University of Sheffield | Department of Automatic Control and Systems Engineering

Industry Training Programme ACS6402, ACS6403 Laser Powder Bed Fusion - Process Monitoring & Defect Forecasting Seminar One

Academic year 2023/24

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Project Objectives

- Review the literature on additive manufacturing porosity detection and localisation
- **Review the industry (AMRC) data and sensing system to understand the input and target values and perform any necessary data treatment (repeated data, data imbalance, missing data, etc.)**
- **Identify and add features to the input data to improve the data set for a machine learning problem**
- Propose a suitable method, and apply, validate, and test a supervised machine learning algorithm for localising the porosities (binary classification problem)

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What is Machine Learning (1)

- Creating representations of the world from observations
- “learning” by example (induction)
  - Training/adapting/estimating/analysing
- Machine learning and more broadly data modelling is for:
  - Understanding (extracting information then knowledge)
  - Prediction
  - Decision & control

The Four Elements of Machine Learning (2)

- **Assumption**
  - What we think the world is like (observations)
- Model
  - A mathematical way of expressing the assumption/thought
- Inference paradigm
  - A framework to match the model to the observation
- Inference engine
  - A means of matching the model to the observation

Figure: It was assumed there are only white swans until 1697 (Photo credit: Fir0002/Flagstaffotos)

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Porosity Localisation Design of Experiment

- $10mm^3$ cubes with varying machine parameters (45 cubes)
  - Border Power: 100, 300, 500 W
  - Hatch Offset: 0.00, 0.05, 0.10 mm
  - Border Speed: 50, 175, 300 mm/s
  - Layer thickness: 0.05 mm
- Lack of fusion porosity
  - Low laser power, high border speed and large hatch offset
- Keyhole porosity
  - High laser power, low border speed, and a small hatch offset

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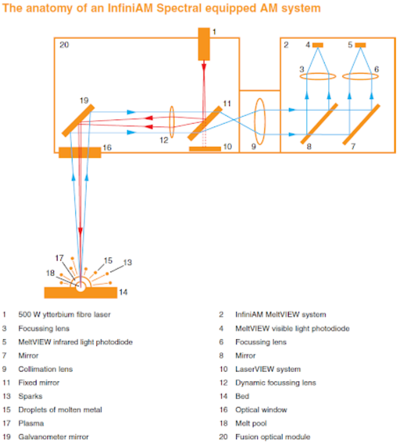
AM Process Data

(a)



(b)

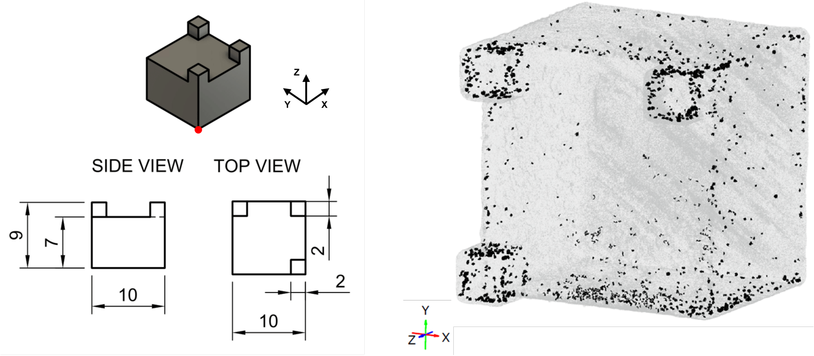
Figure: Renishaw 500M and the InfiniAM spectral emissions sensory systems - Renishaw Additive Manufacturing Systems Brochure-InfiniAM Spectral-Screen (2017), UK.

Process Data Example

Table: Example spectral emissions data from the Renishaw InfiniAM system.

Start Time	Duration (μs)	x position (mm)	y position (mm)	laserView	meltView Plasma	meltView Melt Pool
140000	30.00	55.10	10.00	600.00	300.00	100.00
140030	30.00	55.20	10.00	601.00	303.00	99.00
140060	30.00	55.20	10.00	603.00	300.00	98.00
140090	40.00	55.20	10.00	600.00	301.00	100.00
140130	30.00	55.20	10.00	599.00	302.00	100.00
140160	60.00	55.20	10.00	597.00	299.00	98.00
140220	30.00	55.20	10.00	595.00	303.00	97.00

Part Design & Porosity



(a) (b)

Figure: The part design and dimensions (mm unit) examined in this work and an example X-ray computed tomography scan.

