



# Perception | Line Extraction Autonomous Mobile Robots

**Margarita Chli – University of Edinburgh** 

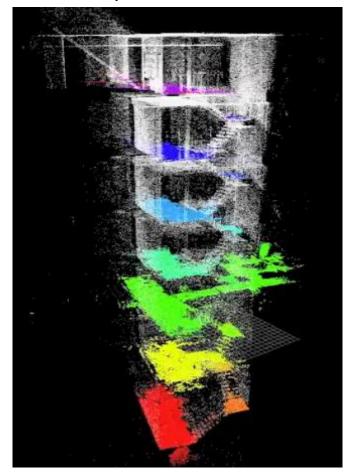
Paul Furgale, Marco Hutter, Martin Rufli, Davide Scaramuzza, Roland Siegwart

#### Line Extraction from a point cloud

Extract lines from a point cloud (e.g. range scan)

- Three main problems:
  - How many lines are there?
  - Segmentation: Which points belong to which line?
  - Line Fitting/Extraction: Given points that belong to a line, how to estimate the line parameters?
- Algorithms we will see:
  - 1. Split-and-merge
  - 2. RANSAC
  - 3. Hough-Transform

Courtesy of F. Pomerleau and F. Colas



- Originates from Computer Vision.
- A recursive procedure of fitting and splitting.
- A slightly different version, called Iterative end-point-fit, simply connects the end points for line fitting.

#### Initialise set **S** to contain all points

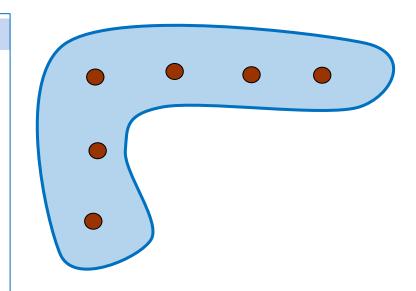
#### **Split**

- Fit a line to points in current set S
- Find the most distant point to the line
- If distance > threshold ⇒ split set & repeat with left & right sets

#### Merge

- If two consecutive segments are close/collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments</li>

Margarita Chli, Paul Furgale, Marco Hutter, Martin Rufli, Davide Scaramuzza, Roland Siegwart



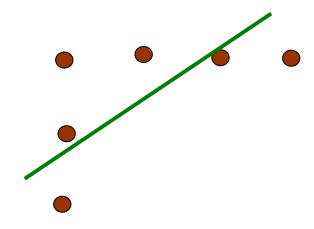
- Originates from Computer Vision.
- A recursive procedure of fitting and splitting.
- A slightly different version, called Iterative end-point-fit, simply connects the end points for line fitting.

#### Initialise set **S** to contain all points

#### **Split**

- Fit a line to points in current set S
- Find the most distant point to the line
- If distance > threshold ⇒ split set & repeat with left & right sets

- If two consecutive segments are close/collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments</li>



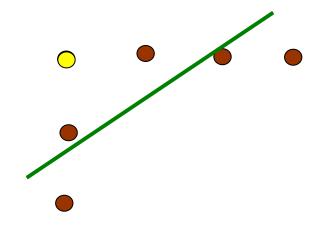
- Originates from Computer Vision.
- A recursive procedure of fitting and splitting.
- A slightly different version, called Iterative end-point-fit, simply connects the end points for line fitting.

#### Initialise set **S** to contain all points

#### **Split**

- Fit a line to points in current set S
- Find the most distant point to the line
- If distance > threshold ⇒ split set & repeat with left & right sets

- If two consecutive segments are close/collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments</li>



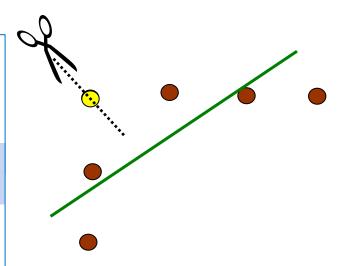
- Originates from Computer Vision.
- A recursive procedure of fitting and splitting.
- A slightly different version, called Iterative end-point-fit, simply connects the end points for line fitting.

