I^2MTC), **2013**

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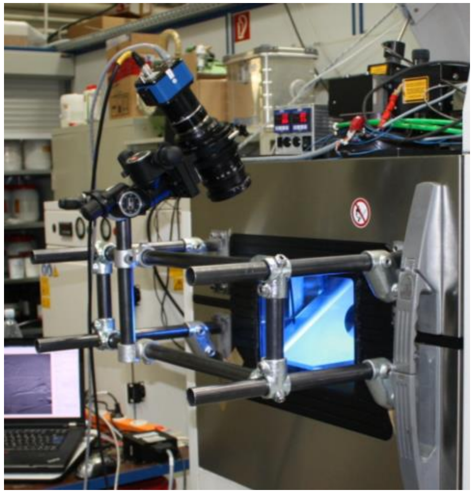
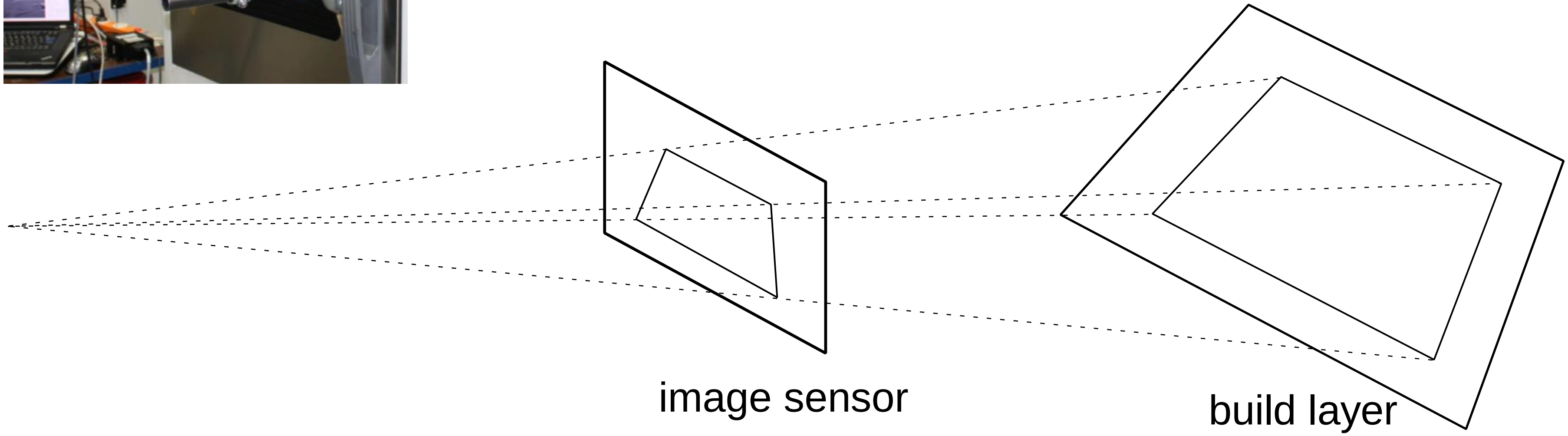
Layer Image Acquisition

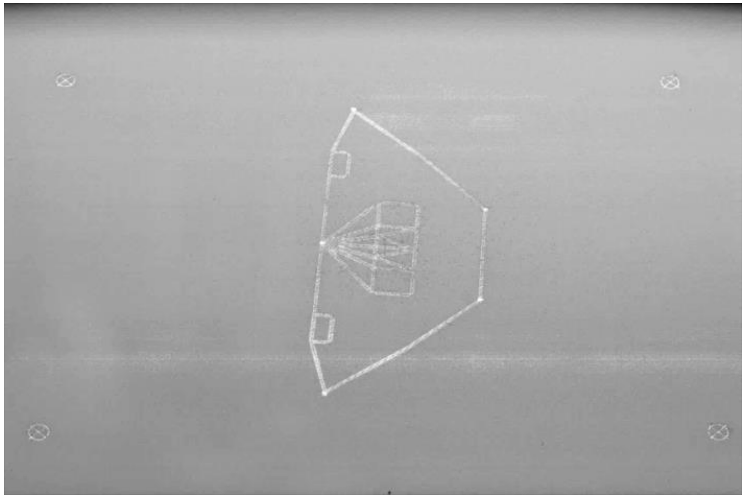
Camera Position Causes Perspective Distortion





Objective

Perspective Correction of Layer Images



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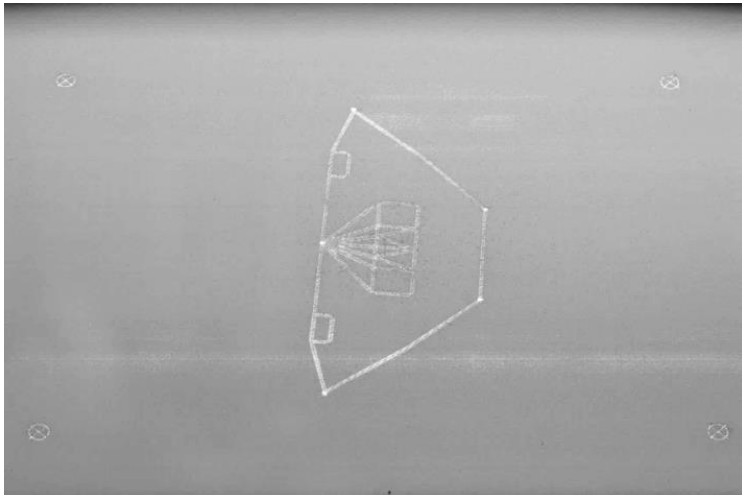
Objective

Perspective Correction of Layer Images

- Analysis requires orthographic images



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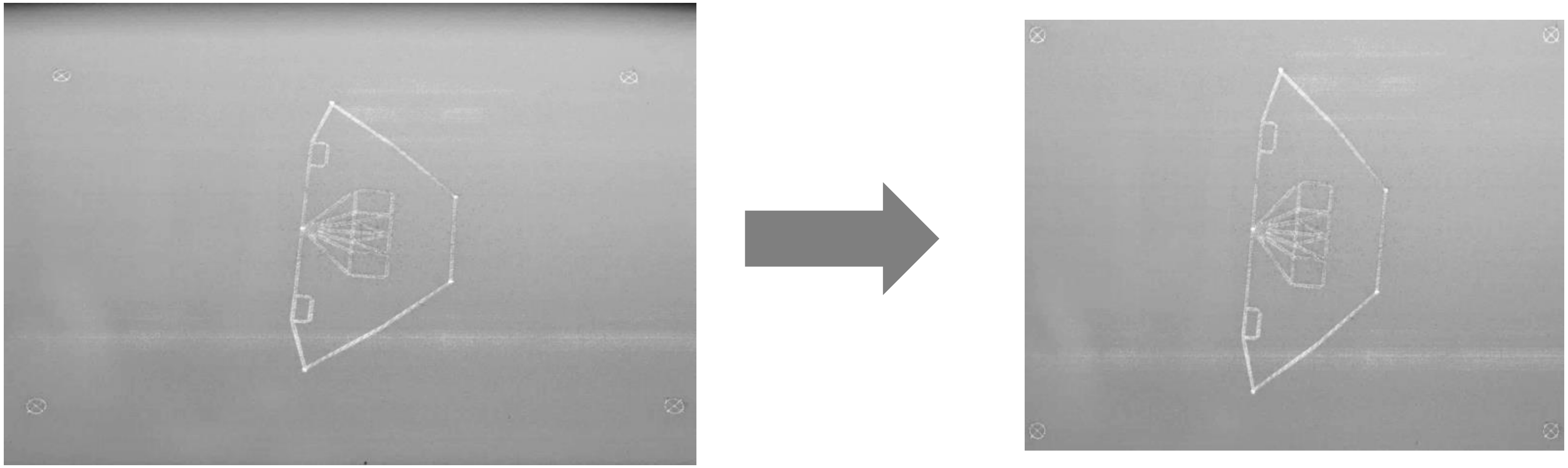

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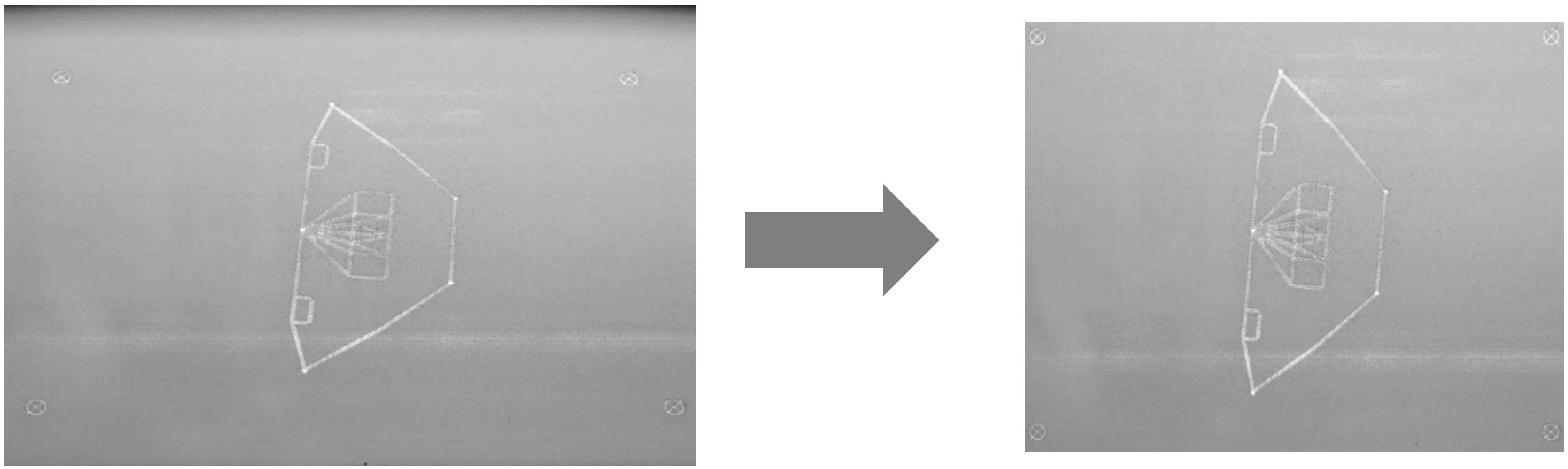

➢ We need a **reliable calibration method**

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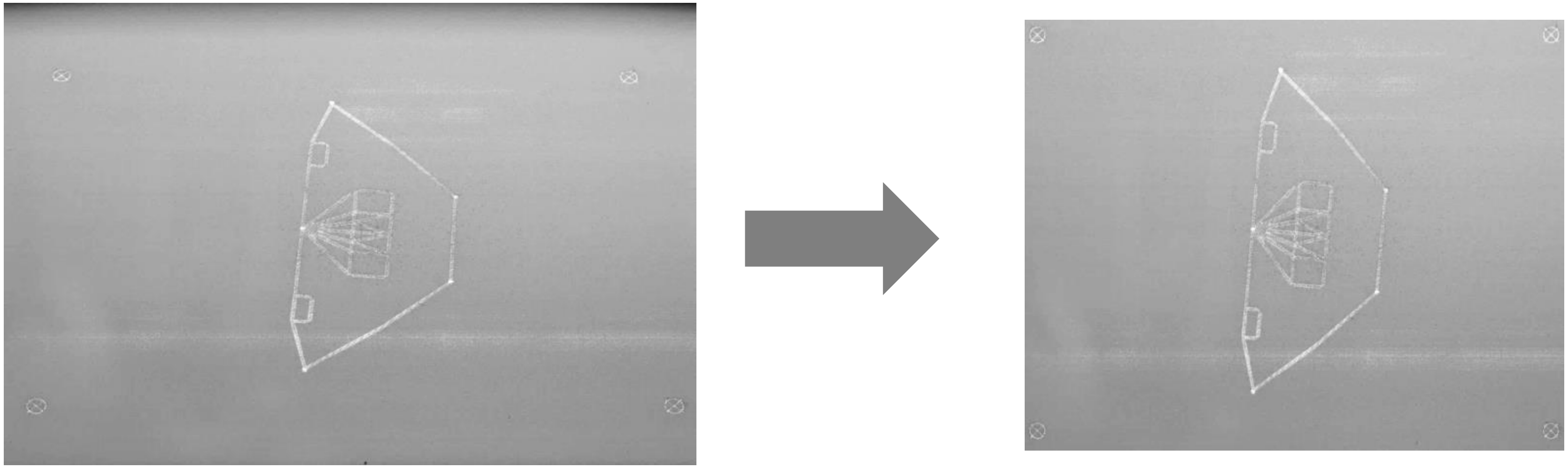

➢ We need a **reliable calibration method**
➢ Support different camera positions and view angles

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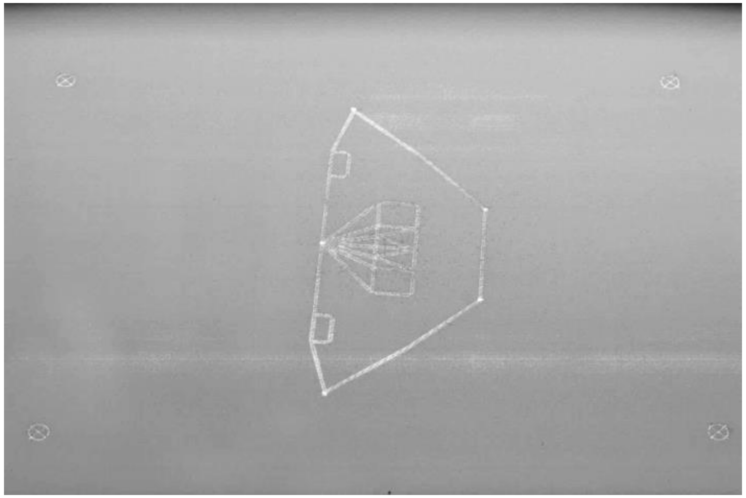
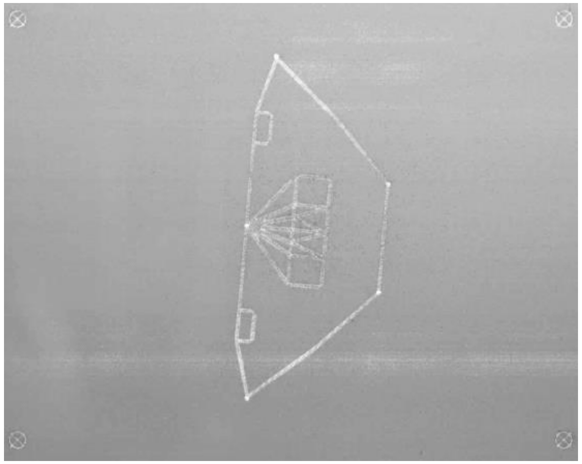


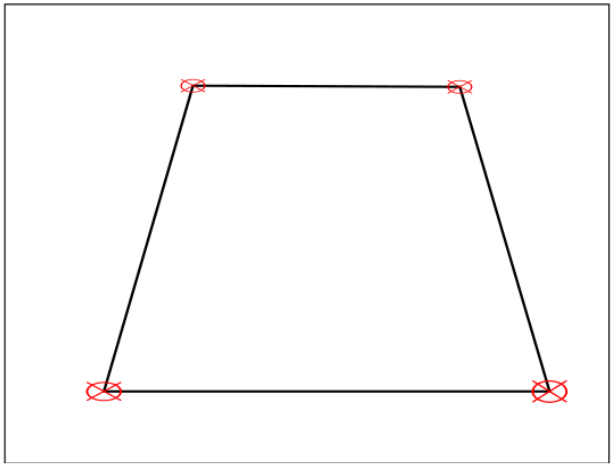


- ➢ We need a **reliable calibration method**
- ➢ Support different camera positions and view angles
- ➢ Automate calibration for best user experience and accuracy

Outline

- ✓ Laser Beam Melting
- ✓ Layer Image Acquisition
- ➢ Methods
  - Perspective Correction
  - Marker Detection
  - Shape Extraction
  - Classification
  - Homography Optimization
- Conclusion

Perspective Correction



Perspective Correction

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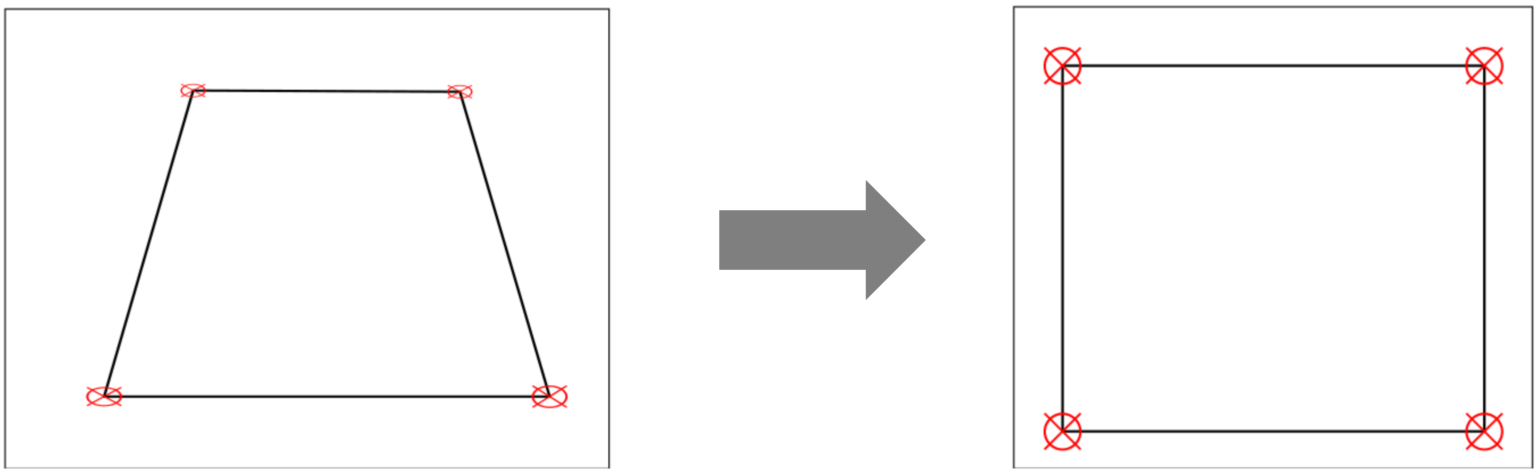
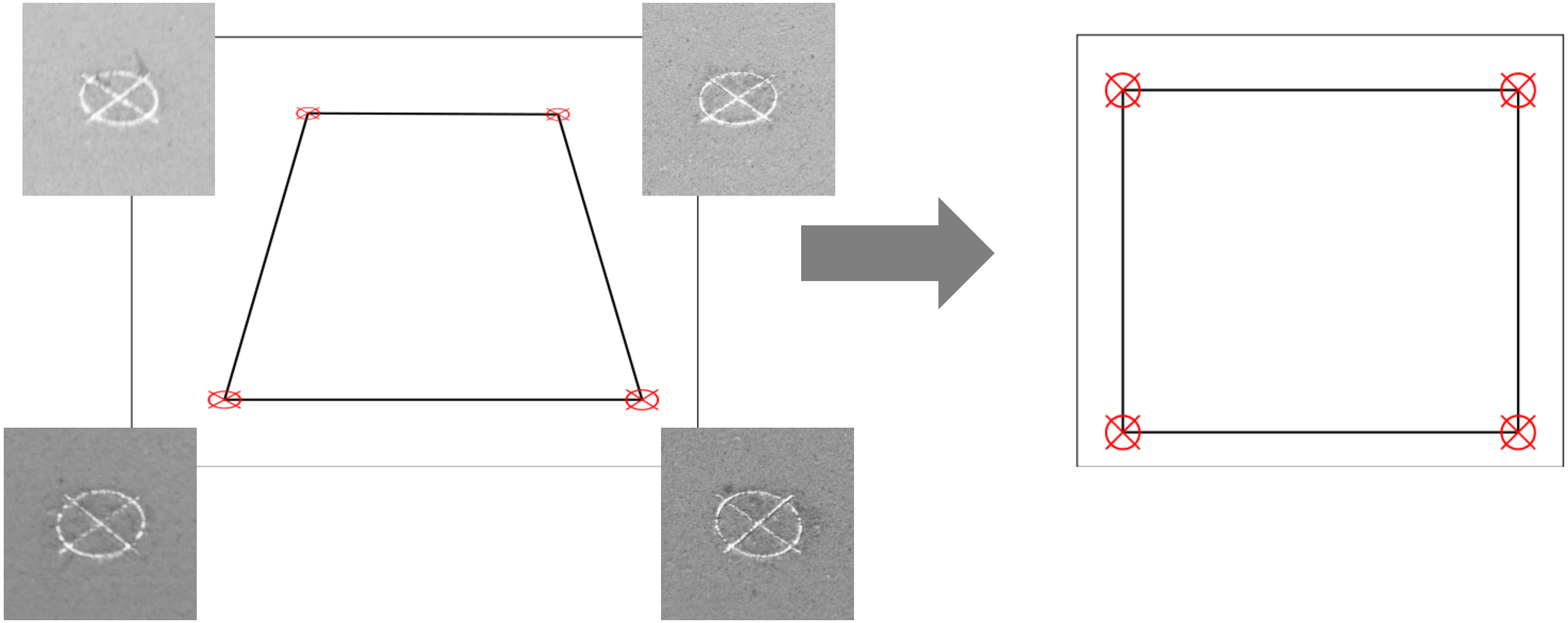