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Machine Learning for Porosity Detection (1)

- Create a supervised learning data set via sensory data and labels
- A supervised machine learning algorithm can predict the probability of porosity at a given three-dimensional coordinate
- For example, initialise the weights of a neural network and minimise the cross-entropy loss

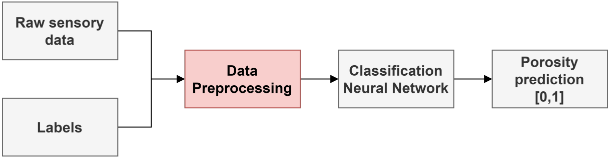

Figure: Neural network porosity classification flowchart.

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Feature Extraction (1)

We developed a short a script which detects and labels the border coordinates based on a 3-sample moving average of the X and Y coordinate gradient.

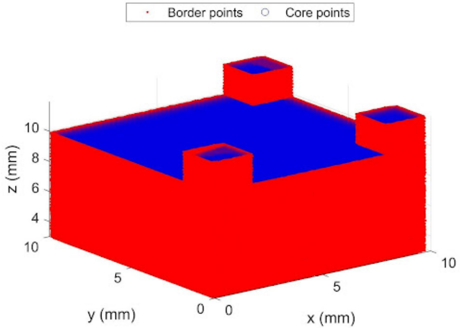


Figure: An example of labelling the border samples (marked in red) across cube 1 data.

Feature Extraction (2)

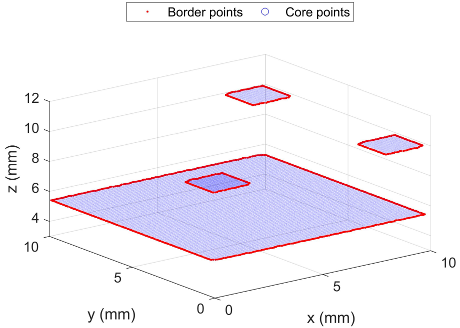
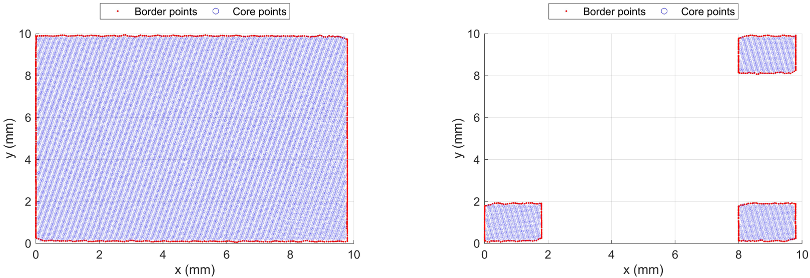


Figure: An example of labelling the border samples (marked in red) across two layers of cube 1; layer 30 corresponding to 4.5 mm on the z coordinate and layer 141 corresponding to 7.05 mm on the z coordinate.

Feature Extraction (3)



(a) (b)

Figure: (a) An example of labelling the border samples (marked in red) across cube 1 layer 30 corresponding to 4.5 mm on the z coordinate. (b) An example of labelling the border samples (marked in red) across cube 1 layer 141 corresponding to 7.05 mm on the z coordinate.

Feature Extraction (4)

The laser speed is calculated via the duration, X and Y coordinate features (Fig. 7).

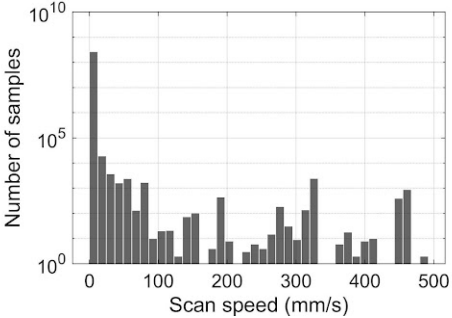


Figure: The scan speed distribution across all 45 cubes.

Feature Extraction (5)

A unitless energy density is calculated via the laser speed, hatch offset, LaserVIEW system photodiode feature, and the layer thickness (Fig. 8).

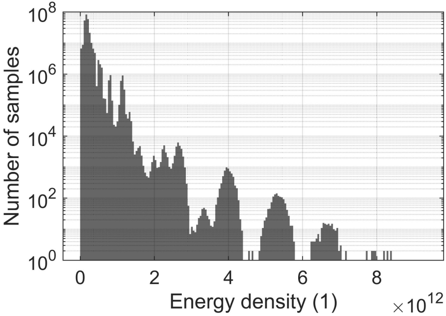


Figure: The energy density (dimensionless) distribution across all 45 cubes.