#### Initialise set **S** to contain all points

#### **Split**

- Fit a line to points in current set S
- Find the most distant point to the line
- If distance > threshold ⇒ split set & repeat with left & right sets

- If two consecutive segments are close/collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments</li>



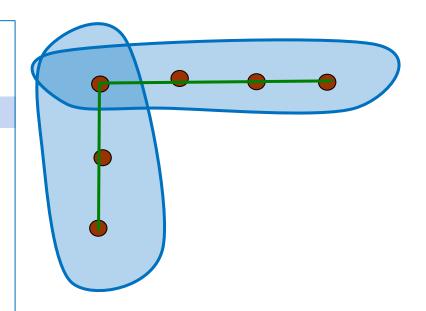
- Originates from Computer Vision.
- A recursive procedure of fitting and splitting.
- A slightly different version, called Iterative end-point-fit, simply connects the end points for line fitting.

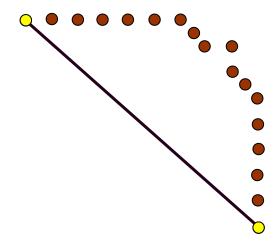
#### Initialise set **S** to contain all points

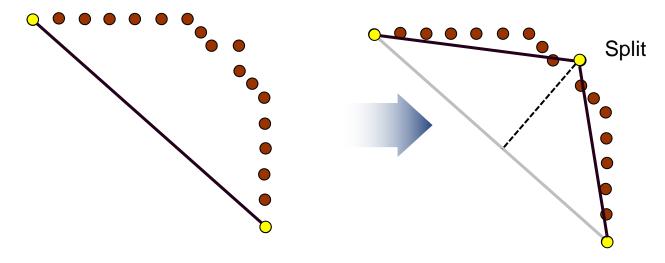
#### **Split**

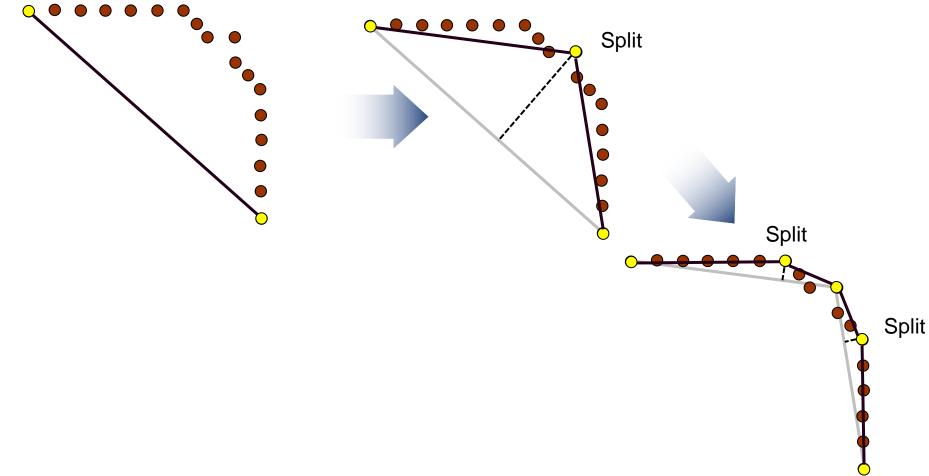
- Fit a line to points in current set S
- Find the most distant point to the line
- If distance > threshold ⇒ split set & repeat with left & right sets