- 2D transformation estimation from four point correspondences (homography)

Perspective Correction



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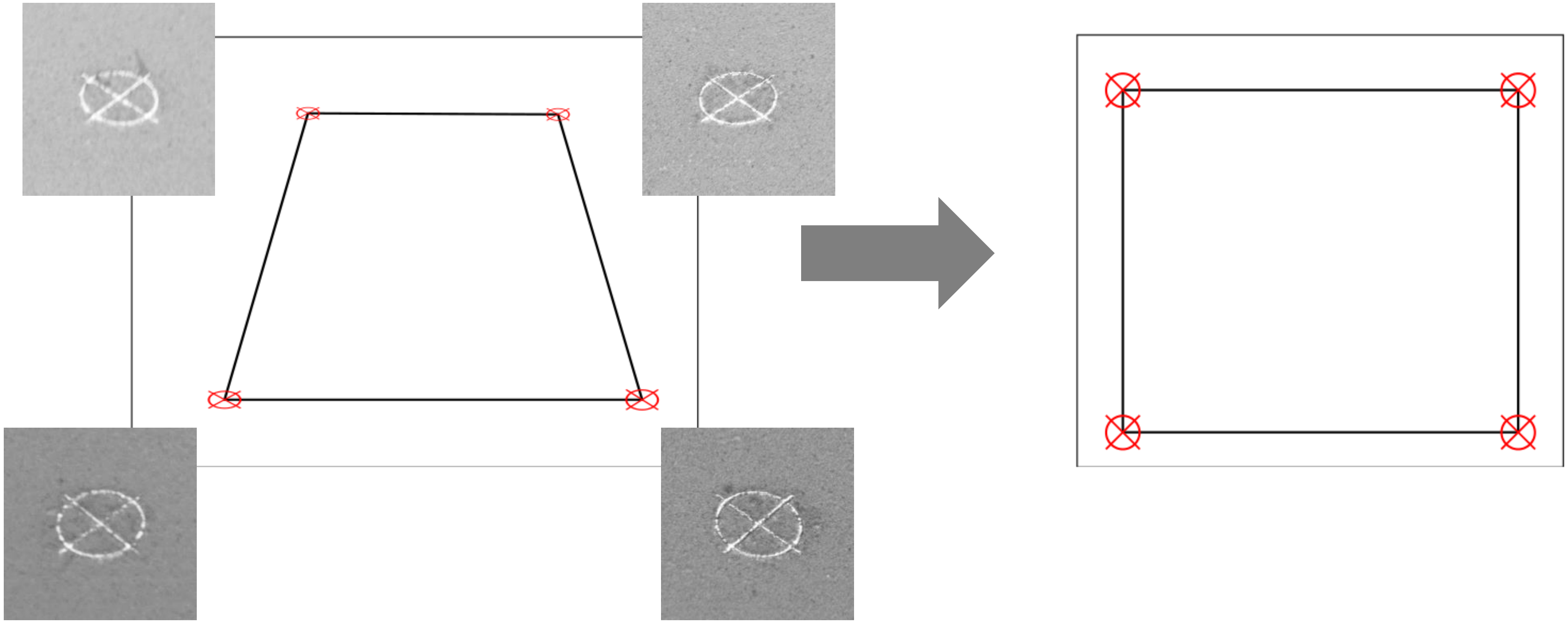

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- Markers are “drawn” by LBM system‘s laser in powder bed

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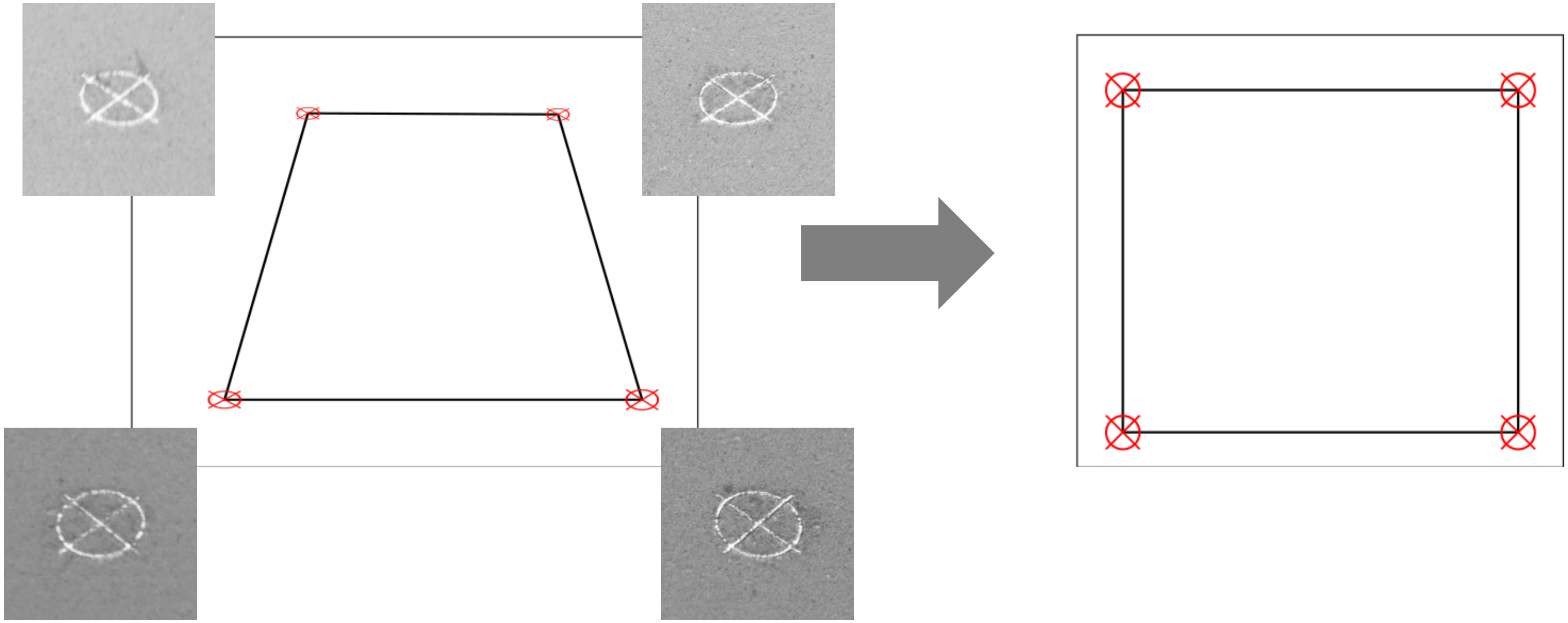
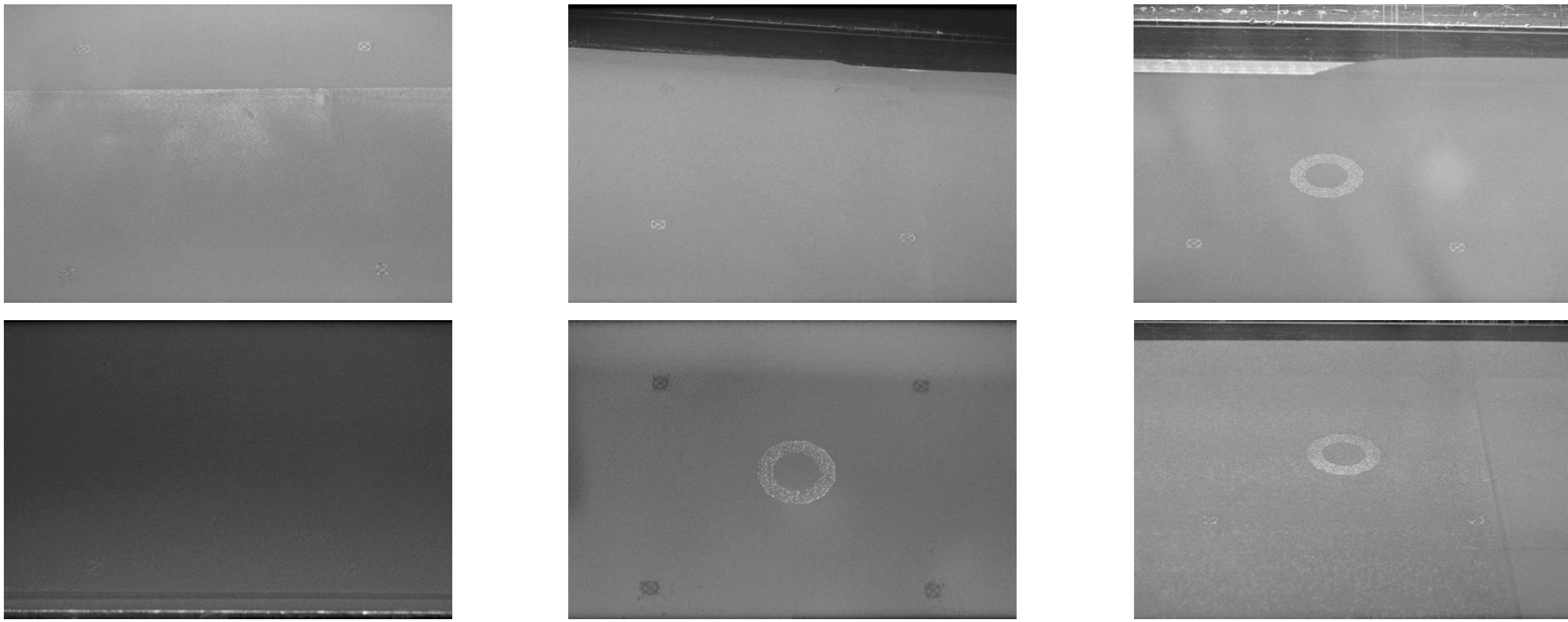


- 2D transformation estimation from four point correspondences (homography)
- Markers are “drawn” by LBM system‘s laser in powder bed
- ➢ Detect marker center points

Sample Powder Bed Images



- Full resolution: 6576 x 4384 px, 20…35 µm/px (different field of view)
- *N* = 265 images from 54 different build jobs for training and testing

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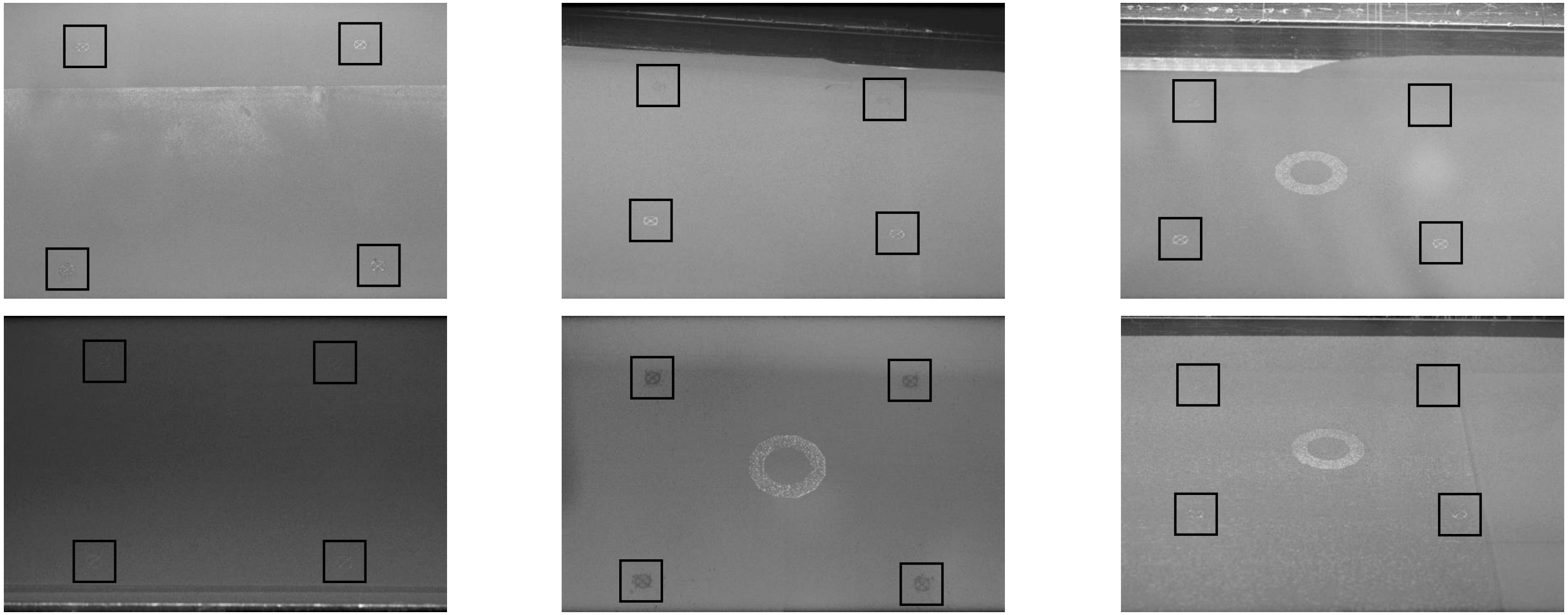

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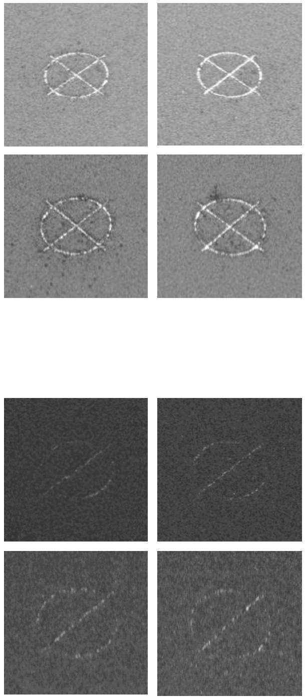
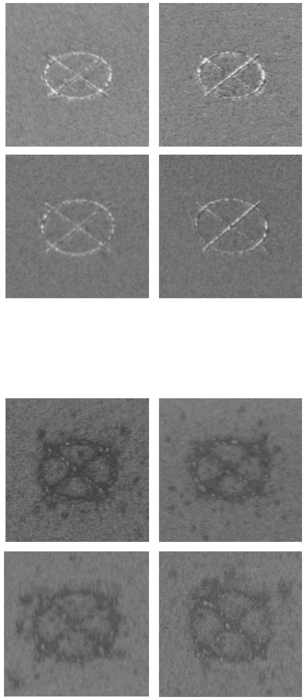
Sample Marker Images

