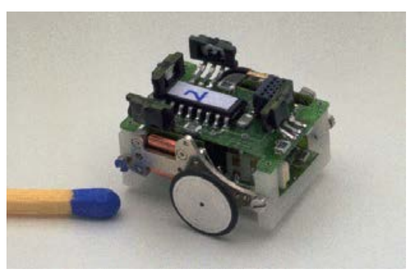
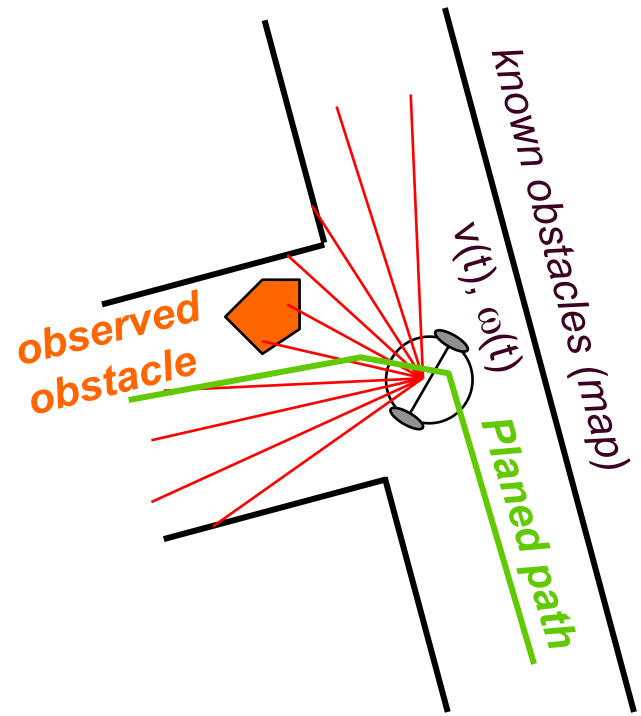
Obstacle Avoidance (Local Path Planning)

- The goal of the obstacle avoidance algorithms is to avoid collisions with obstacles
- It is usually based on *local map*
- Often implemented as a more or less *independent task*
- However, efficient obstacle avoidance should be optimal with respect to
  - *the overall goal*
  - *the actual speed and kinematics of the robot*
  - *the on board sensors*
  - *the actual and future risk of collision*