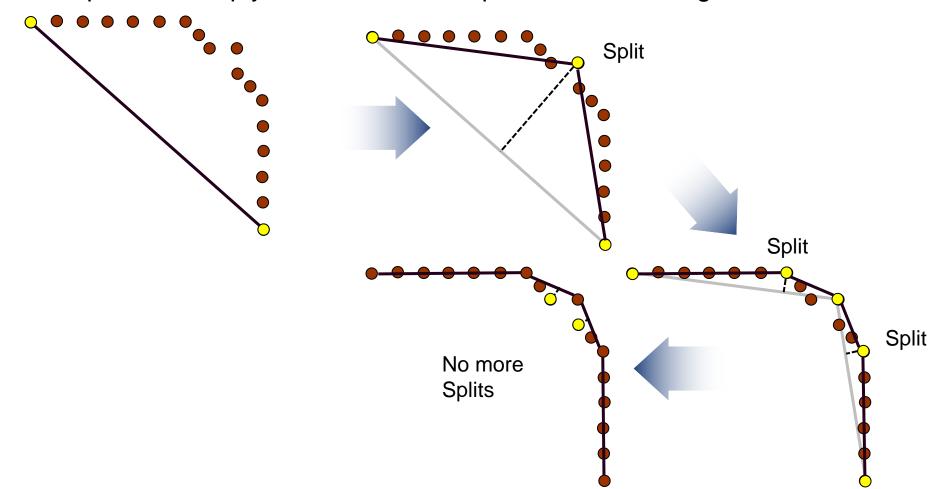
- If two consecutive segments are close/collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments</li>

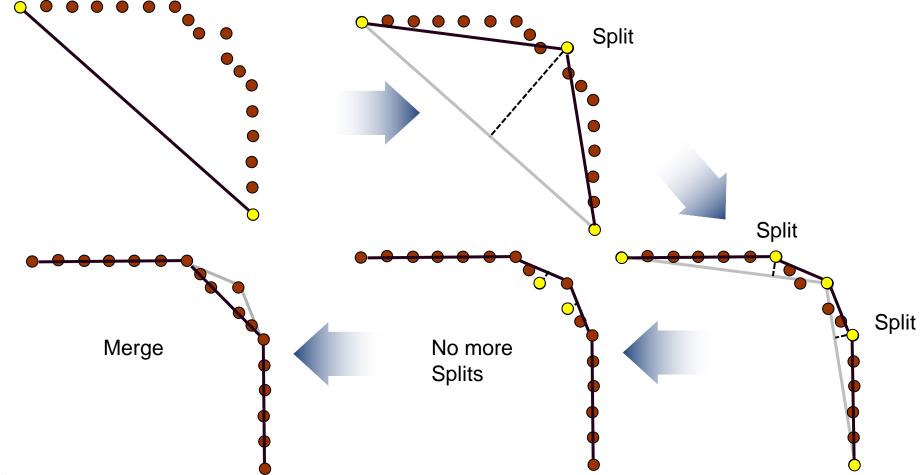






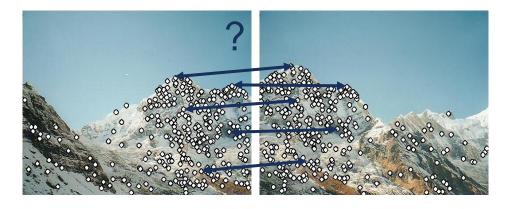






#### **Line Extraction** | RANSAC

- RANSAC = RANdom SAmple Consensus.
- A generic & robust fitting algorithm of models in the presence of outliers (i.e. points which do not satisfy a model)
- Applicable to any problem where the goal is to identify the inliers which satisfy a predefined model.
- Typical applications in robotics are: line/plane extraction, feature matching, structure from motion, ...