Feature Extraction (6)

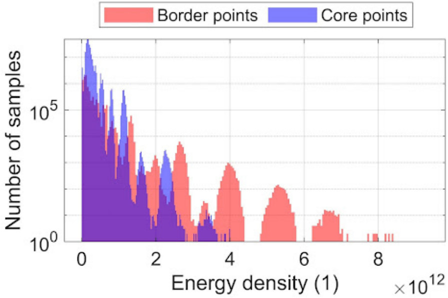


Figure: A comparison of the energy density (dimensionless) distribution across the border and core points for all 45 cubes.

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Data Pre-processing (1)

- The X, Y, and Z coordinate measurements are converted to mm
- The X, Y, and Z coordinates are centred per cube
- Seven artefact in the three-dimensional scan images are omitted from the study (cubes 30, 35, 37, and 38)
- Defects with coordinate location errors are centred to fit within the cube edges (Cubes 2, 3, 5, 10, 17, 18, 19, 20, 23, 30, 33, 37, and 40)
- 3 mm of sensor data along the Z axis [0, 3] is removed from the bottom of the cube due to omit the bandsaw porosities/saw marks

Data Pre-processing (2)

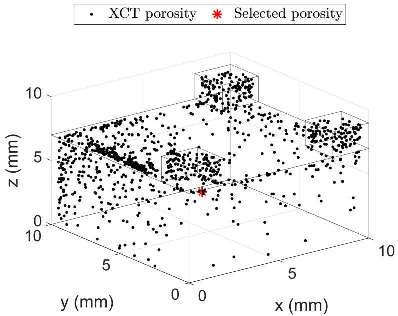
- Due to the sensor acquisition rate, there are occasions where multiple consecutive samples are acquired at the same x and y coordinates
- Consecutive samples per cube per Z layer that have the same x and y coordinates are combined into one sample as follows: the duration feature is summed and the three sensor data features are averaged
- After combining samples with repeated X and Y coordinates, the total number of samples is reduced by 1,758,037 samples from 267,867,956 to 266,109,919

Data Pre-processing (3)

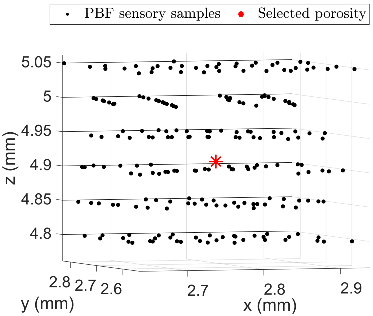
- So far, we have 266,109,919 sensory samples and six input features
  - $[X, Y, Z]$ coordinates
  - Three photodiode features
  - Laser speed
  - Hatch spacing
  - Energy density
- We also have 4733 porosity coordinates from the XCT scans
- To have a balanced data set, we pick 4733 porosity-free coordinates from the 266,109,919 sensory samples
- In total, we have 9466 $[X, Y, Z]$ coordinates, half of which represent a porosity and half are porosity-free

Data Pre-processing (4)

How do we go about selecting which sensory samples represent each of the 9466 coordinates?



(a)

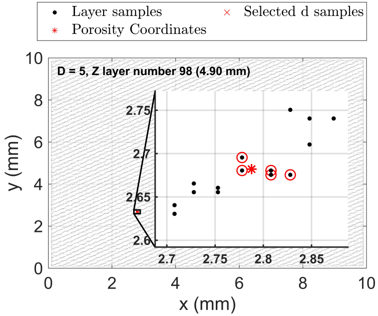


(b)

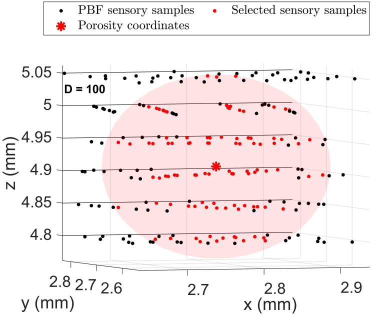
Figure: An example X-ray computed tomography scan and the coordinates of the sensory data surrounding one of the porosities.

Data Pre-processing (5)

We can select the closest D samples in terms of the 3-D Euclidean distance and apply feature extraction.