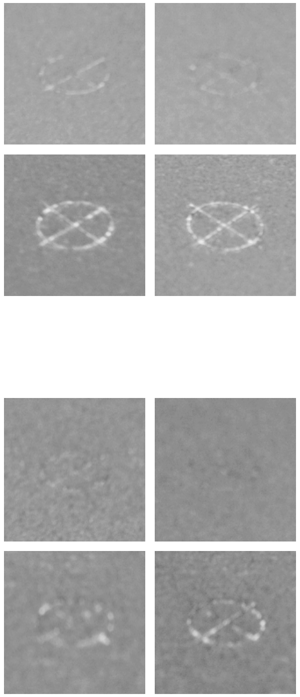
Large Variations between Builds



incomplete markers

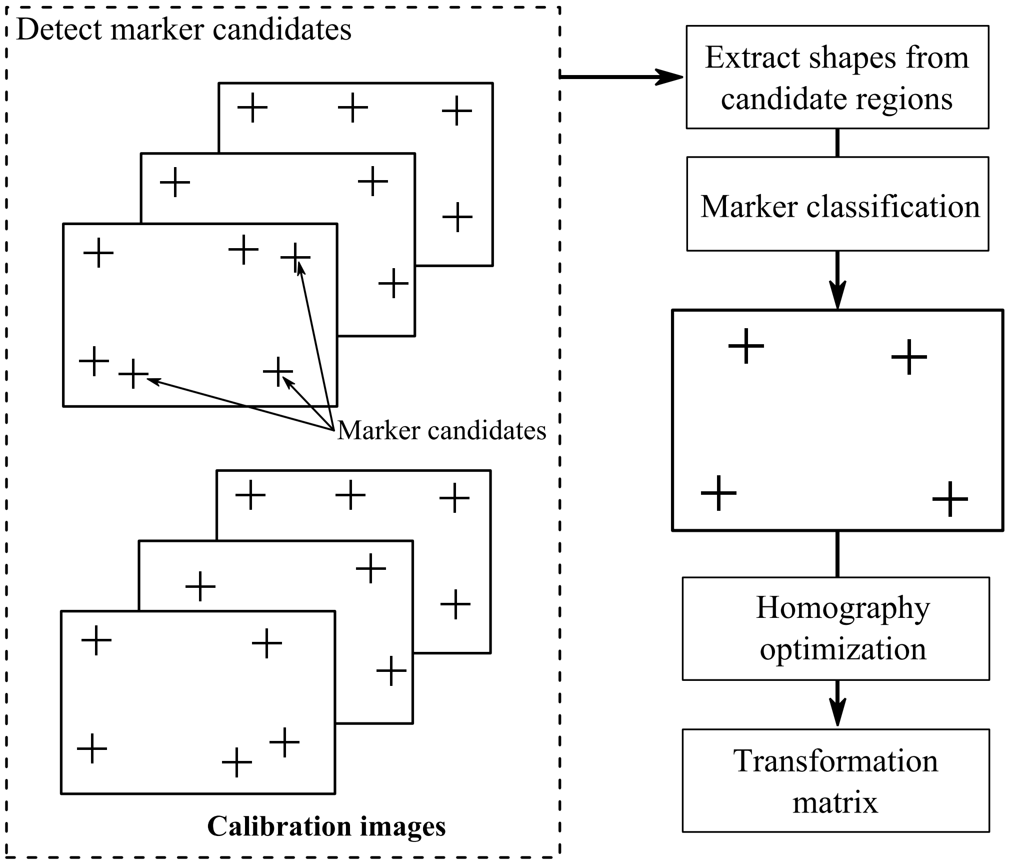


particles

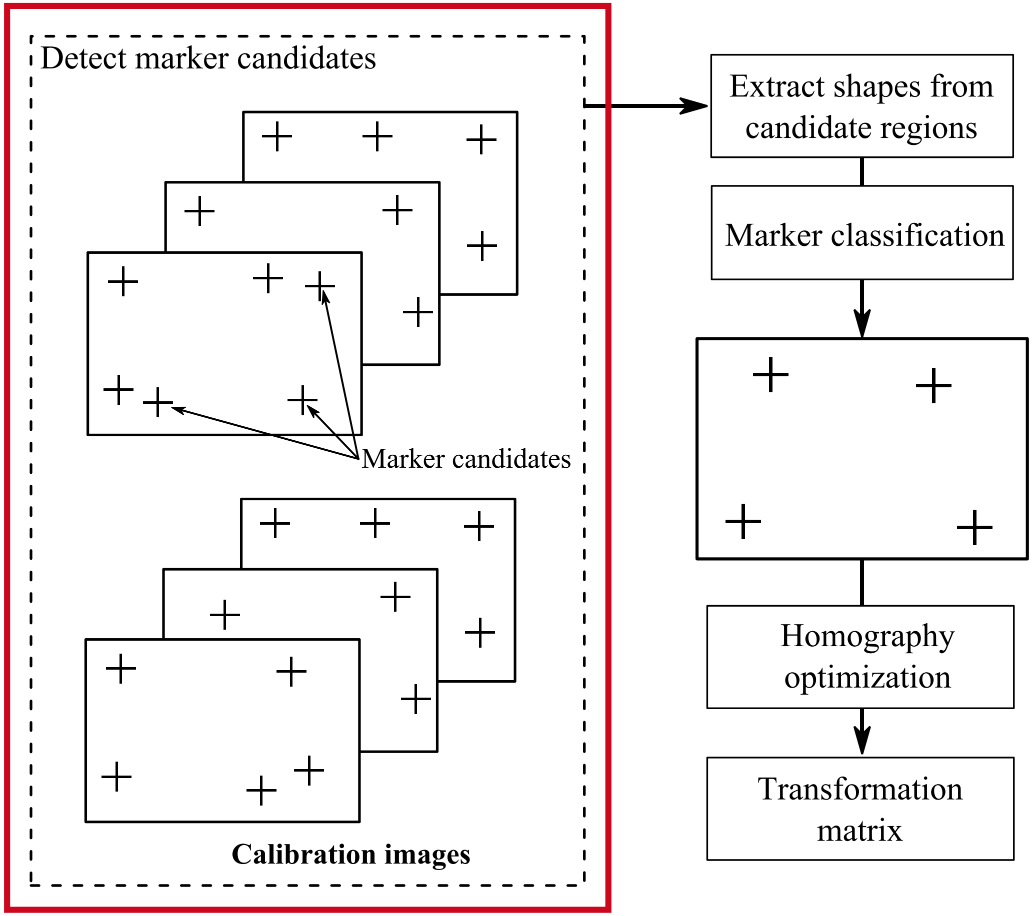


out of focus blur

Marker Detection Flow Chart



Marker Detection Flow Chart



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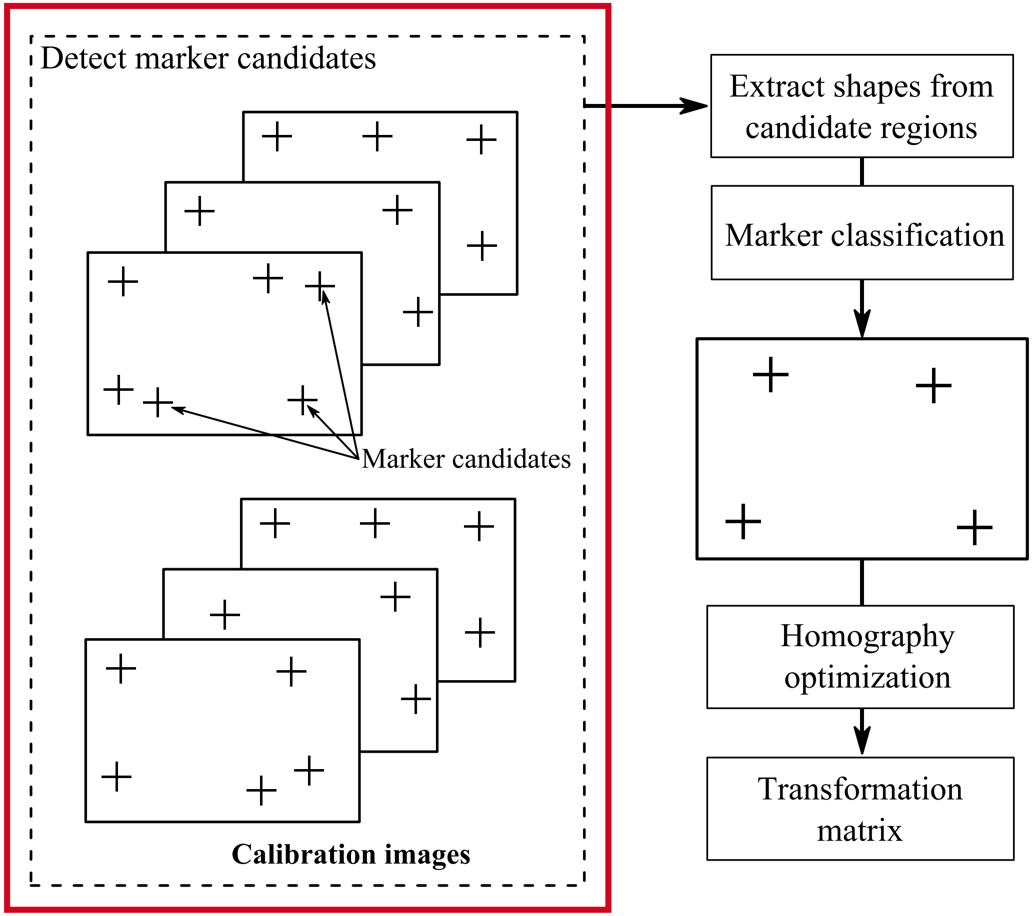
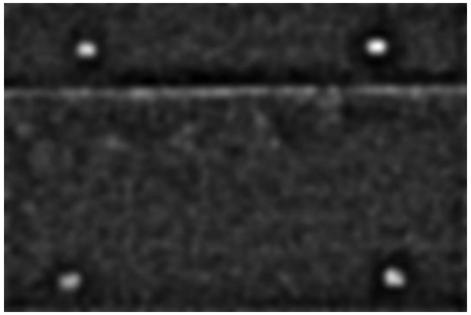
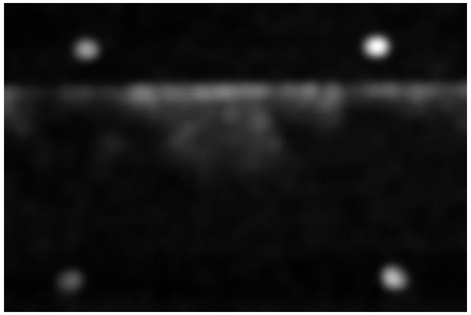
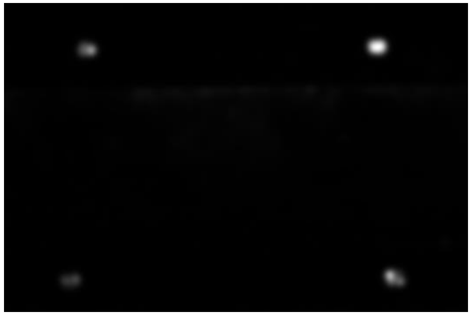


Exposure series (T = 105, 125, 145 ms)
for each lighting

Candidate Detection Methods







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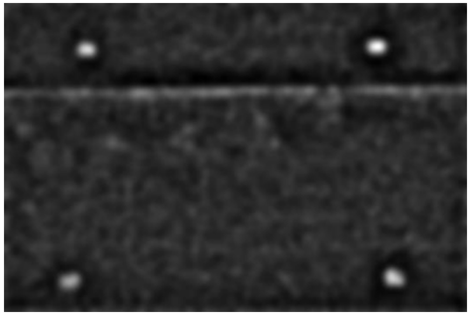
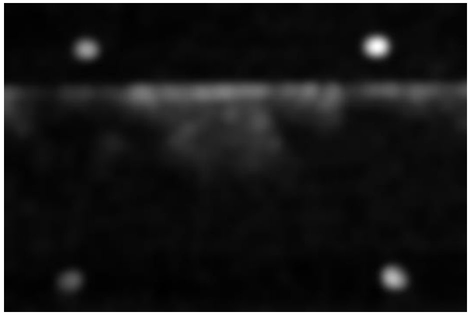
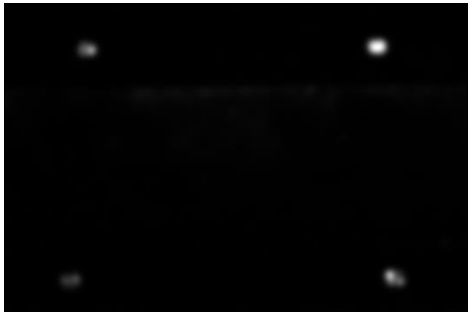
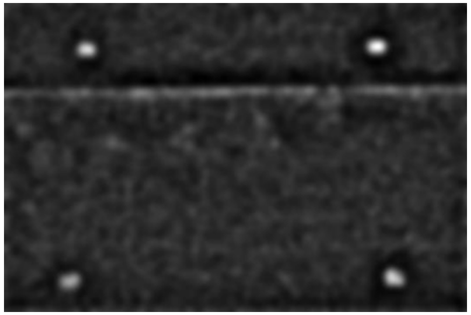
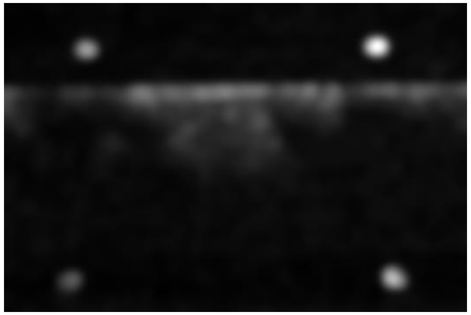
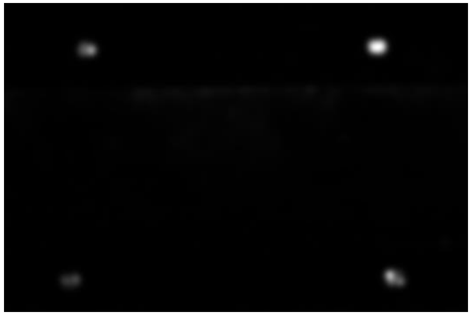






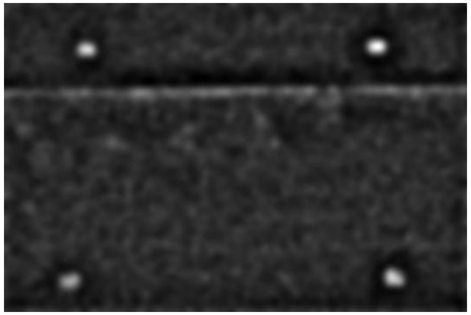
- Identify regions of interest

Candidate Detection Methods

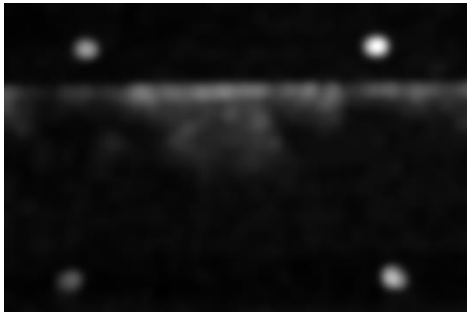




- Identify regions of interest
- Cannot use direct template matching
  - Varying appearance of markers
  - False positives

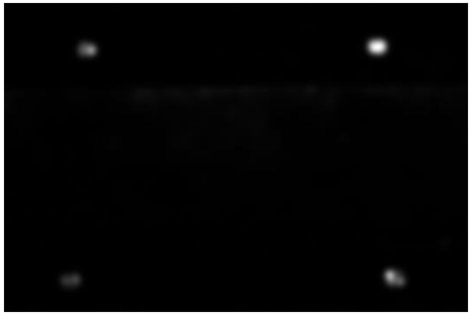
Candidate Detection Methods



Quotient of Gaussians (G)



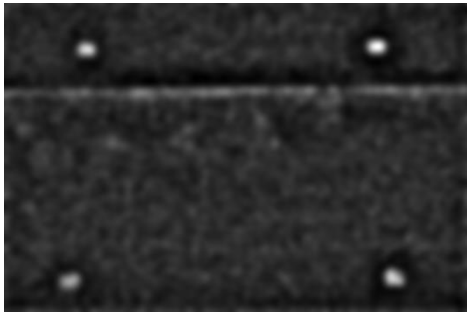
Percentile of DoG (P)



Local variance (V)

- Identify regions of interest
- Cannot use direct template matching
  - Varying appearance of markers
  - False positives

Candidate Detection Methods



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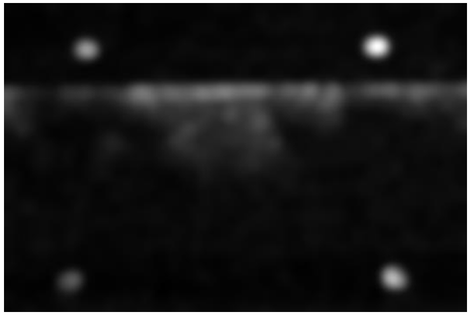

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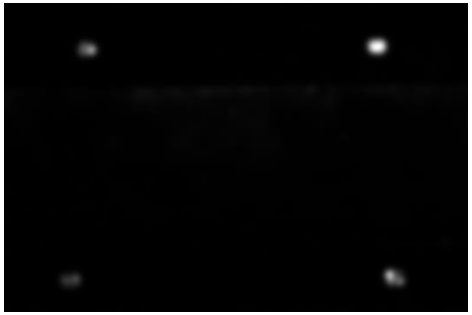

Local variance (V)

- Identify regions of interest
- Cannot use direct template matching
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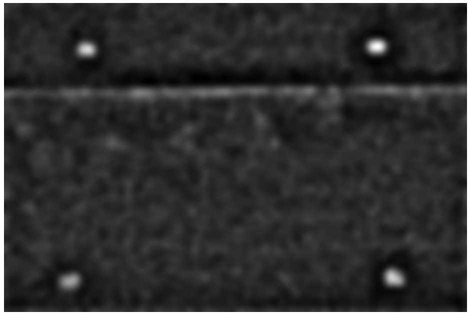
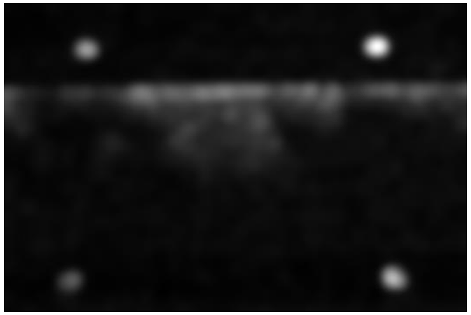
➢ All methods achieve 100% sensitivity using 6 calibration images

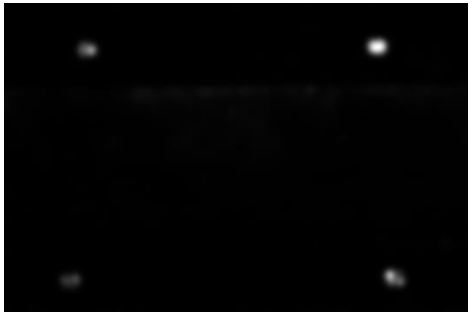
Candidate Detection Methods



Quotient of Gaussians (G)



Percentile of DoG (P)



Local variance (V)

- Identify regions of interest
- Cannot use direct template matching
  - Varying appearance of markers
  - False positives

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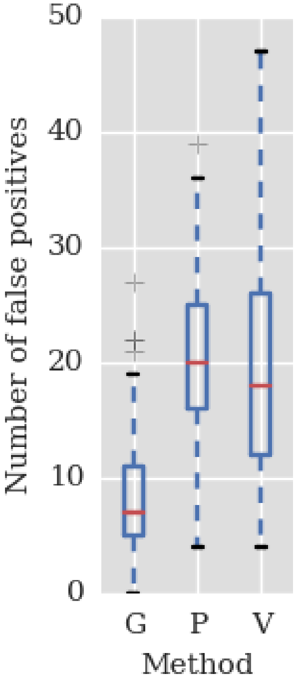

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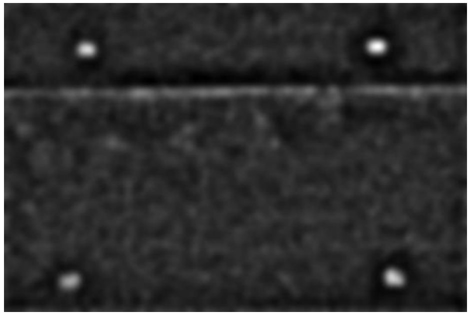
Candidate Detection Methods



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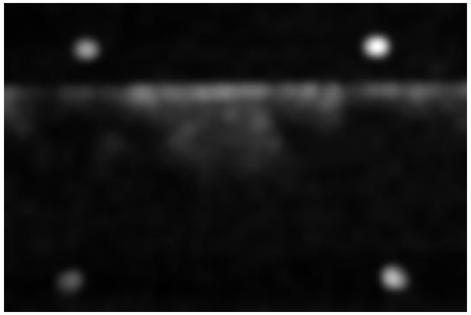

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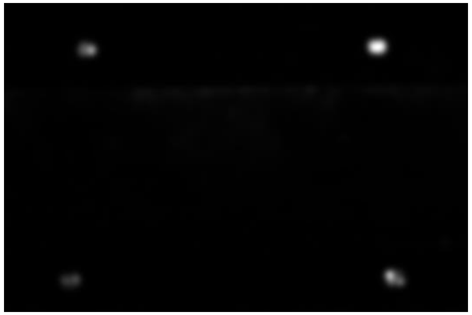

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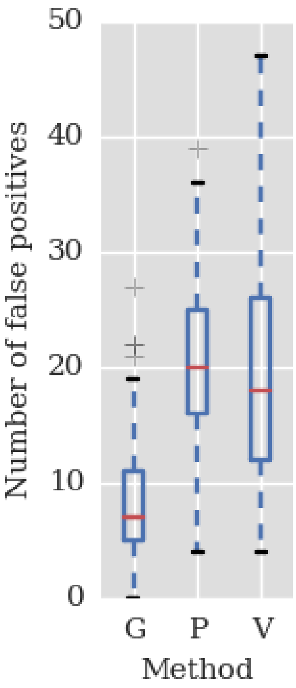