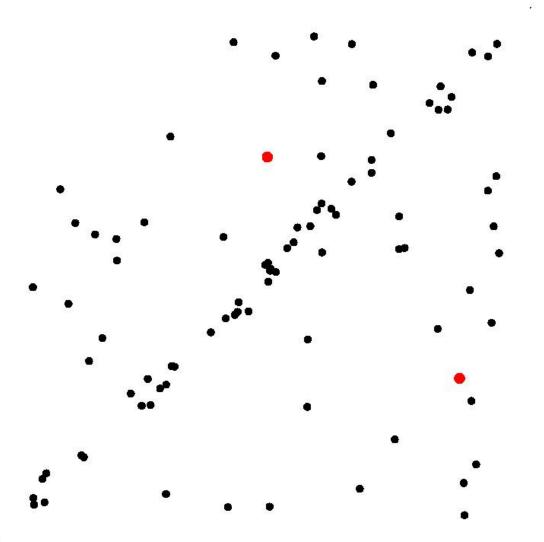


- RANSAC is iterative and non-deterministic ⇒ the probability to find a set free of outliers increases as more iterations are used
- Drawback: A non-deterministic method, results are different between runs.

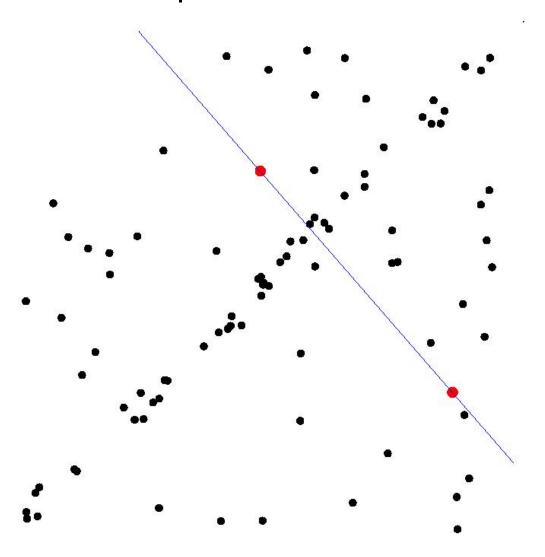




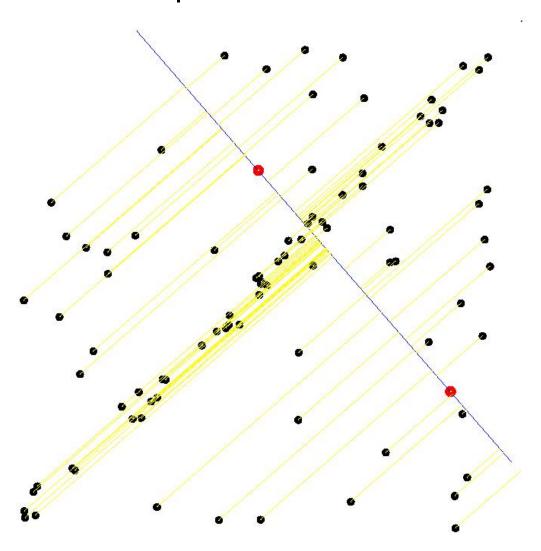




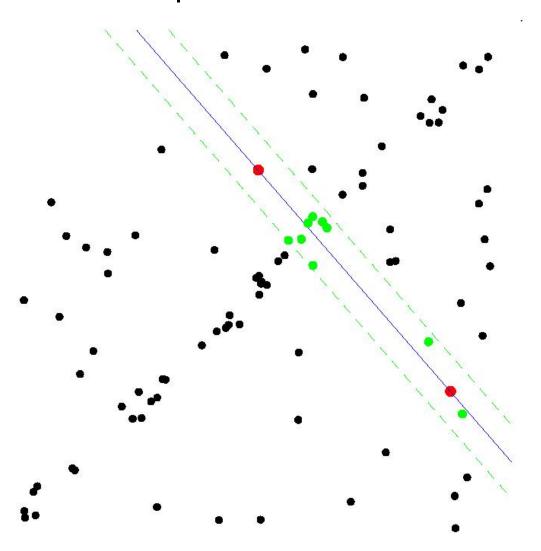
Select sample of 2 points at random



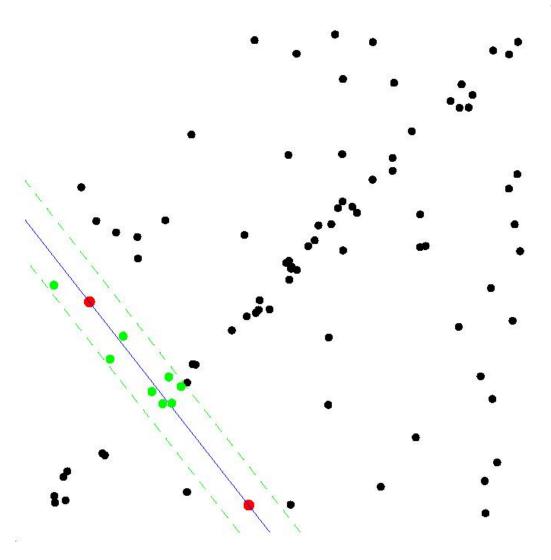
- Select sample of 2 points at random
- Calculate model parameters that fit the data in the sample



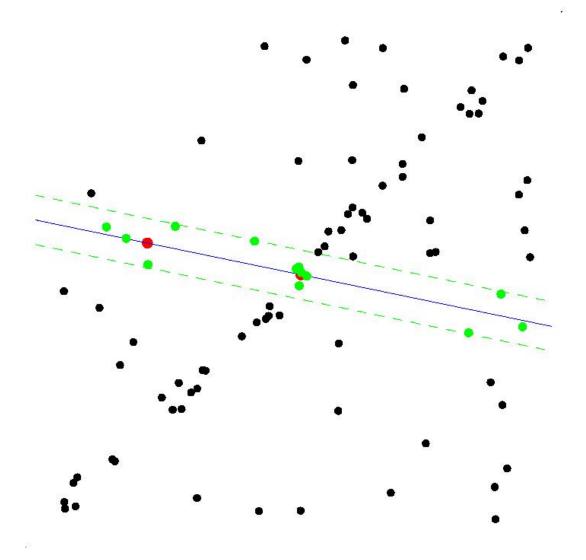
- Select sample of 2 points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point



- Select sample of 2 points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that supports current hypothesis