(a)



(b)

Figure: An example X-ray computed tomography scan and the coordinates of the sensory data surrounding one of the porosities.

Data Pre-processing (6)

- For each D representative sensory samples per coordinate in our 9644 samples, we utilize the mean, variance and skewness as feature extraction methods.
- The supervised machine learning input data set consists of 9644 samples with 15 columns including:
- The mean, variance, and skewness of the three spectral emission sensors
- The mean and variance of the scan speed, hatch spacing, and energy density

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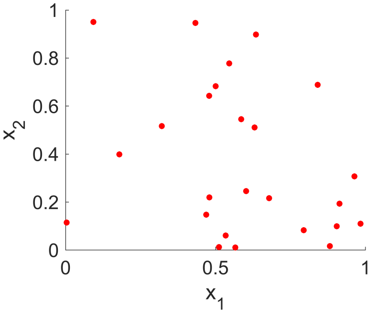
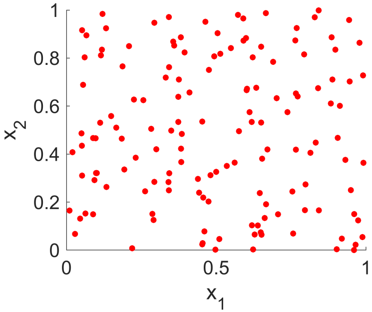
Data in Machine Learning (1)

- We assume we have “enough” data
- Machine learning is only effective where the data is dense enough



(a)

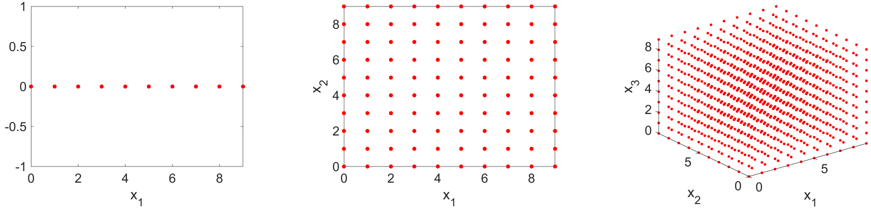


(b)

Figure: Low versus medium density (relatively) data in two-dimensions.

Data in Machine Learning (2)

- The higher the input dimension, the more data required
- For example, given 10 samples in 1D, we need 100 samples in 2D
- n^d samples in d-D maintains sampling density given by n in 1-D (exponential)
- "Curse of dimensionality"



(a) (b) (c)

Figure: A visualisation of the number of samples required in 2-D and 3-D to maintain the sampling density of given by 10 samples in 1-D

Data in Machine Learning (3)

- Given a data set, we need to train, validate, and test a model
- Before training model, it is necessary to arrange a method to test its performance
- We need as much data as possible to train the model and equally as much data to test the model and be confident with its predictions
- Unless there is a good application-dependent reason, split the data in half
- Half the data should be used to train and validate the model (in-sample data)
- Half the data should be used to test the model (out-of-sample data)
- The out-of-sample data should only be used once the models are developed (trained and validated)
- In this project, you are only provided the in-sample data
- The out-of-sample data will be used to test your proposed model's after submission

Data in Machine Learning (4)

- Numeric values of inputs are often arbitrary (patterns contain information)
- Normalisation helps relate numbers to a reference value (e.g. operating point or average)
  - Avoid numerical instability in the optimiser and allow faster convergence
- Normalisation transform is computed from the training (in-sample) data
  - The same transformation is applied to the in-sample, out-of-sample, and operational data
- Each regressor (column/ input feature) should be normalised independently
  - Standardise – subtract the mean and divide by the standard deviation
  - Min/Max – subtract the min and divide by (max-min)

Data in Machine Learning (5)

- Always check the data for missing values
  - Can ignore rows if not too many and depending on the data set size
  - Can replace missing values by the mean of the column (feature) or stratified mean (e.g. class mean)
  - Can ignore column (feature) if one feature is largely missing)
- Always check the data for repeated samples (rows)
  - Data provenance (are you expecting repeated rows or is it a human-error?)