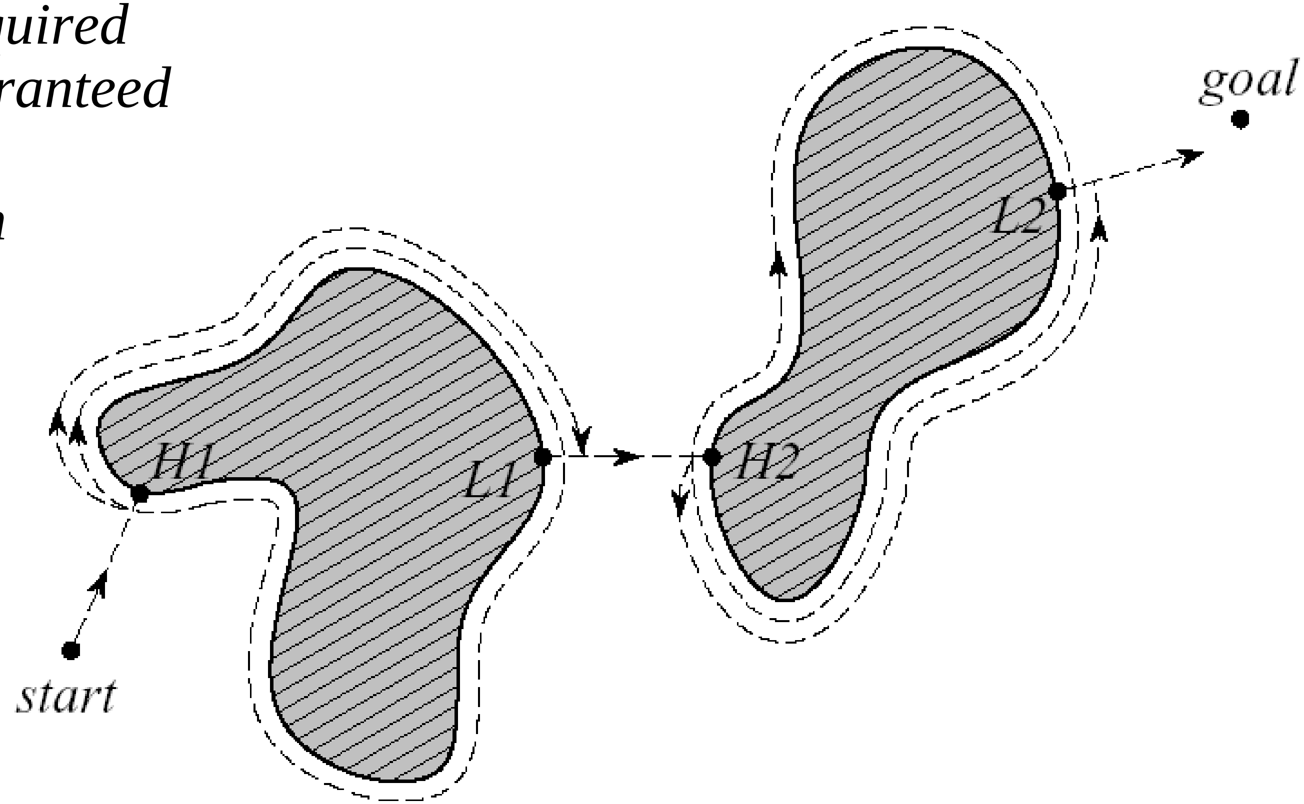




Adapted from © R. Siegwart, I. Nourbakhsh

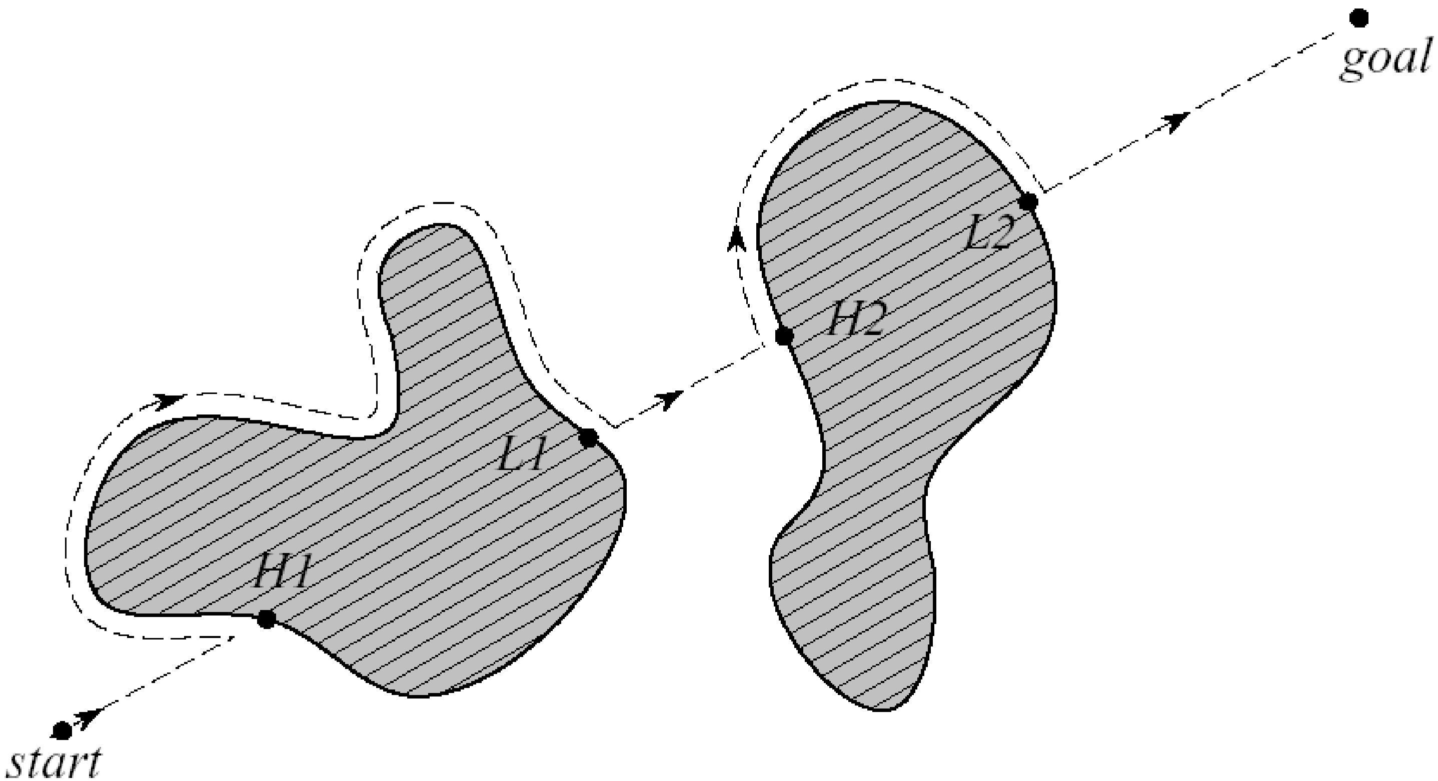
Obstacle Avoidance: **Bug1**

- Follow along the obstacle to avoid it
- Each encountered obstacle is one fully circled before it is left at the point closest to the goal
- Move toward the goal and repeat for any future encountered obstacle
- Advantages:
  - *No global map required*
  - *Completeness guaranteed*
- Disadvantages:
  - *Solutions are often highly suboptimal*



Obstacle Avoidance: **Bug2**

- *Follow the obstacle always on the left or right side*
- *Leave the obstacle if the direct connection between start and goal is crossed*



Practical Implementation of Bug2

- Two states of robot motion:
  - *(1) moving toward goal (GOALSEEK)*
  - *(2) moving around contour of obstacle (WALLFOLLOW)*
- Describe robot motion as function of sensor values and relative direction to goal
- Decide how to switch between these two states

```
while (!atGoal)
     {   if (goalDist < goalThreshold)
             We're at the goal!  Halt.
         else
           { forwardVel = ComputeTranslation(&sonars)
             if (robotState == GOALSEEK)
                 { rotationVel = ComputeGoalSeekRot(goalAngle)
                   if (ObstaclesInWay())
                        robotState <- WALLFOLLOW
                 }
             if (robotState == WALLFOLLOW)
                 { rotationVel = ComputeRightWallFollowRot(&sonars)
                   if (!ObstaclesInWay())
                        robotState <- GOALSEEK)
                 }
           }
         robotSetVelocity(forwardVel, rotationVel)
     }
```