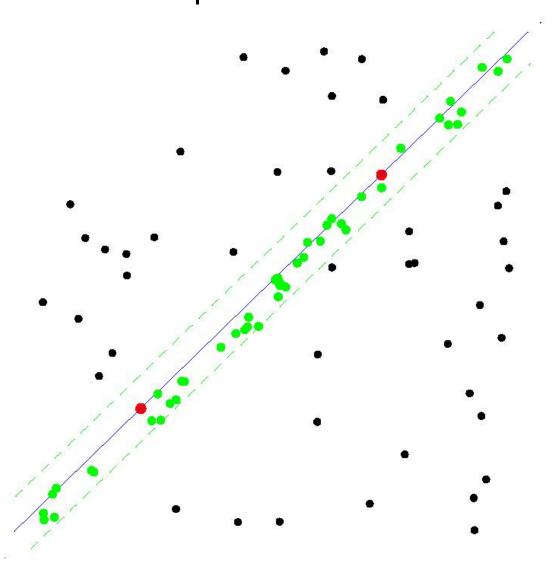


- Select sample of 2 points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that supports current hypothesis
- Repeat sampling



- Select sample of 2 points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that supports current hypothesis
- Repeat sampling





Set with the maximum number of inliers obtained within *k* iterations

- We cannot know in advance if the observed set contains the max. no. inliers
  ⇒ ideally: check all possible combinations of 2 points in a dataset of N points.
- No. all pairwise combinations: N(N-1)/2
  ⇒ computationally infeasible if N is too large.
  example: laser scan of 360 points ⇒ need to check all 360\*359/2= 64'620 possibilities!