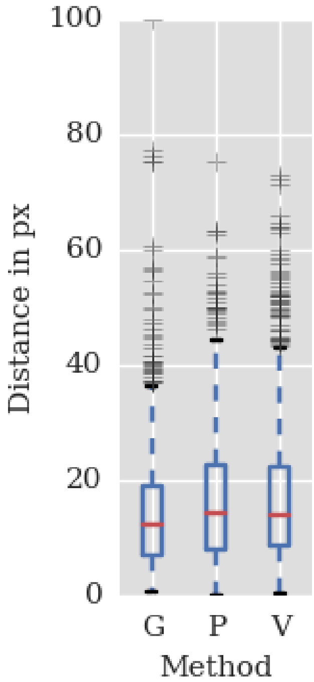

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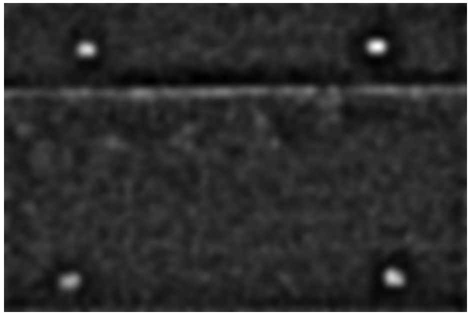
Candidate Detection Methods



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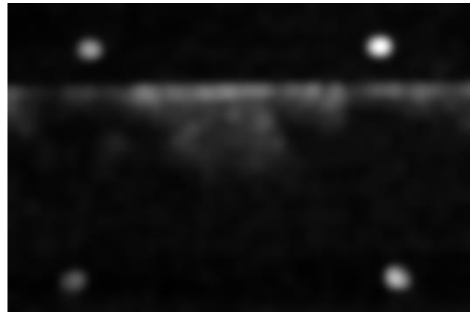

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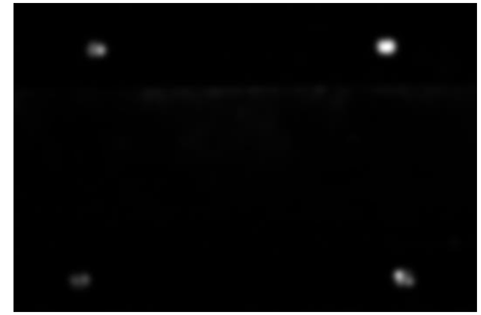

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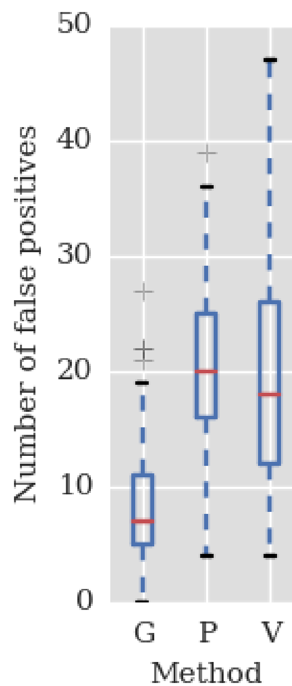

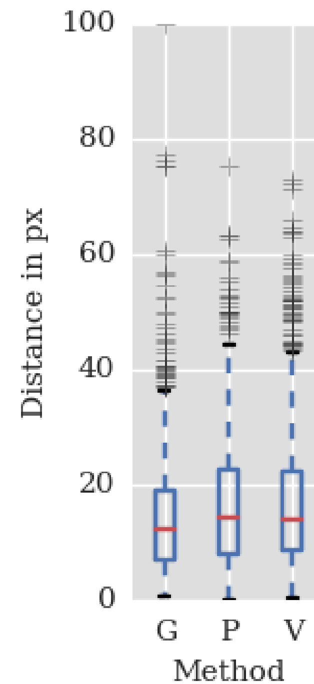

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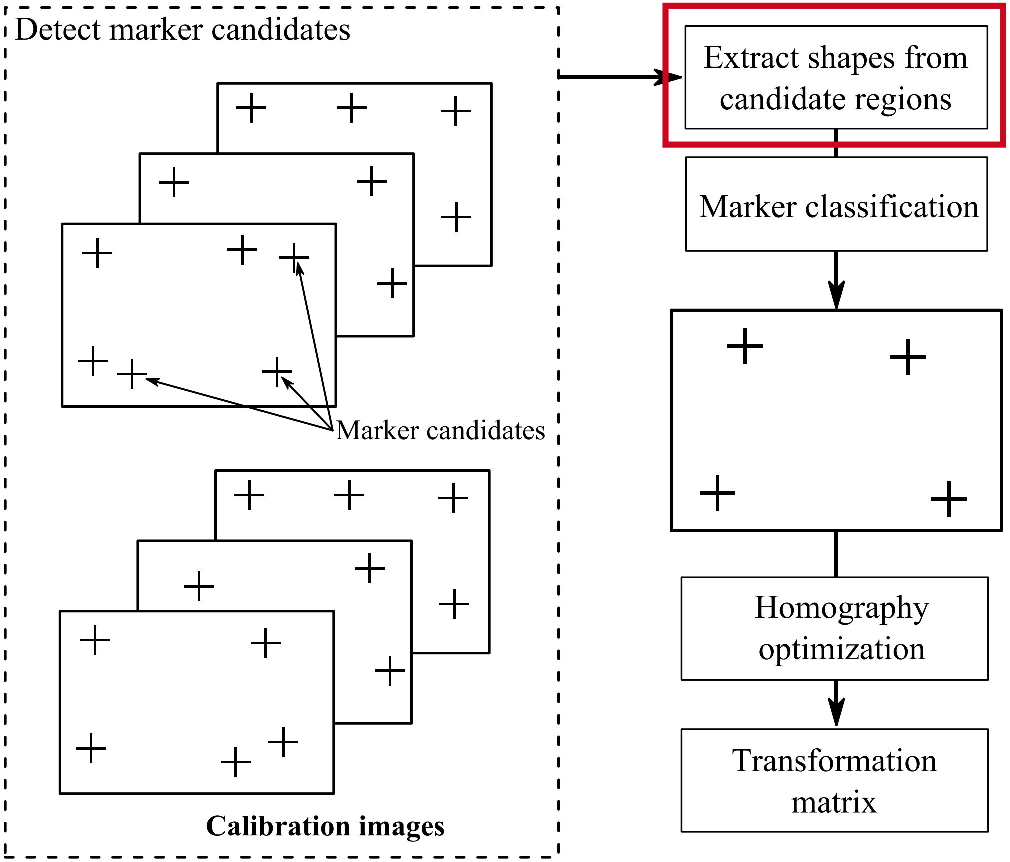
Marker Detection Flow Chart



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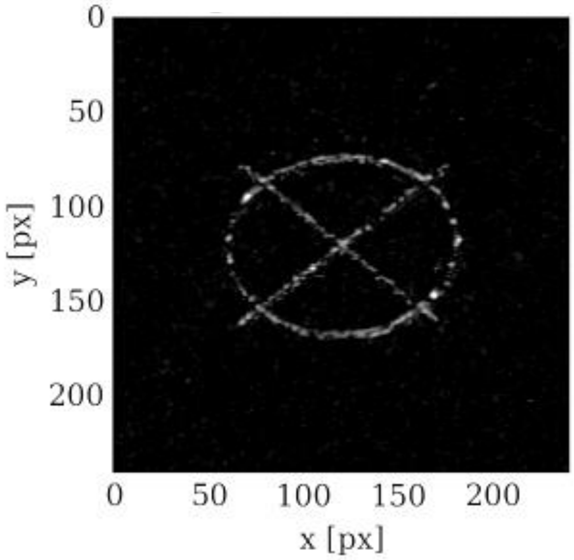
Shape Extraction

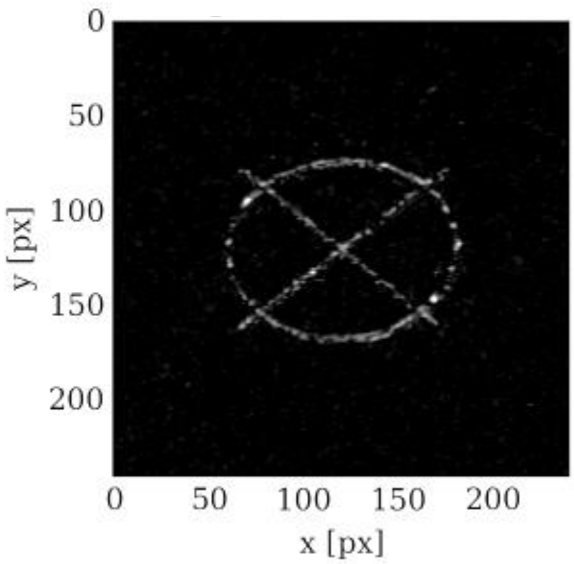
Detect Lines in Candidate Regions



Shape Extraction

Detect Lines in Candidate Regions

- Radon Transform for robust shape extraction



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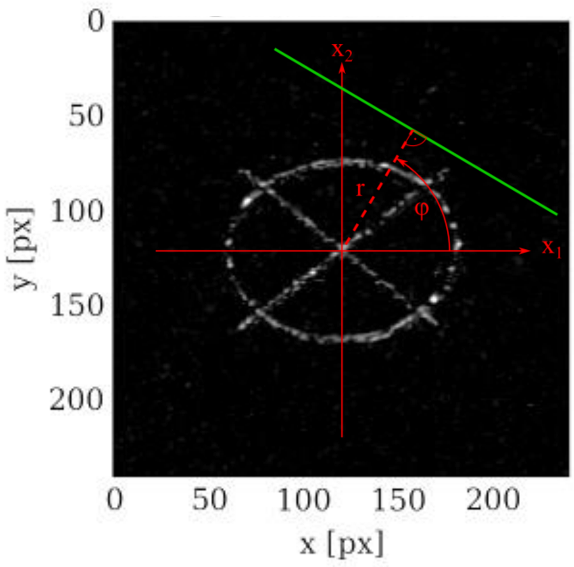

$$P(r,\varphi) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} i(x,y)\delta(x\cos\varphi + y\sin\varphi - r)\mathrm{d}x\,\mathrm{d}y$$

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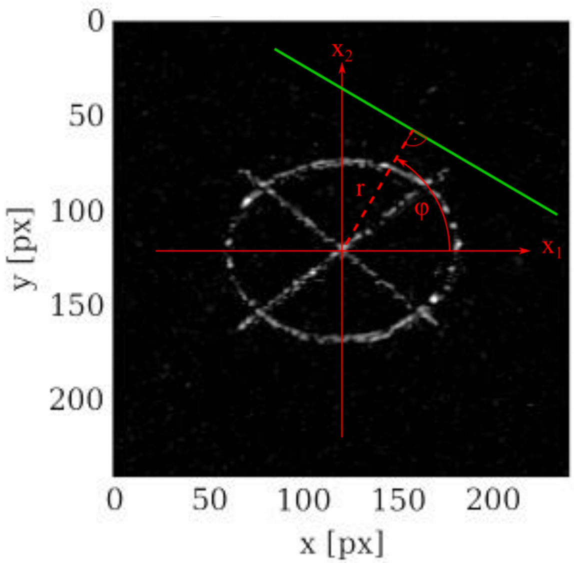

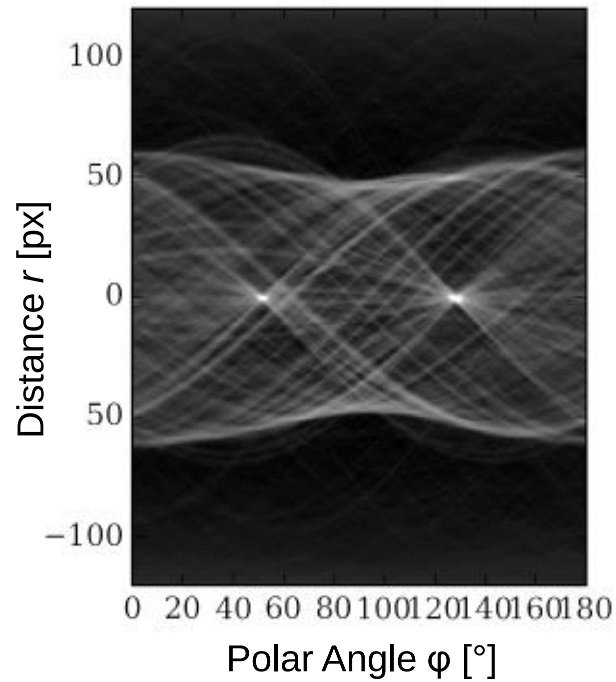

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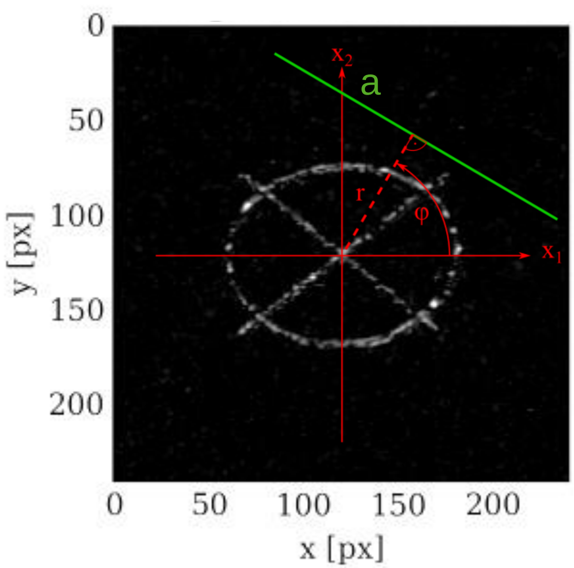

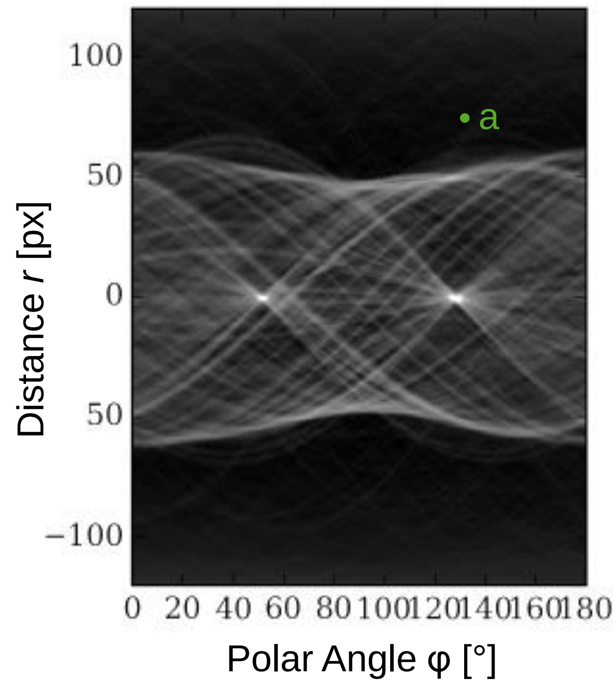

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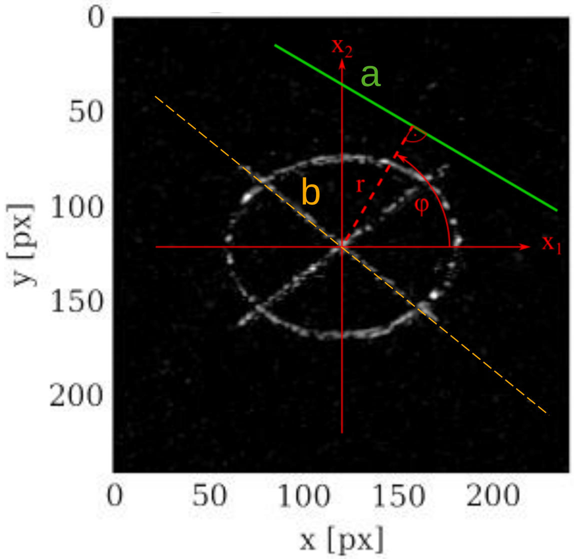

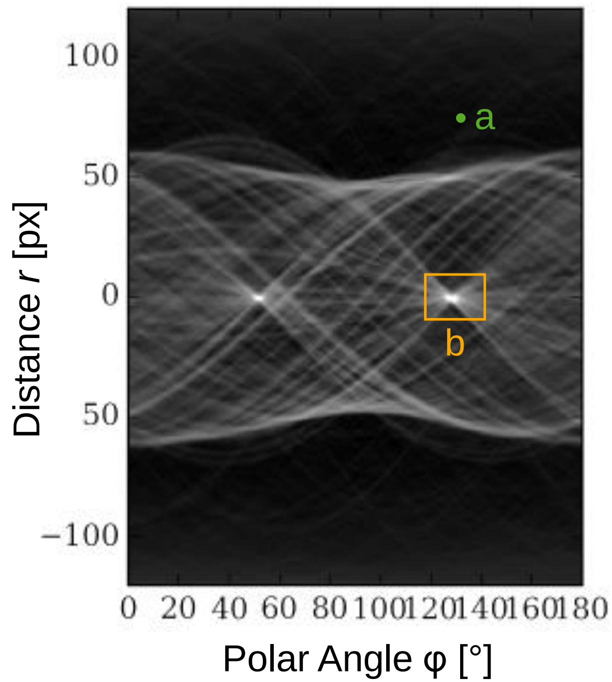

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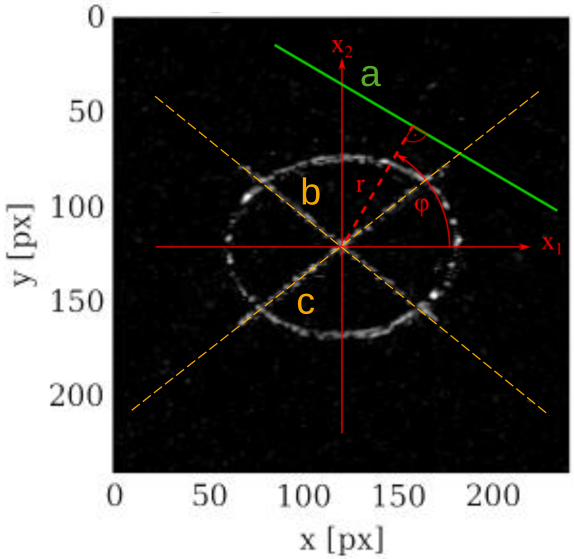