Practical Implementation of Bug2 (con't.)

- `ObstaclesInWay():` is true whenever any sonar range reading in the direction of the goal (i.e., within 45^o of the goal) is too short

- `ComputeTranslation():` proportional to largest range reading in robot's approximate forward direction
  - *// Note similarity to potential field approach!*
  - *If minSonarFront (i.e., within 45^o of the goal) < min_dist*
    - *return 0*
  - *Else return min (max_velocity, minSonarFront – min_dist)*

Practical Implementation of Bug2 (con't.)

- For computing rotation direction and speed, popular method is:
  - *Subtract left and right range readings*
  - *The larger the difference, the faster the robot will turn in the direction of the longer range readings*

- `ComputeGoalSeekRot():   // returns rotational velocity`
  - *`if (abs(angle_to_goal)) < PI/10`*
    - *`return 0`*
  - *`else return (angle_to_goal * k)  // k is a gain`*

- `ComputeRightWallFollowRot():  // returns rotational velocity`
  - *`if max(minRightSonar, minLeftSonar) < min_dist`*
    - *`return hard_left_turn_value  // this is for a right wall follower`*
  - *`else`*
    - *`desiredTurn = (hard_left_turn_value – minRightSonar) * 2`*
    - *`translate desiredTurn into proper range`*
    - *`return desiredTurn`*

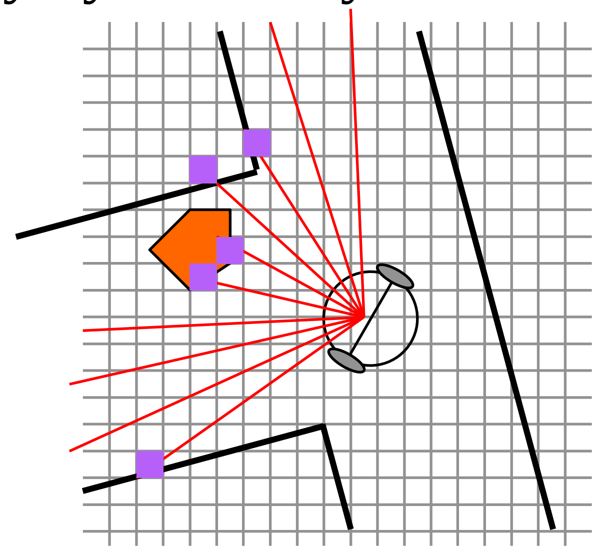
Pros/Cons of Bug2

- Pros:
  - *Simple*
  - *Easy to understand*
  - *Popularly used*
- Cons:
  - *Does not take into account robot kinematics*
  - *Since it only uses most recent sensor values, it can be negatively impacted by noise*
- More complex algorithms (in the following) attempt to overcome these shortcomings