- Do we really need to check all possibilities or can we stop RANSAC after iterations?
  Checking a subset of combinations is enough if we have a rough estimate of the percentage of inliers in our dataset
- This can be done in a probabilistic way

- w = number of inliers / N
  - **N**:= tot. no. data points
  - $\Rightarrow$  w: fraction of inliers in the dataset  $\Rightarrow$  w = P(selecting an inlier-point from the dataset)
- Let **p** := P(selecting a minimal set of points free of outliers)
- Assumption: the 2 points necessary to estimate a line are selected independently
  - = P(both selected points are inliers)
  - $\Rightarrow$  ? = P(at least one of these two points is an outlier)

- w := number of inliers / N
  - **N**:= tot. no. data points
  - $\Rightarrow$  w: fraction of inliers in the dataset  $\Rightarrow$  w = P(selecting an inlier-point from the dataset)
- Let **p** := P(selecting a minimal set of points free of outliers)
- Assumption: the 2 points necessary to estimate a line are selected independently
  - $\Rightarrow$  **w**<sup>2</sup> = P(both selected points are inliers)
  - $\Rightarrow$  1-w<sup>2</sup> = P(at least one of these two points is an outlier)
- Let k := no. RANSAC iterations executed so far
  - = P(RANSAC never selects two points that are both inliers)

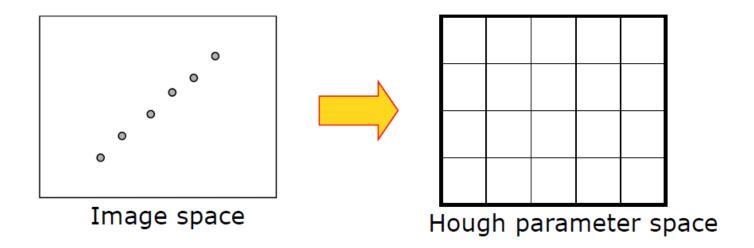
- w := number of inliers / N
  - **N**:= tot. no. data points
  - $\Rightarrow$  w: fraction of inliers in the dataset  $\Rightarrow$  w = P(selecting an inlier-point from the dataset)
- Let **p** := P(selecting a minimal set of points free of outliers)
- Assumption: the 2 points necessary to estimate a line are selected independently
  - $\Rightarrow$  **w**<sup>2</sup> = P(both selected points are inliers)
  - $\Rightarrow$  1-w<sup>2</sup> = P(at least one of these two points is an outlier)
- Let k := no. RANSAC iterations executed so far
  - $\Rightarrow$  ( 1-w<sup>2</sup>) k = P(RANSAC never selects two points that are both inliers)
  - $\Rightarrow$  1-p =  $(1-w^2)^k$  and therefore:

$$k = \frac{\log(1-p)}{\log(1-w^2)}$$

In practice we need only a rough estimate of **w**. More advanced variants of RANSAC estimate the fraction of inliers & adaptively set it on every iteration.

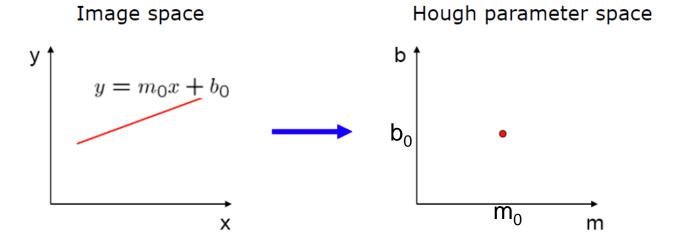
# **Line Extraction** | Hough-transform

- Edges vote for plausible line locations
- Map image space into Hough parameter space
- Hough space parameterizes coordinate space w.r.t line characteristics
- In practice, it's a discretized accumulator array (comprising of voting bins)



### Hough-Transform | Hough space

A line in the image corresponds to a point in Hough space



What does a point (x<sub>0</sub>, y<sub>0</sub>) in the image space map to in the Hough space?

### Hough-Transform | Hough space

A line in the image corresponds to a point in Hough space

What does a point  $(x_0, y_0)$  in the image space map to in the Hough space?