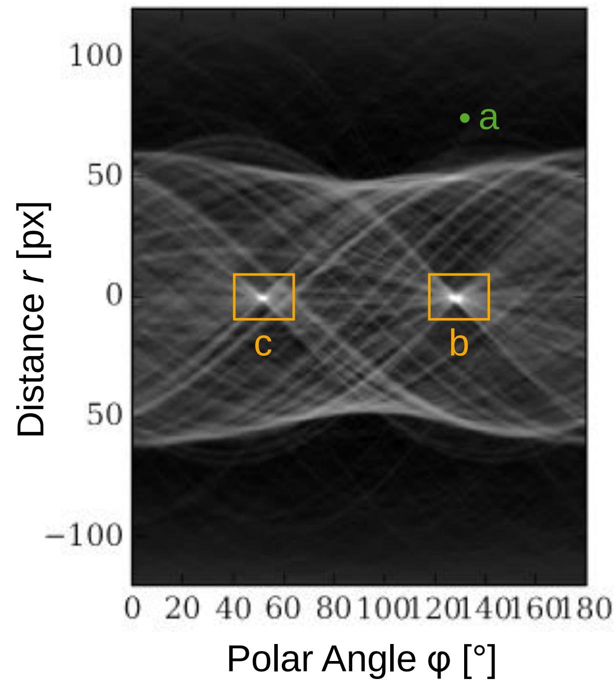

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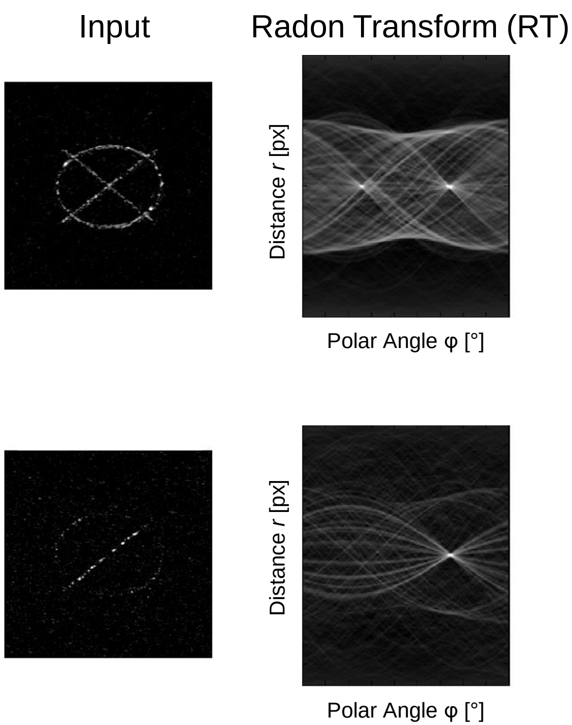
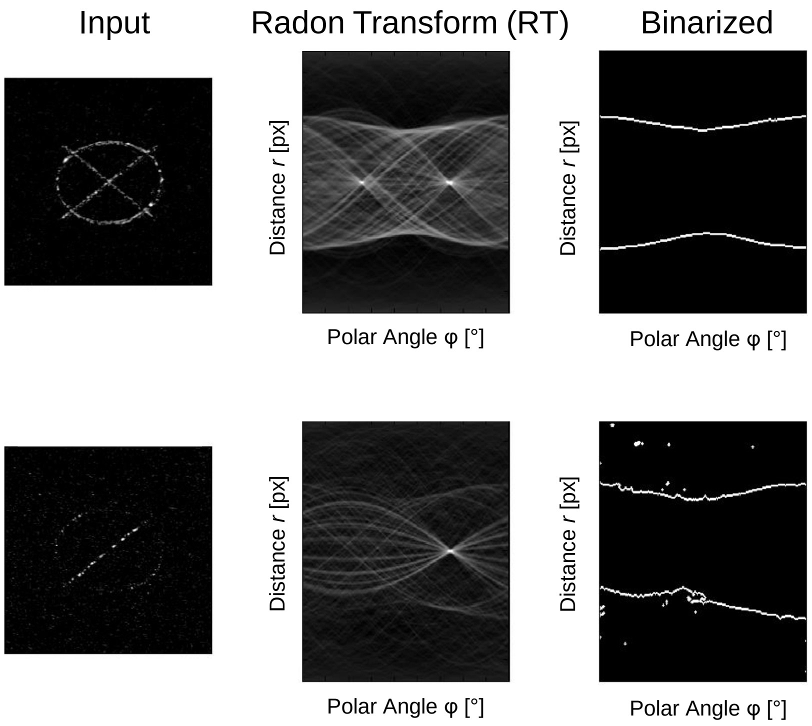
Shape Extraction: Ellipse



Shape Extraction: Ellipse



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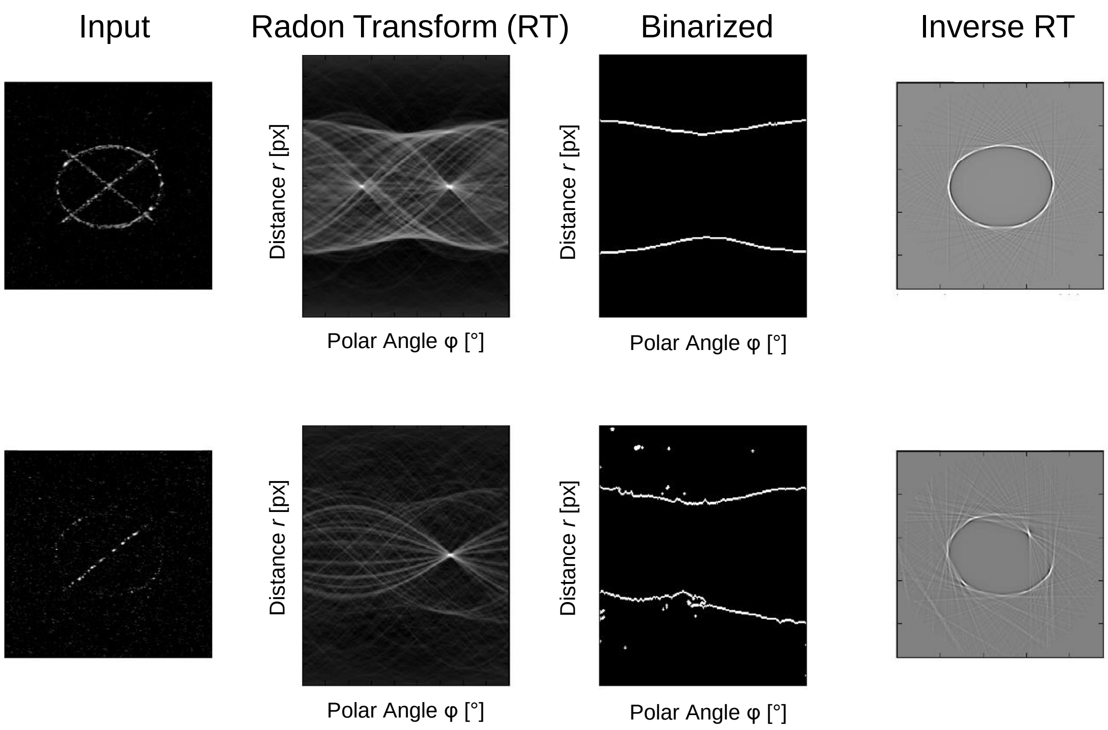

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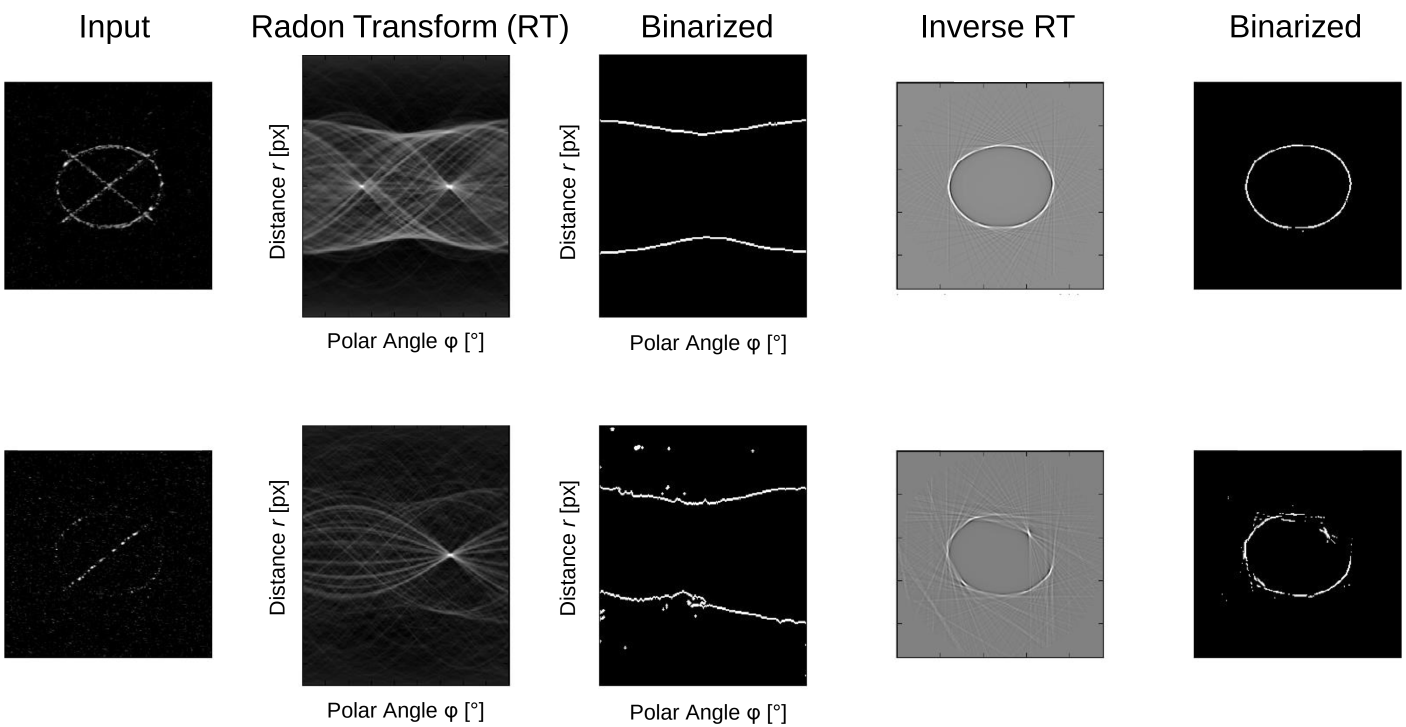
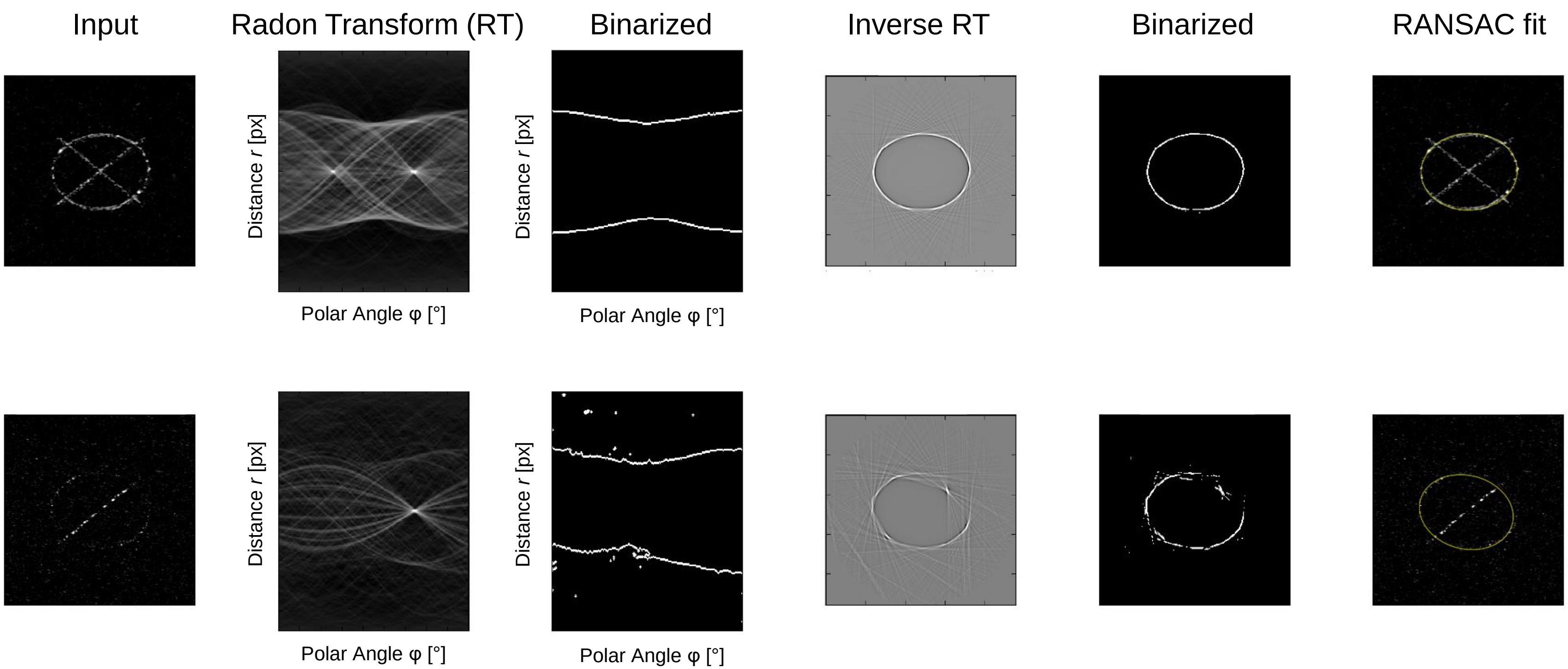
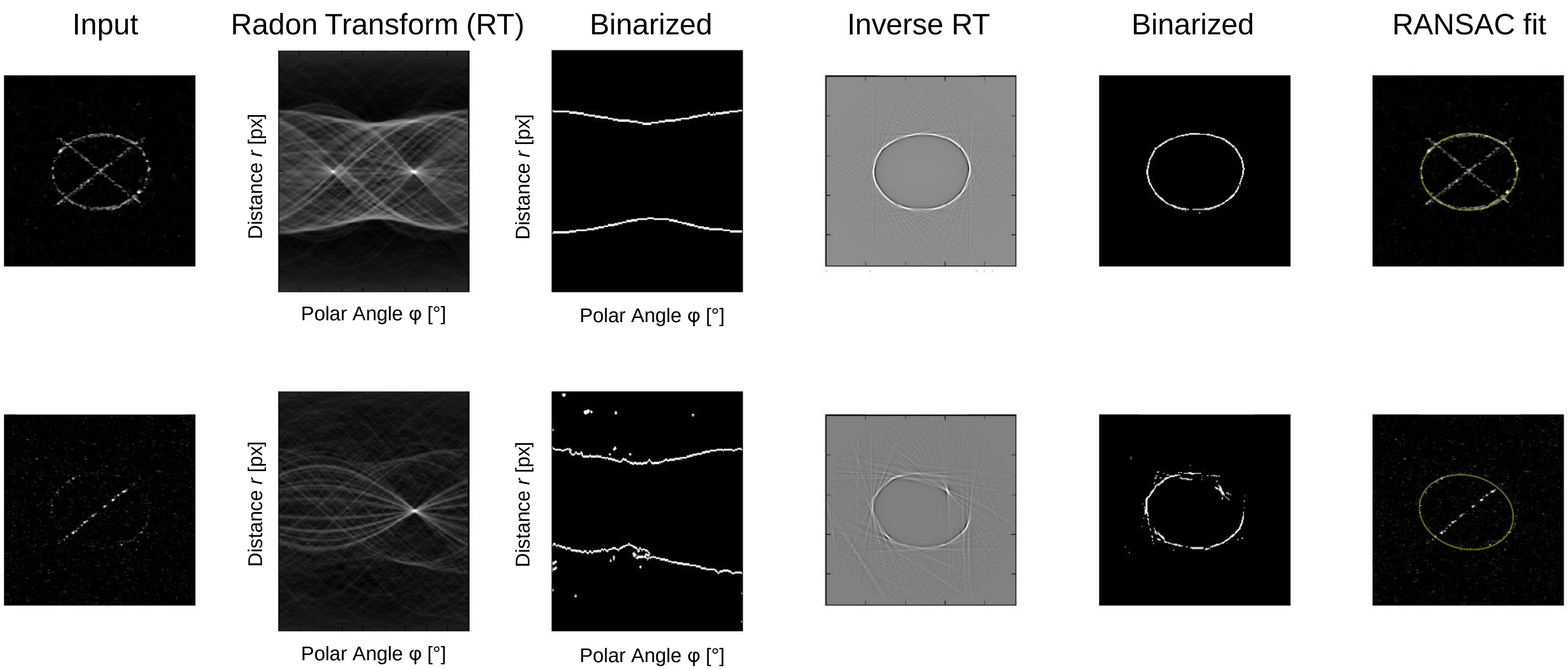


Shape Extraction: Ellipse

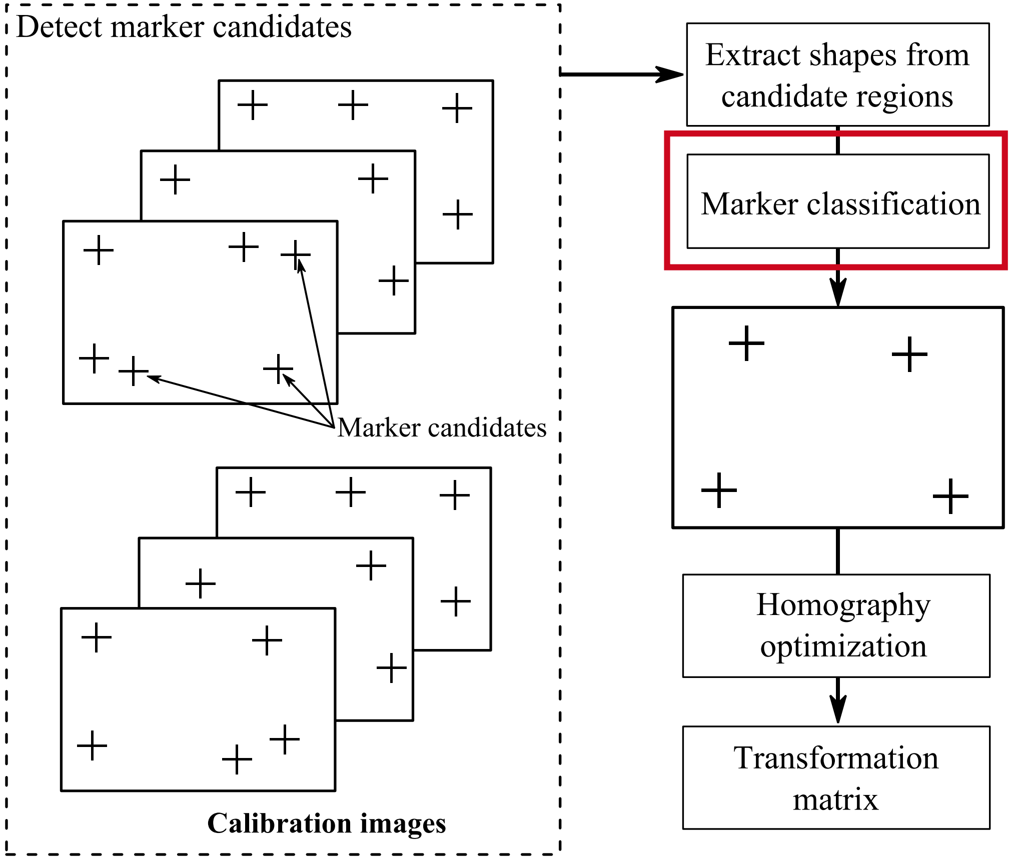


Shape Extraction: Ellipse



Robust ellipse fit even for weak, discontinuous lines

Marker Detection Flow Chart



Features for Classification of Candidates

Discard non-marker matches

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Discard non-marker matches

Ellipse detection

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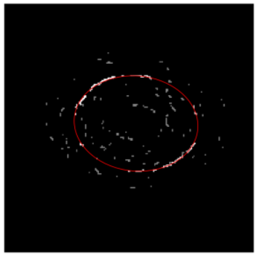

$$\frac{\#\ \text{inliers}}{\#\ \text{binarized points}}$$

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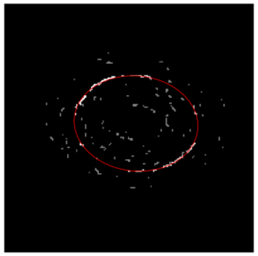