Data in Machine Learning (6)

- The data order (row-wise) must be randomised
- Assuming x_norm is a matrix of the normalised input features and y is the output target below is a MATLB example of data order randomisation
- Setting the number random generator seed is important for repeatability

```
// Set the random generator - repeatability
rng(500);
randId      = randperm( size(x_norm , 1) );
x_norm_rand = x_norm( randId , :);
y_rand      = y( randId , : );
```

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Possible Additional Feature Extraction (1)

- Signal to noise ratio (SNR) is the ratio of the amplitude of the desired signal to the amplitude of noise signals at a given point in time
- In this case, the desired signal is considered the nominal samples and the noise can be considered variations in the spectral emissions due to a porosity
- The SNR can be computed using the signal mean and standard deviation (Eq. 1)
- Be aware that for neural networks and other models, highly correlated input features can result in redundancy, over-fitting, and optimiser instability

$$SNR = 10 log(\mu_{signal}/\sigma_{signal}), \tag{1}$$

where μ is the signal mean and σ is the signal standard deviation.

Possible Additional Feature Extraction (2)

- When sintering a part, the energy density differs near edges and the contour due to thermal conductivity and the laser speed/power
- The he differences in energy density between the edges or surface of the part and the core of the part can result in porosity
- Distance to Nearest-Contour (DTNC)
  - DTNC to border 1 = y
  - DTNC to border 2 = 10 − x
  - DTNC to border 3 = 10 − y
  - DTCN to border 4 = x
- What about the three smaller cubes?

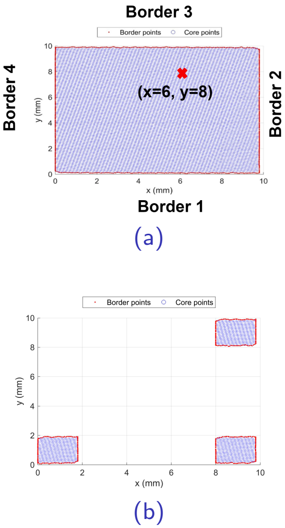


Figure: DTNC example.

Possible Additional Feature Extraction (3)

- Hatch Length is the length of a single track.
- A long hatch length results in more cool down time between adjacent tracks which may result in the material not fully melting when the next track is printed
- Before calculating the hatch length we need to consider:
  - Hatch offset
  - Hatch strategy

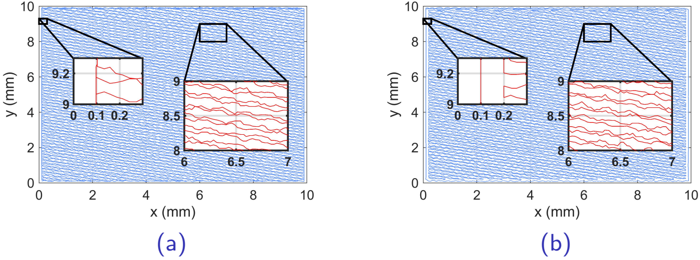
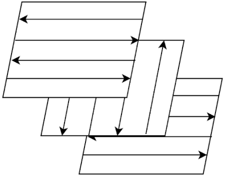


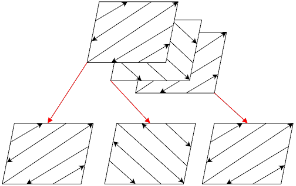
Figure: A comparison of a null hatch offset (cube 3) and a 0.10 mm hatch offset (cube 2).

Possible Additional Feature Extraction (4)

- There is different hatch strategies possible:
  - 90° alternate hatches, $0^{\circ}$and 90° alternating hatch angle, single laser pass
  - 90° alternate hatches, $45^{\circ}$and -45° alternating hatch angle, single laser pass
  - Our case: 90° alternate hatches, $\pm 31.4038^{\circ}$ alternating hatch angle for the main cube, $\pm 16.077^{\circ}$ alternating hatch angle for the three feature cubes , double laser pass
    - Odd Z layers have a negative hatch angle
    - Even Z layers have a positive hatch angle



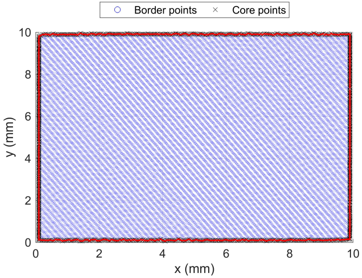
(a)



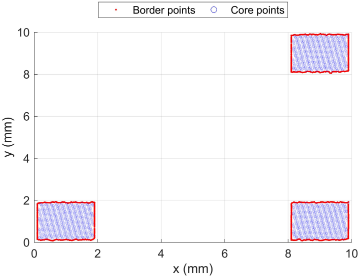
(b)

Figure: A comparison of hatch strategies.

