

Feature Extraction

- Sometimes sensor values are interpreted directly (e.g. front sonar sensor tied to emergency stop command)
- However, we often require higher-level information
- A **feature** abstracts away the particular sensor values to yield a description of some characteristic of the environment (or its appearance)
 - Low-level: lines and other geometric features
 - High-level: objects (e.g. doors, cars)
- The process of **feature extraction** extracts a feature's description (i.e. its parameters) from the raw sensor data
- Features are very useful for localization and mapping

Line Extraction

- Assume we have a sensor (e.g. laser rangefinder) that returns a sequence of (range, angle) points
- For the moment, we assume that all of these points come from a single line in the environment (e.g. a wall)
- If we have more than two points then it is unlikely that we can find a single line which passes through all of them
 - The system is *overdetermined* (too many equations)
 - We apply least squares optimization to find a line of best fit
 - In fact, we apply *weighted least squares* using the uncertainty of data points to weight their impact on the solution





$$d_i = \rho_i \cos(\theta_i - \alpha) - r$$

This equation gives the \perp distance to the line. It also serves as an equation for the line when $d_i = 0$.

To determine how line parameters r and α fit with the data, we could take the sum of squared distances,

$$S = \sum_{i} d_i^2 = \sum_{i} (\rho_i \cos(\theta_i - \alpha) - r)^2$$

We would then find parameters to minimize S. This approach is reasonable, but does not take advantage of the uncertainty of data points. We should pay more attention to data points with the least variance... We wish to weight individual data points by our confidence in their values. We will be more confident about values which are closer. Therefore, we employ the following weight:

 $w_i = 1/\rho_i$

We can now redefine S to incorporate the estimated uncertainty of the data points,

$$S = \sum_{i} w_i d_i^2 = \sum_{i} w_i (\rho_i \cos(\theta_i - \alpha) - r)^2$$

We wish to find r and α that yield a minimum value of S. A standard technique is to differentiate S w.r.t. r and α and solve for these values when the derivative is zero.

$$\frac{\partial S}{\partial r} = 0 \qquad \qquad \frac{\partial S}{\partial \alpha} = 0$$

First apply the following trigonometric identity to S

$$\cos(a-b) = \cos a \cos b + \sin a \sin b$$

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Perception, Part 2

June 8, 20<u>18</u>

9 / 19

$$S = \sum_{i=1}^{n} w_i (\rho_i \cos \theta_i \cos \alpha + \rho_i \sin \theta_i \sin \alpha - r)^2$$

$$\frac{\partial S}{\partial r} = 0 = \sum 2 w_i (\rho_i \cos \theta_i \cos \alpha + \rho_i \sin \theta_i \sin \alpha - r)(-1)$$

$$= -2 \sum w_i \rho_i (\cos \theta_i \cos \alpha + \sin \theta_i \sin \alpha) + 2 \sum w_i r$$

$$= -2 \sum w_i \rho_i \cos(\theta_i - \alpha) + 2r \sum w_i$$

$$2r \sum w_i = 2 \sum w_i \rho_i \cos(\theta_i - \alpha)$$

$$r = \frac{\sum w_i \rho_i \cos(\theta_i - \alpha)}{\sum w_i}$$

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Segmentation

• We made the assumption above that all same line \rightarrow this is generally a poor as	ll data points came from the sumption
• It is necessary to separate a set of measure belong to the same feature; This is known of the same feature is the same feature of the same feature is the same feature of the same featu	surements into subsets that all wwn as segmentation
• The <i>Split-and-Merge</i> algorithm describe and was found to be the fastest, and an recent study [Nguyen et al., 2005]	ed below is relatively simple mong the most accurate in a
 The idea: Fit a line using all points Determine the point at maximum dist If the distance of this worst fit point i the line in two Continue fitting and splitting until no Merge similar lines together 	tance to this line is greater than a threshold, split splittable segments remain

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June 8, 2018

13 / 19

Split-and-Merge

- Initialize a list of lists L. Create list of all points and place it into L.
- 2 Get the next list, l_i from L. Fit a line to l_i .
- **(3)** Detect the worst fit point p, which has the largest distance d_p to the line.
- If d_p is less than a threshold, go to step 2.
- Otherwise, split I_i at p into I_{i1} and I_{i2} . Replace I_i in L with I_{i1} and I_{i2} . Go to step 2.
- When all lists in *L* have been checked, merge similar lines.

More details are required for steps 3 and 6...

Step 3:

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We introduce a parameter called minPointsPerLine to prevent fitting lines to small sets of points to reduce the impact of noise. Therefore, the worst fit point should not be one of the first or last minPointsPerLine/2 points of the list.

Perception Part 2

Further details...

Step 6: "When all lists in *L* have been checked, merge similar lines."

We can measure the similarity of two lines $A = (r_1, \alpha_1)$ and $B = (r_2, \alpha_2)$ by comparing the two differences $|r_1 - r_2|$ and $|\alpha_1 - \alpha_2|$ to threshold values. Note that some care must be taken in computing $|\alpha_1 - \alpha_2|$. e.g. The difference between 170° and -170° is 20° , not 340° .

Perception, Part 2

Similar adjacent lines are merged by taking all of their source points and fitting a new line.

(The method described above is similar, but slightly simplified from that described in [Nguyen et al., 2005])

Once we have lines, we can use them directly or else determine line segments; The projection of the start and end data points onto the line yield a line segment.



June 8, 2018

14 / 19

Corners are points of intersection between two lines. We may require that the angle between the lines is large. A corner can be further classified as convex or concave depending upon the orientation of the lines w.r.t. the robot.[Tomatis et al., 2003]



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