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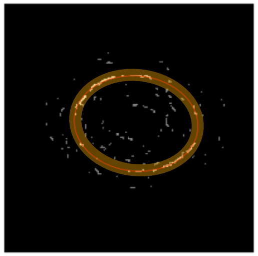

$$\frac{\text{Data points} \cap \text{mask}}{\#\ \text{pixel in mask}}$$

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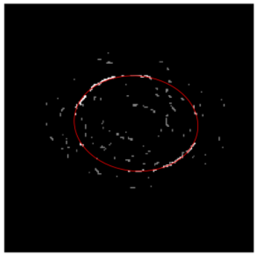

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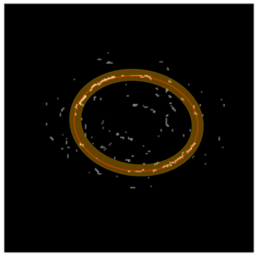

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- Goodness of fit

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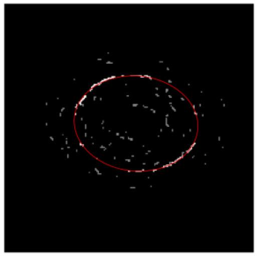
Marker template built from detected shapes



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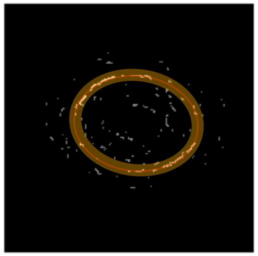

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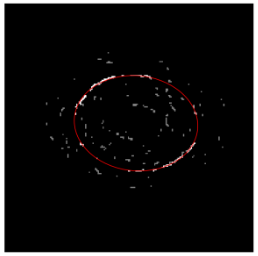

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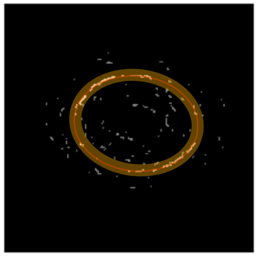

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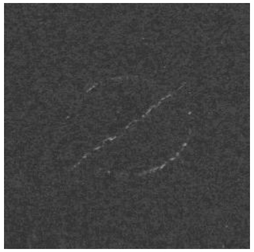

$$\frac{\text{mask} \cap \text{binary patch}}{\#\ \text{pixels in mask}}$$

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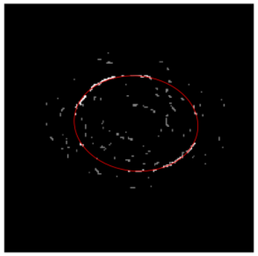

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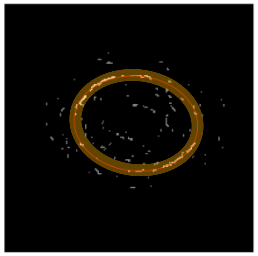

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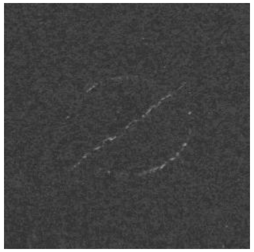

$$\frac{\text{mask} \cap \text{binary patch}}{\#\ \text{pixels in mask}}$$

Correlation

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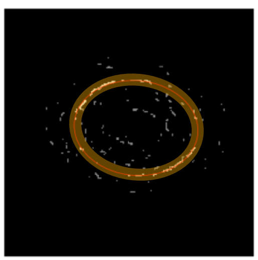

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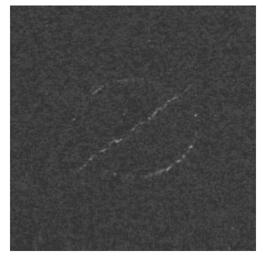

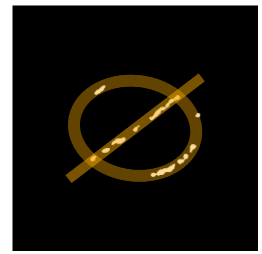

$$\frac{\text{mask} \cap \text{binary patch}}{\#\text{ pixels in mask}}$$

Correlation

- ➢ Verify shape detection

Classification of Marker Candidates

Identify True Markers

Classification of Marker Candidates

Identify True Markers

- Random Forest classifier

Classification of Marker Candidates

Identify True Markers

- Random Forest classifier
  - Supports few samples with high dimensionality

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Classification of Marker Candidates

Identify True Markers

- Random Forest classifier
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Classification of Marker Candidates

Identify True Markers

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- Split 54 build processes into training and test set

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Classification of Marker Candidates

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- Evaluate by 10-fold cross validation
  (repeated 10 times)

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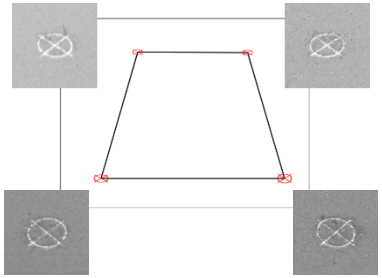

correct results

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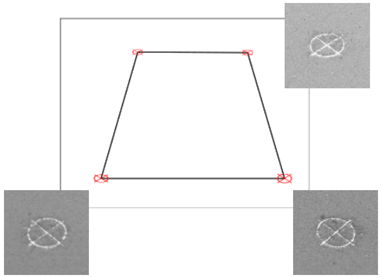

correct results

detectable errors

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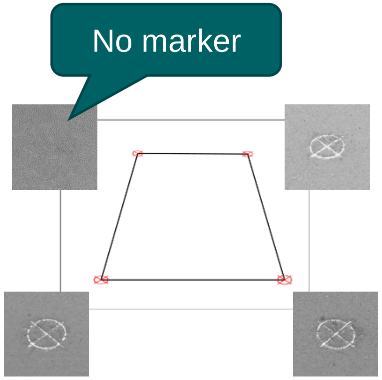

correct results

detectable errors

unrecognizable errors

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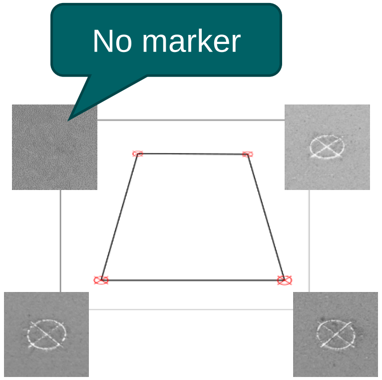
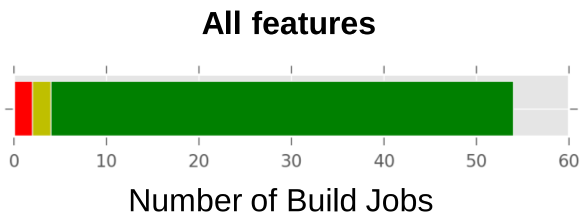


correct results

detectable errors

unrecognizable errors



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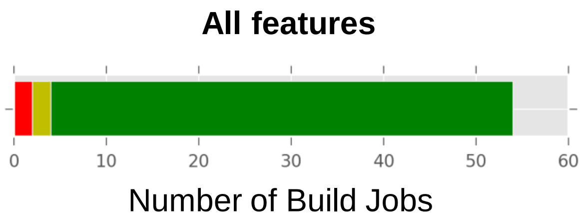

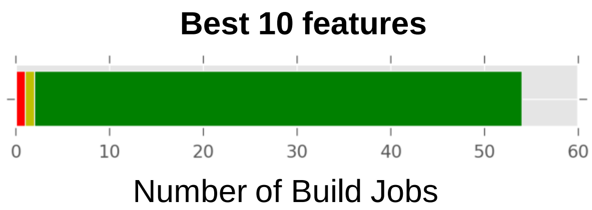

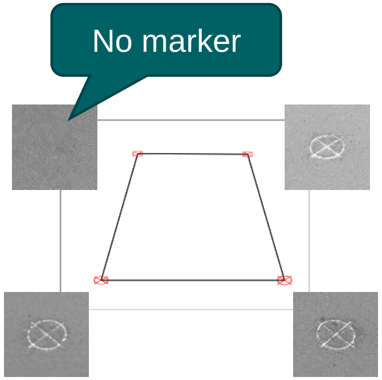

correct results

detectable errors

unrecognizable errors

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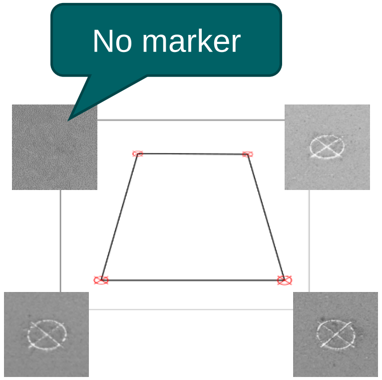
Classification of Marker Candidates

Identify True Markers

- Random Forest classifier
  - Supports few samples with high dimensionality
  - Implicit feature selection
- Split 54 build processes into training and test set
- Evaluate by 10-fold cross validation (repeated 10 times)



correct results
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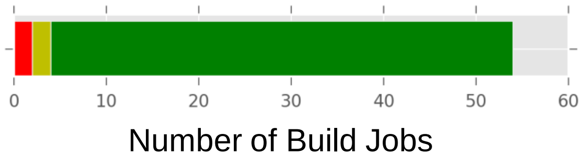
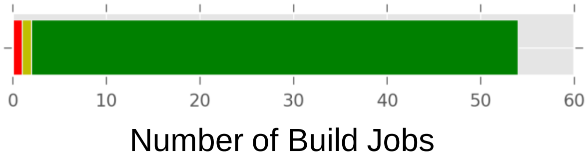
All features



Best 10 features



➢ 96.3 % correct,1 detectable error, 1 unrecognizable error

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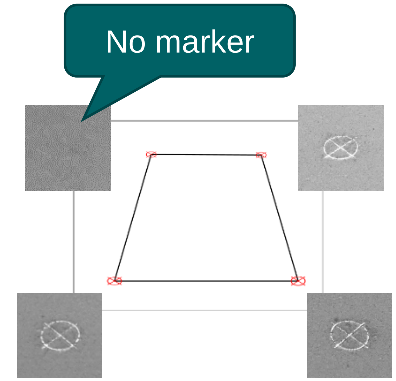

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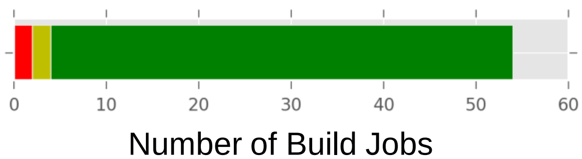

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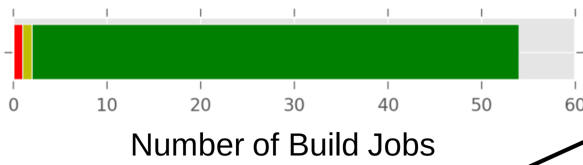
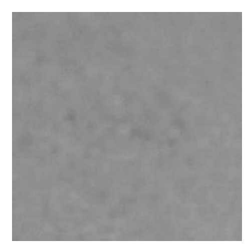


Difficult markers



False negative

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Classification of Marker Candidates

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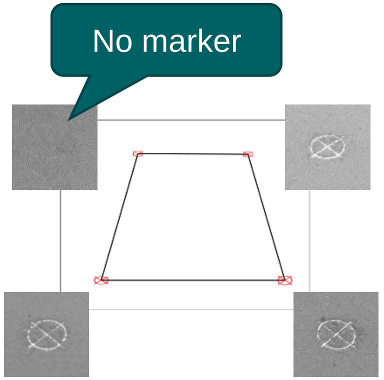

correct results

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unrecognizable errors

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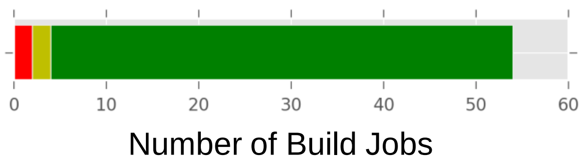

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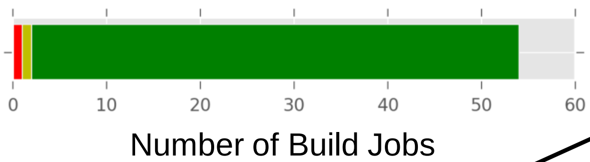

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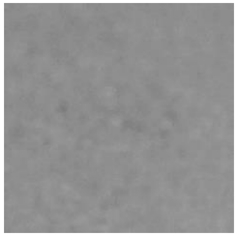

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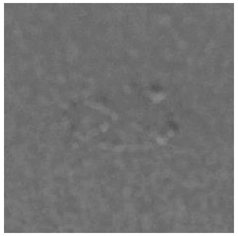

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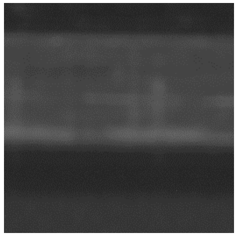

False positive

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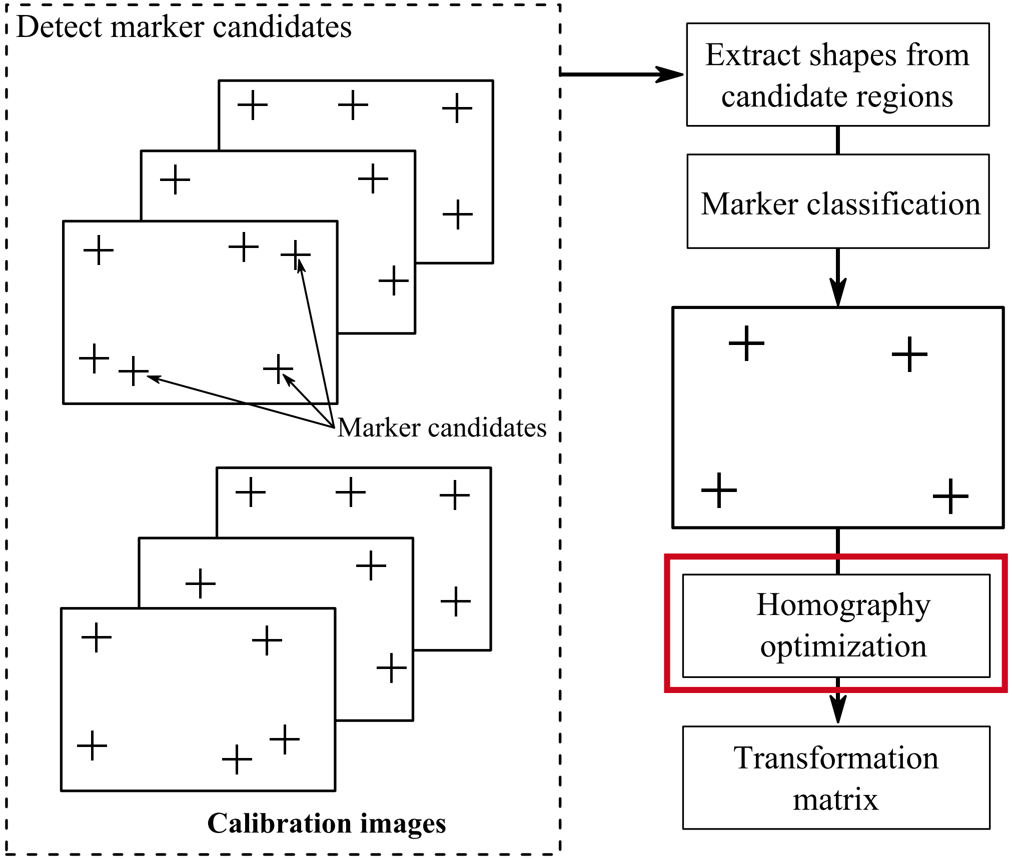
Marker Detection Flow Chart



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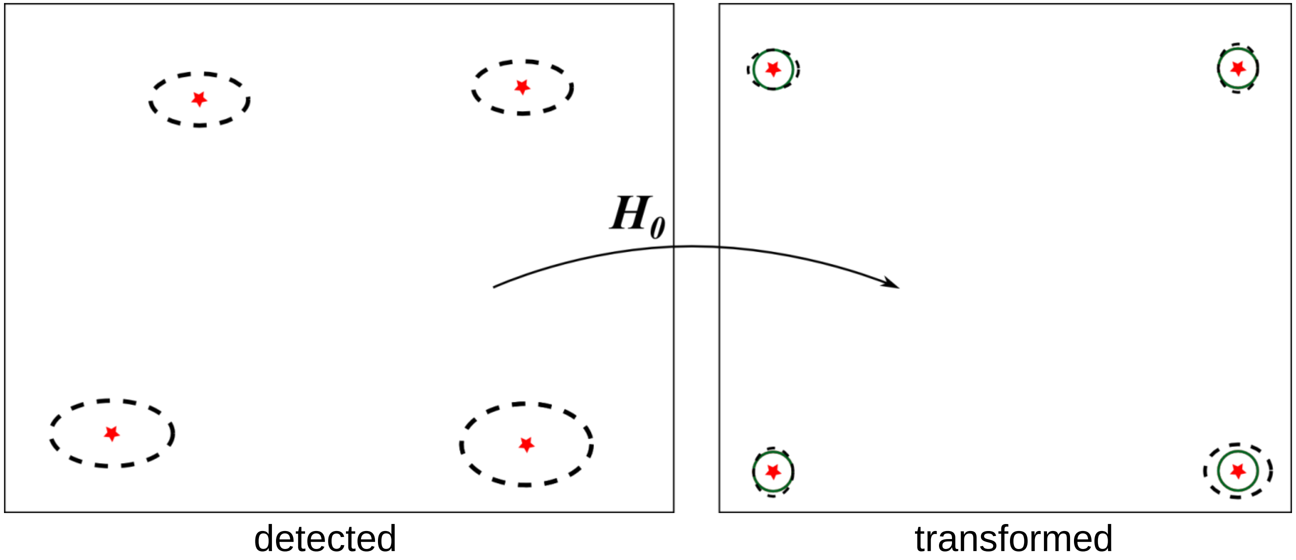
Homography Optimization