Where is the line that contains both  $(x_0, y_0)$  and  $(x_1, y_1)$ ?

Margarita Chli, Paul Furgale, Marco Hutter, Martin Rufli, Davide Scaramuzza, Roland Siegwart

• At the intersection of:  $b = -x_0m + y_0$  and  $b = -x_1 m + y_1$ 

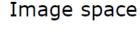
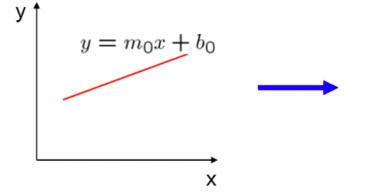
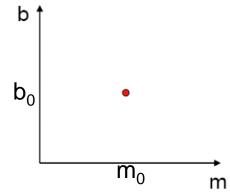


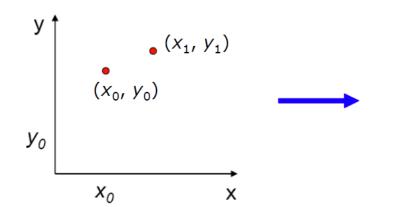
Image space

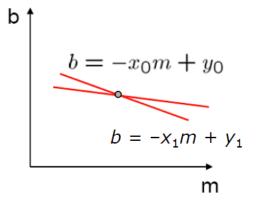


#### Hough parameter space



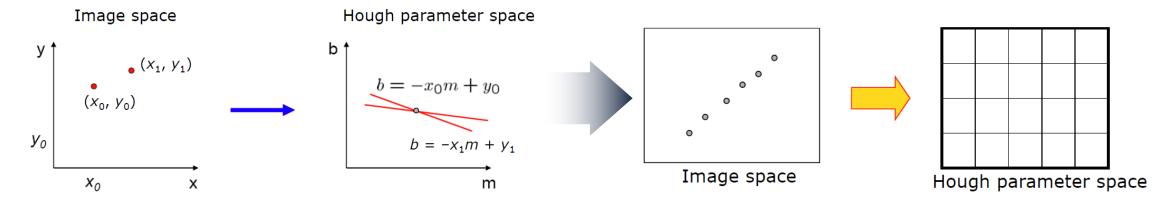
#### Hough parameter space



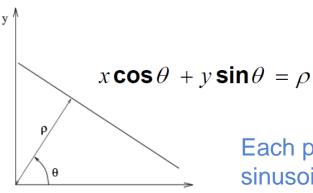


#### **Hough-Transform** | how it works

Each point in image space, votes for line-parameters in Hough parameter space



- Problems with the (m,b) space:
  - Unbounded parameter domain
  - Vertical lines require infinite m
- Alternative: polar representation

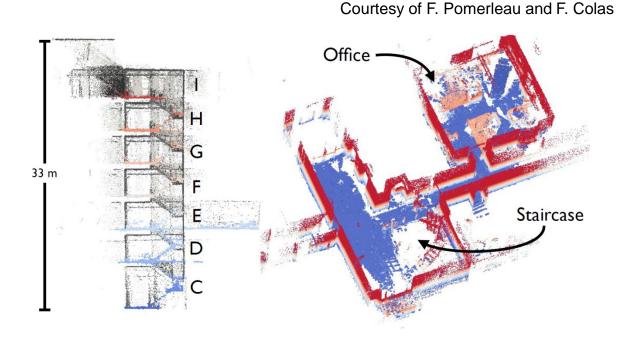


Each point in image space will map to a sinusoid in the  $(\rho,\theta)$  parameter space

# **Line Extraction** | relative merits

- Split-and-merge: fastest
  - Deterministic & makes use of the sequential ordering of raw scan points (: points captured according to the rotation direction of the laser beam)

- If applied on randomly captured points only RANSAC and Hough-Transform would segment all lines.
- RANSAC and Hough-Transform: more robust to outliers



**Autonomous Mobile Robots**