Possible Additional Feature Extraction (5)



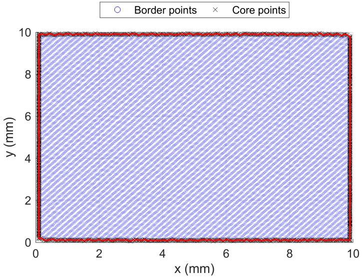
(a)



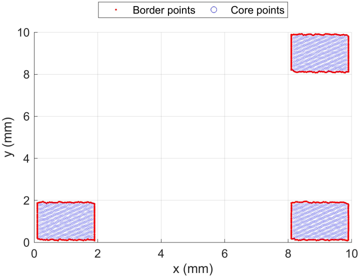
(b)

Figure: Layer 1 and layers 141 showing a negative hatch angle.

Possible Additional Feature Extraction (6)



(a)



(b)

Figure: Layer 2 and layers 142 showing a positive hatch angle.

Possible Additional Feature Extraction (7)

- For the first line with a point at (0,10)
  $\tan(\theta) = b/10$
  $b = 5.2107$
  $(0, 10)$ and $(5.2107, 0)$
  $y = -1.919x + 10$
- For the second line with a point at (10,0)
  $y = -1.919x + c$
  $y = -1.919x + 19.19$
- Given a coordinate (x,y) we have three conditions:
  $y < -1.919x + 10$
  $-1.919x + 10 < y < -1.919x + 19.19$
  $y > -1.919x + 19.19$

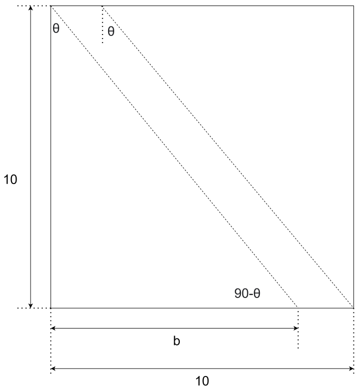


Figure: Negative hatch example.

Possible Additional Feature Extraction (8)

- Given a coordinate (x,y), the hatch length (HL) is:
- If $y < -1.919x + 10$
  Then $HL = \frac{y}{\cos(\theta)} + \frac{x}{\cos(90-\theta)}$
- If $-1.919x + 10 < y < -1.919x + 19.19$
  Then $HL = \frac{y}{\cos(\theta)} + \frac{10-y}{\cos(\theta)}$
- If $y > -1.919x + 19.19$ Then
  $HL = \frac{10-x}{\cos(90-\theta)} + \frac{10-y}{\cos(\theta)}$

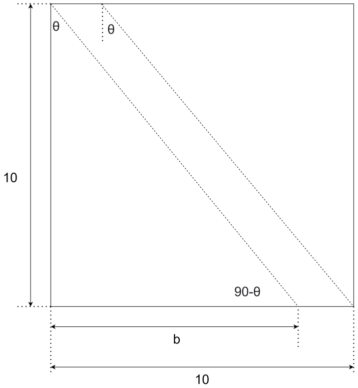


Figure: Negative hatch example.

Possible Additional Feature Extraction (9)

For For example, given a coordinate (x,y) where $y > -1.919x + 19.19$, the HL is:

- If $y > -1.919x + 19.19$
  Then $HL = H_1 + H_2$
  Where
  $H_1 = \frac{10-x}{\cos(90-\theta)}$
  $H_2 = \frac{10-y}{\cos(\theta)}$

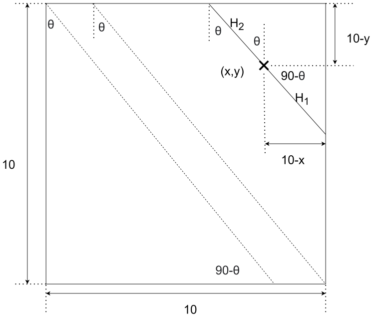


Figure: Negative hatch example.

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Next Steps

- Good progress so far:
  - Have you read the ITP handbook?
  - Have you managed to meet as a group already?
  - Do you have a preliminary top level WBS and Gantt chart?
  - Have you gathered some questions for next week?
- What to do next
  - Meet as a group
  - Continue preparing your Gantt chart, WBS, and a list of questions for next week
  - Structure/outline your preliminary report and assign responsibilities
  - Be mindful of forthcoming milestones (week 4 progress meeting and week 7 preliminary report)