Problem: Imprecise Detection



Homography Optimization

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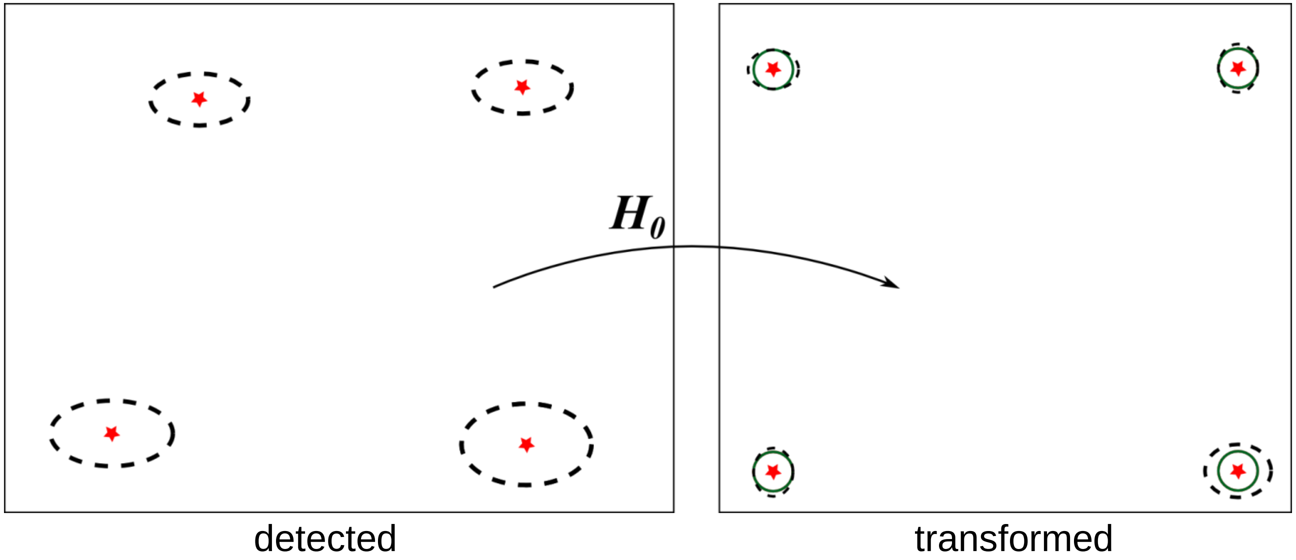

• Ellipses are not mapped to circles (original shape)

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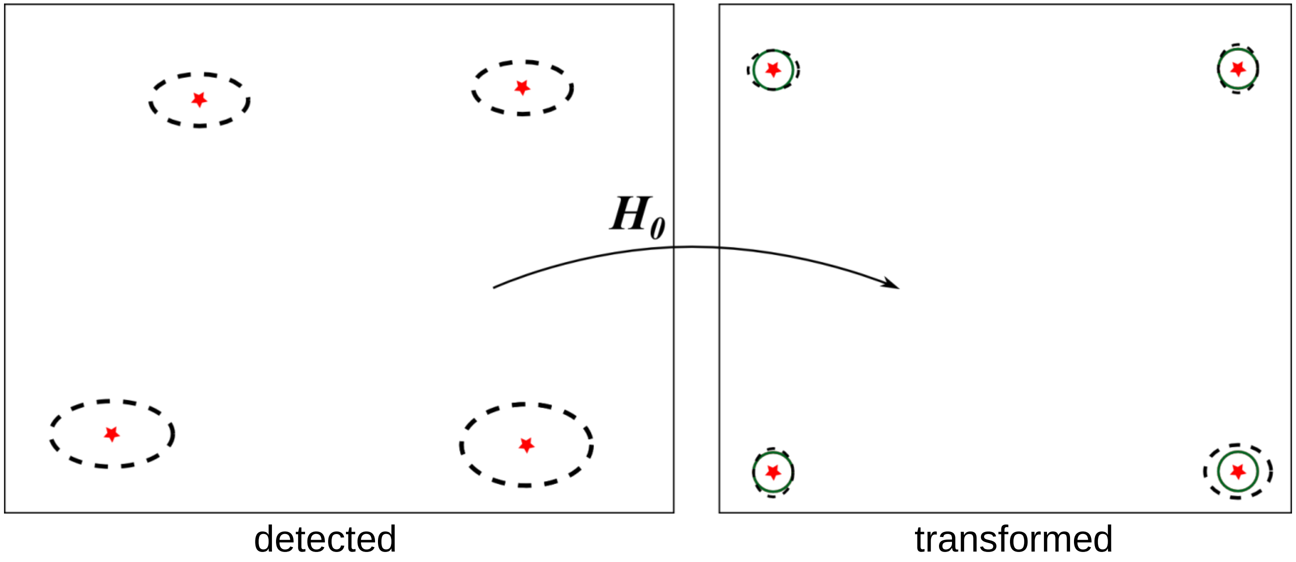

•Ellipses are not mapped to circles (original shape)

➢Improve mapping by minimizing back-projection error

Homography Optimization

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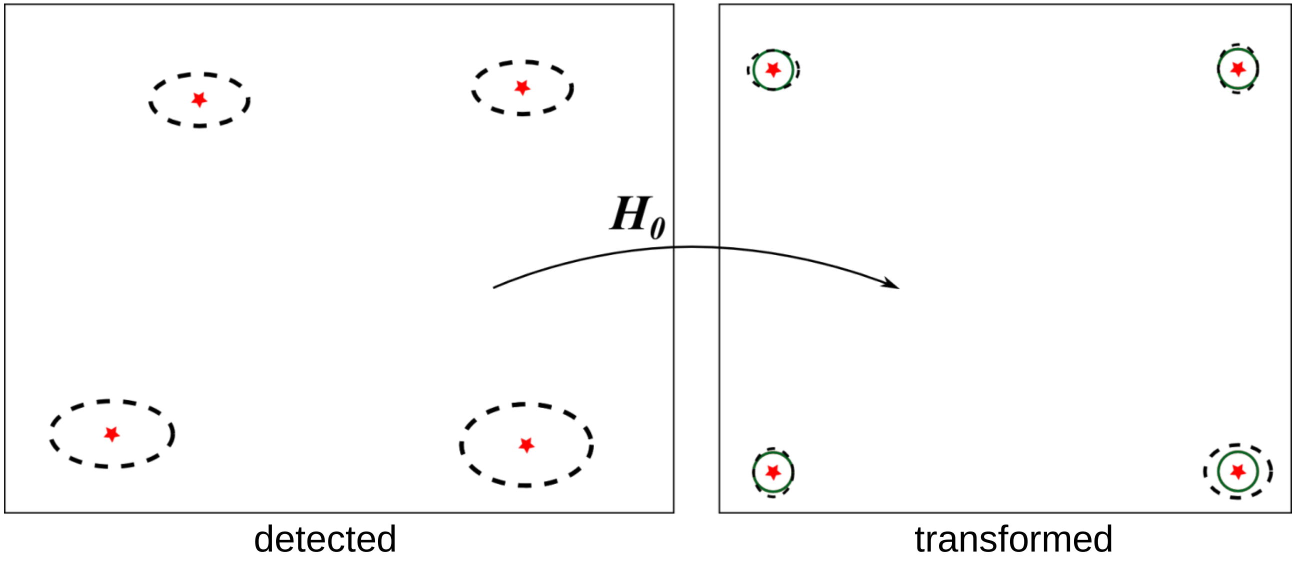
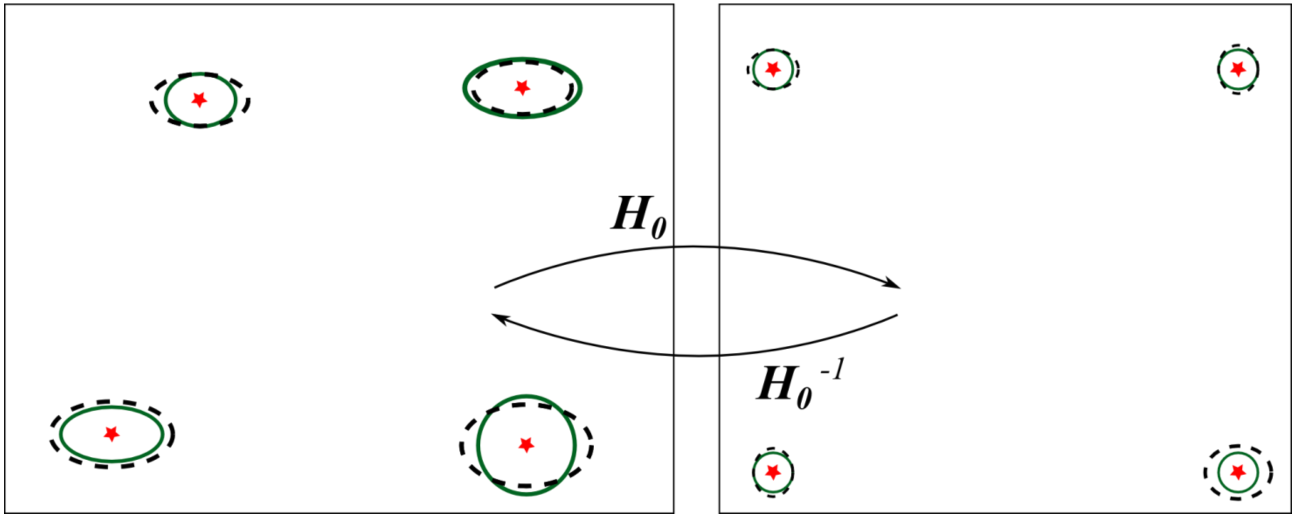


•Ellipses are not mapped to circles (original shape)

➢Improve mapping by minimizing back-projection error
➢Keep original aspect ratio to enable comparison to CAD drawing

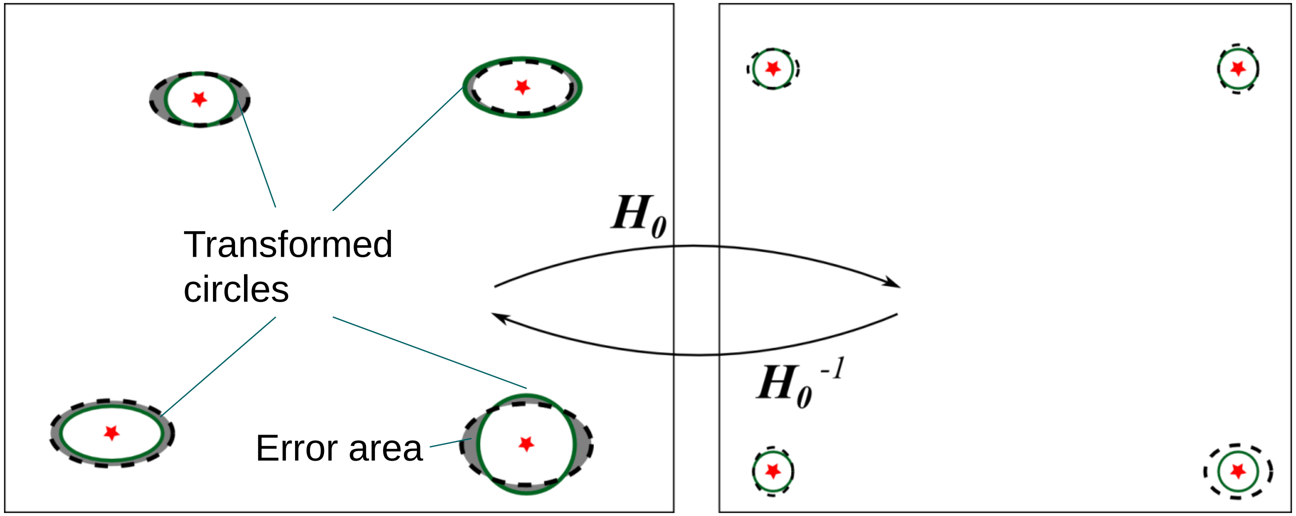
Homography Optimization

Back-projection of circles from CAD model



Homography Optimization

Define error measure



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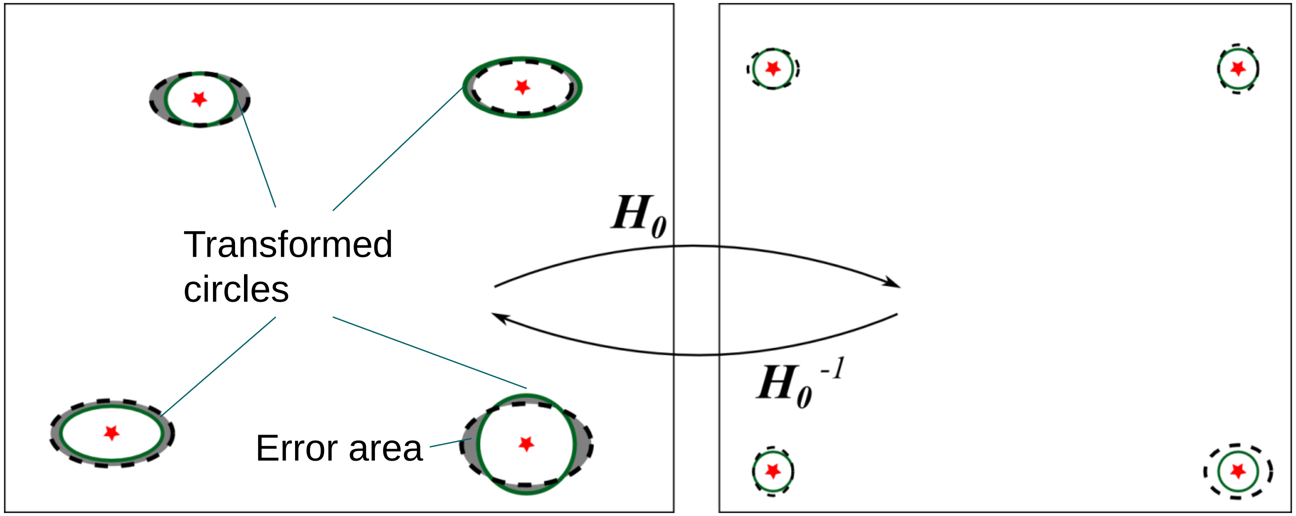
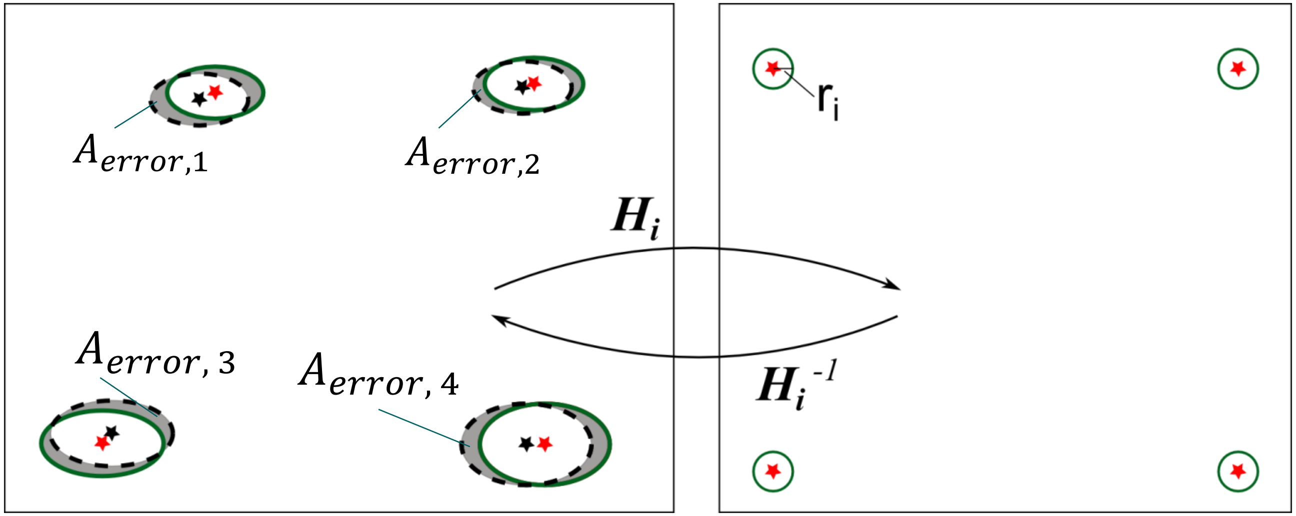


- Imaging scale is unknown: circle radius in pixels has to be estimated

Homography Optimization

Minimize shape error



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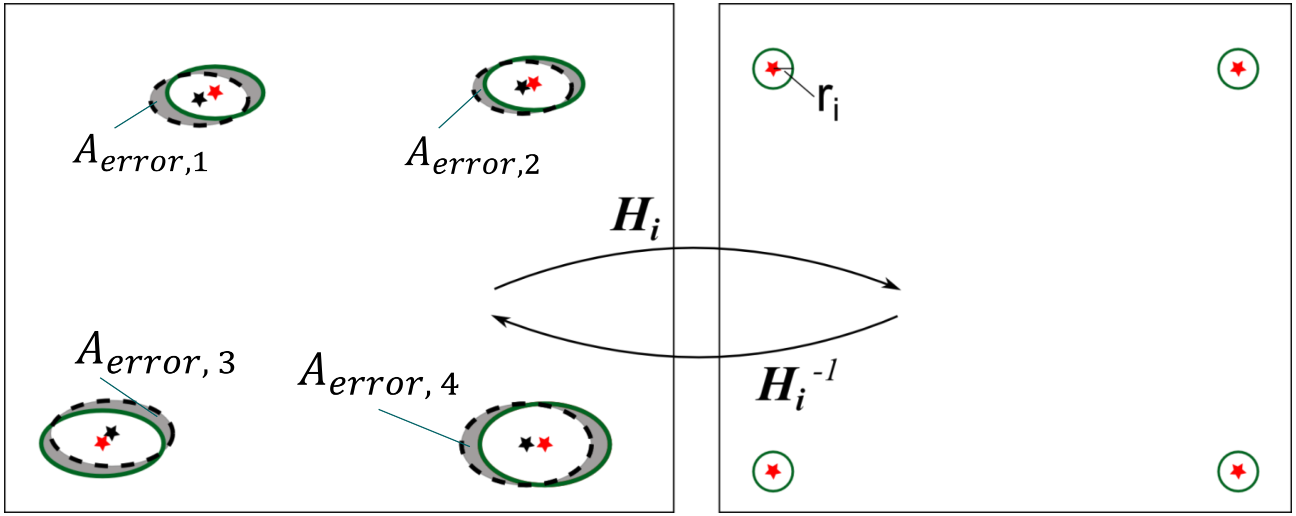
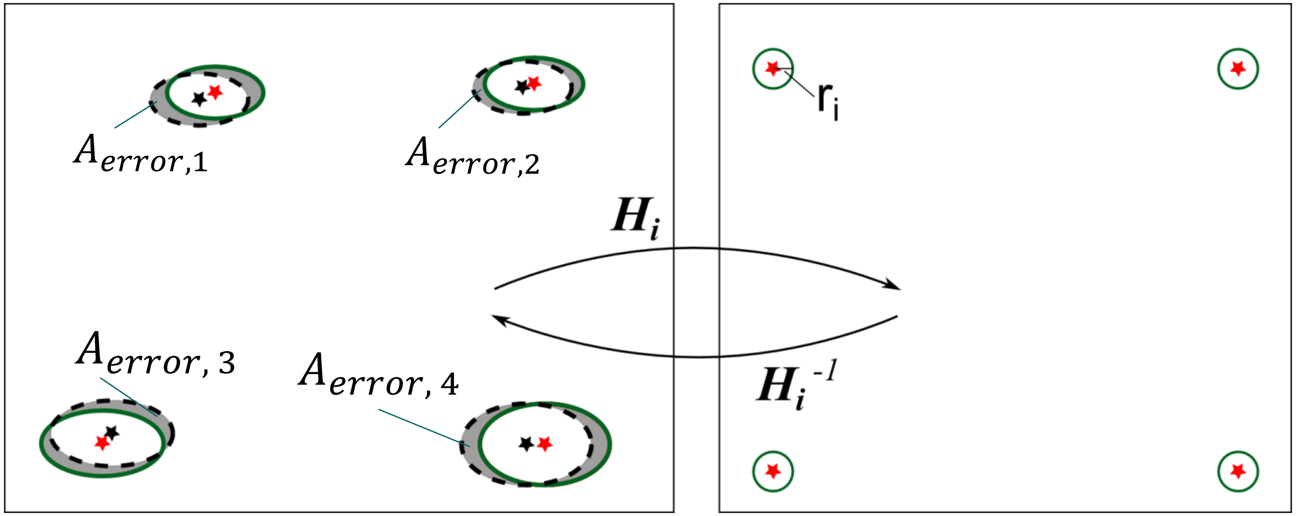


- Compute shape error using polygonal representation

Homography Optimization

Minimize shape error

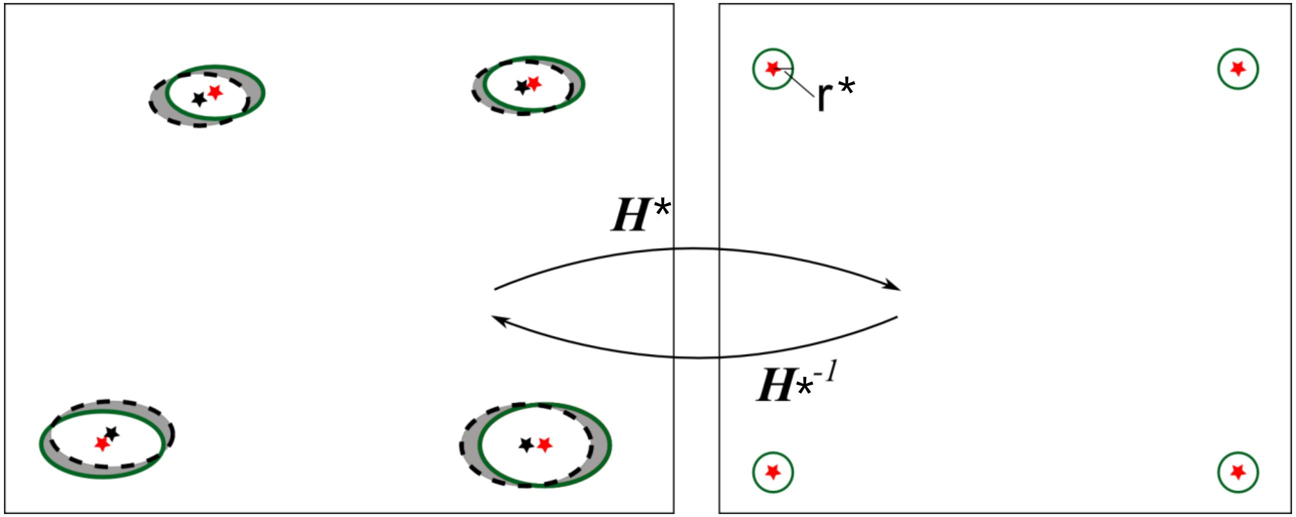


- Compute shape error using polygonal representation
- Optimization problem:

$$\{r^*, H^*\} = \min_{r\in\mathbb{R},\, H\in\mathbb{R}^{3\times3}} \sum_i A_{error,\,i}$$

solved using Nelder-Mead

Result of Optimization

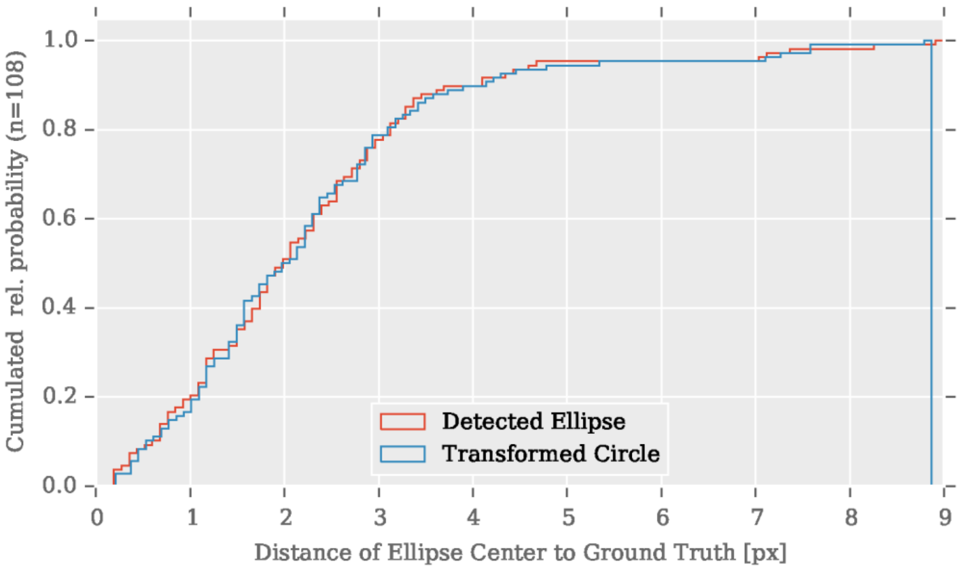


- Transformation matrix H* and circle radius r*
- Ellipses which are mapped to perfect circles with radius r*
- Minimal error area between ellipses and detected ellipses

➢ Corrects errors of ellipse detection

Homography Optimization: Results

Detections Compared to Manually Defined Ellipse Center



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Homography Optimization: Results

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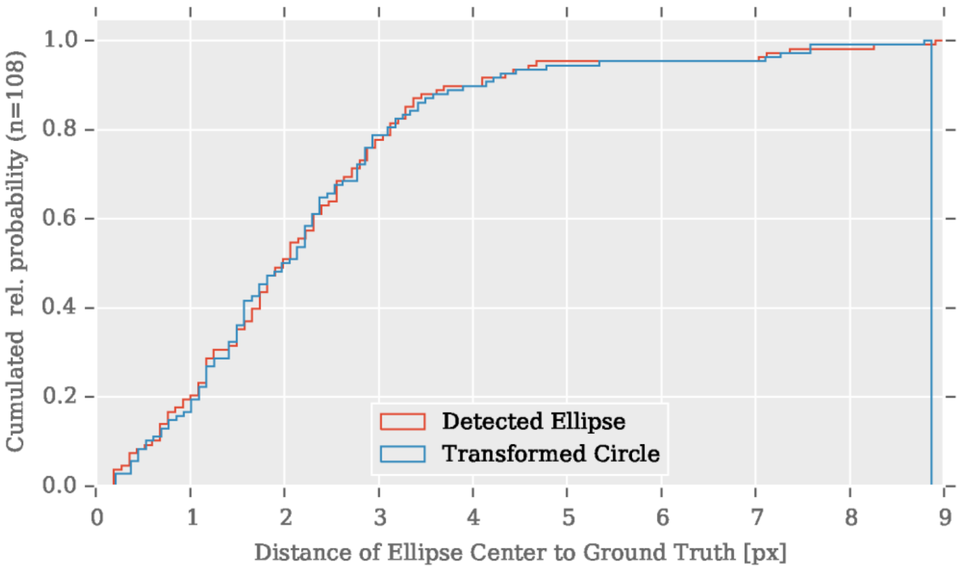

Median: 2.0 px (40 – 60 µm)

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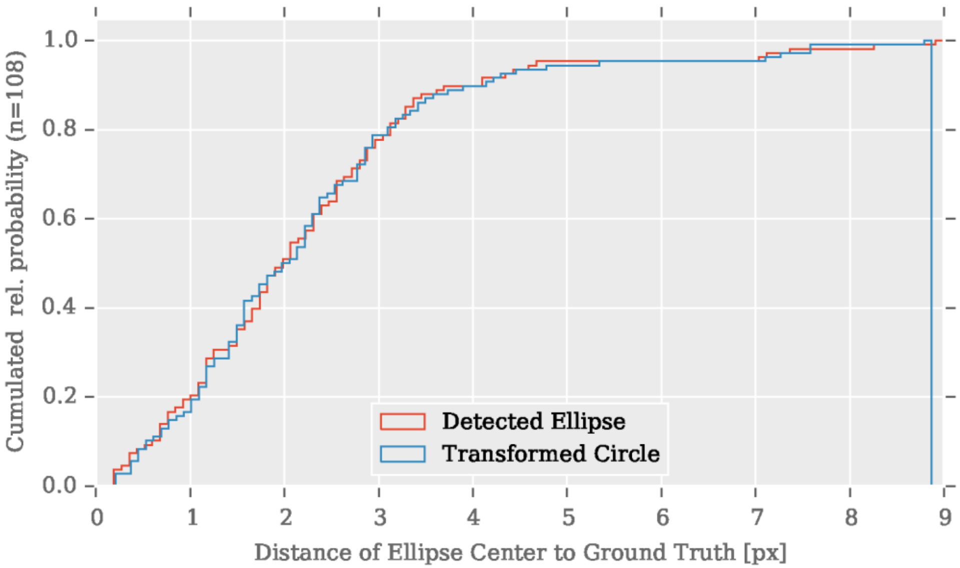

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Homography Optimization: Results

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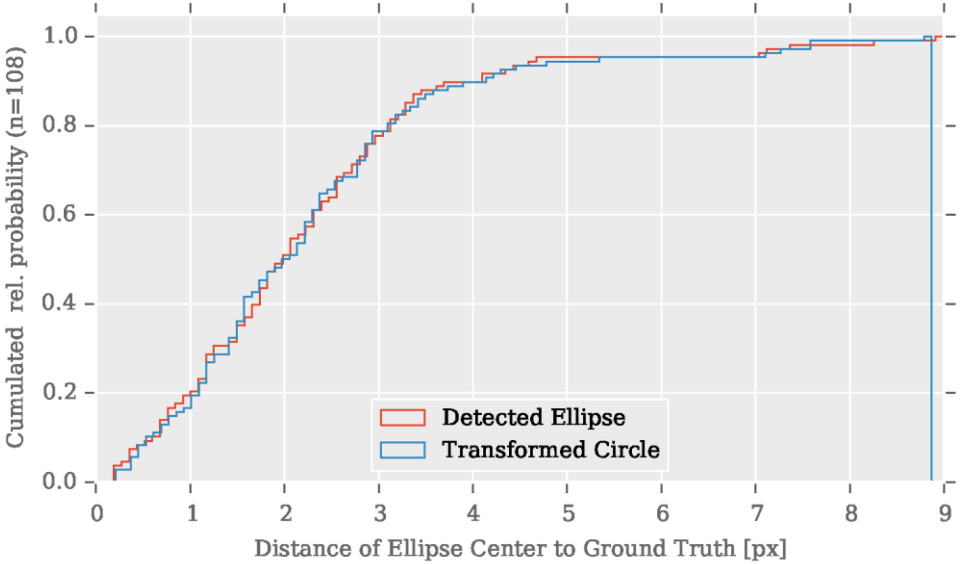

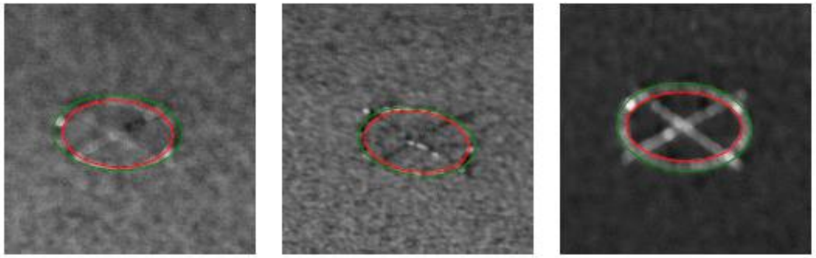

Markers with minimum distance to ground truth

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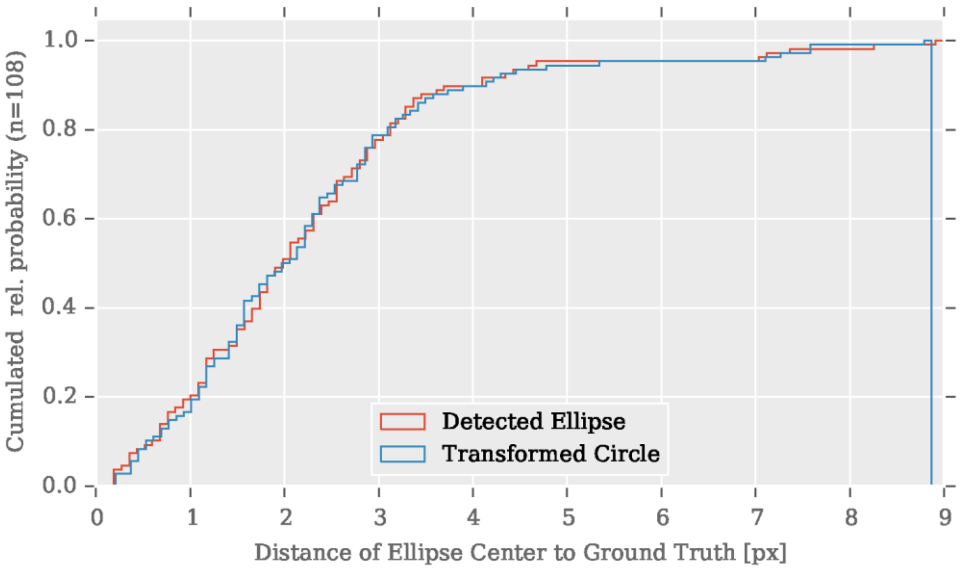

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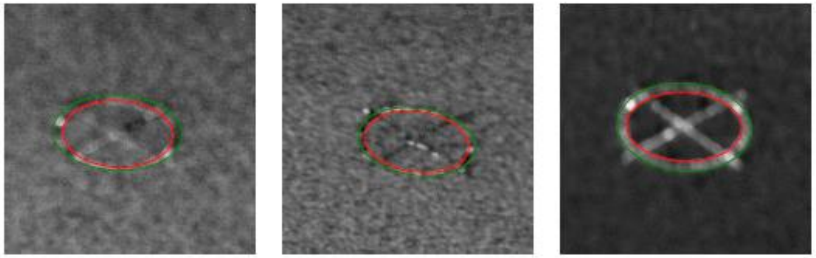

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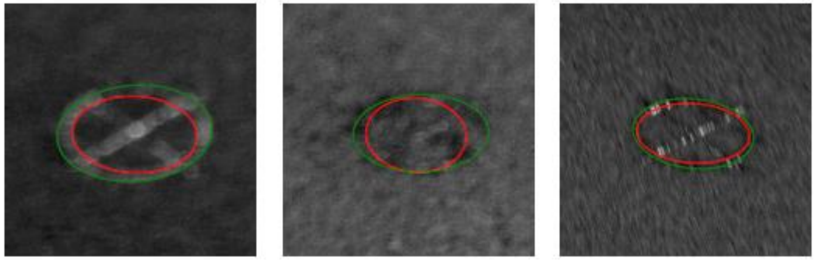

Markers with maximum distance to ground truth

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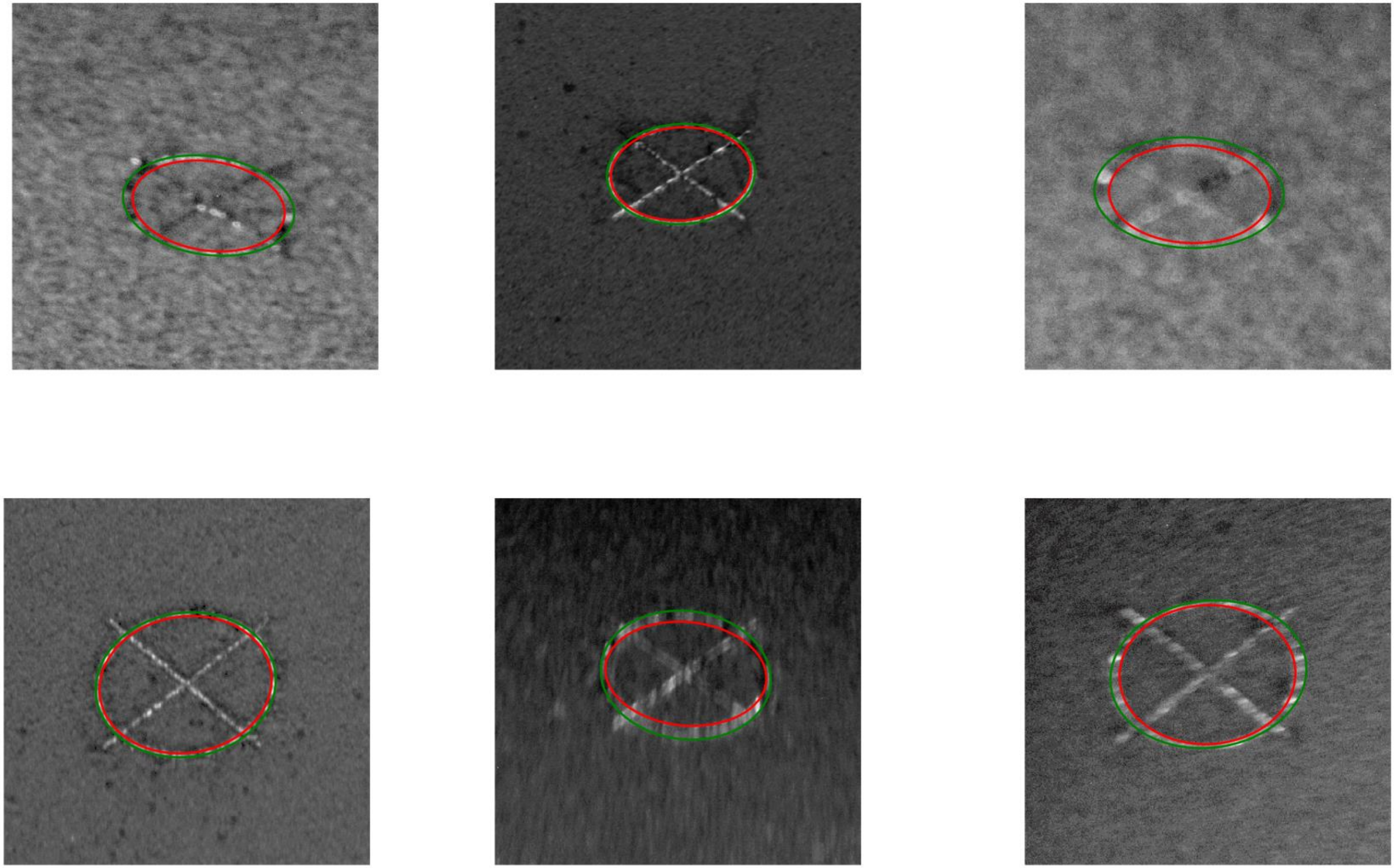
Detection Results



Conclusion

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  - ✓ different appearance
  - ✓ incomplete markers

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➢ Enables automatic calibration of perspective correction for powder bed image inspection

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Robust Calibration Marker Detection in Powder Bed Images from Laser Beam Melting Processes

TF-010464

Joschka zur Jacobsmühlen, Jan Achterhold, Stefan Kleszczynski,
Gerd Witt and Dorit Merhof

ICIT 2016
Taipei
Taiwan

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