Obstacle Avoidance: **Vector Field Histogram (VFH)**

Koren & Borenstein, ICRA 1990

- Overcomes Bug2's limitation of only using most recent sensor data by creating local map of the environment around the robot
- Local map is a small occupancy grid
  - *Grid cell values equal to the probability that there is an obstacle in that cell*
- This grid is populated only by relatively recent sensor data

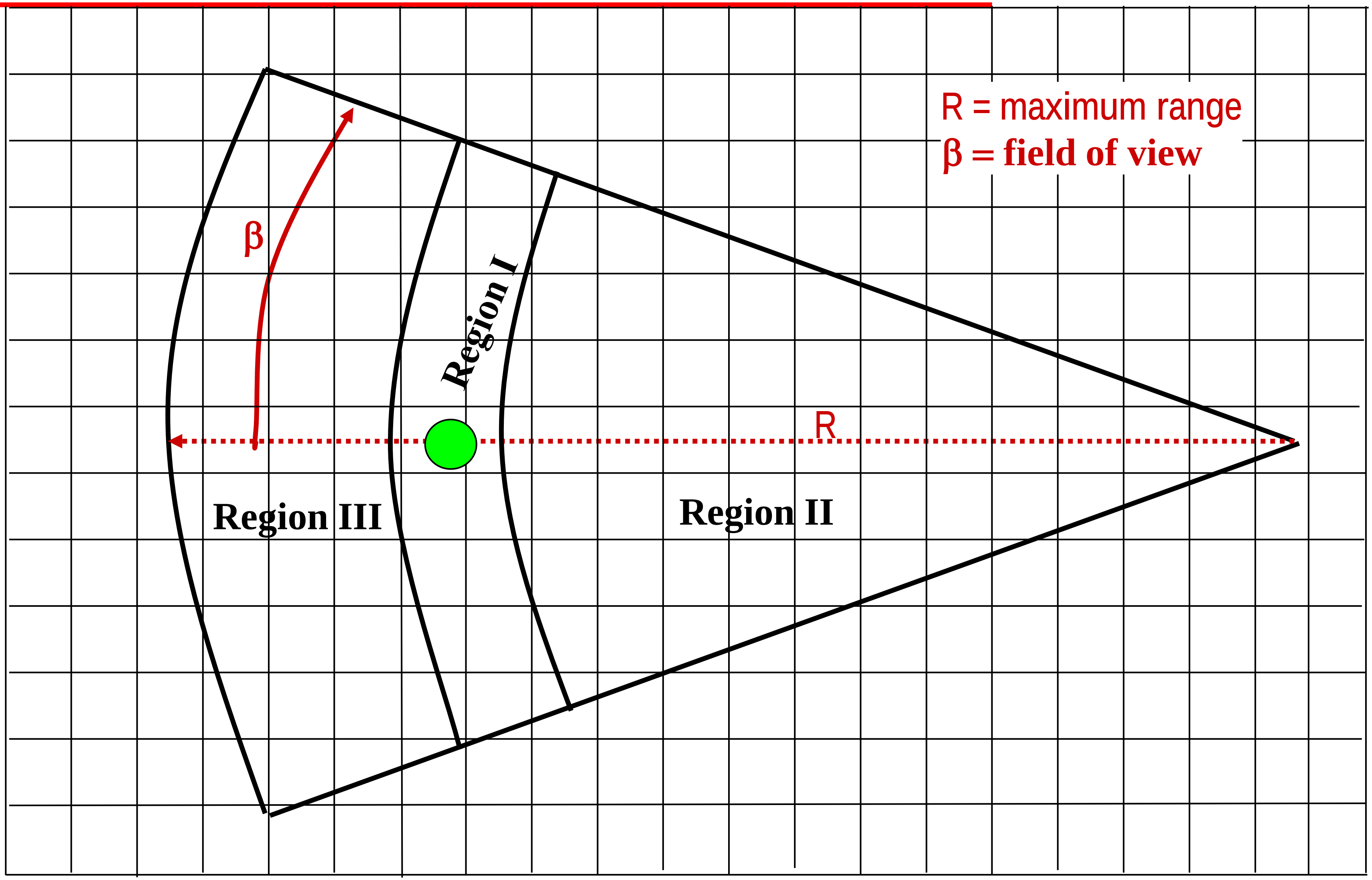


How to calculate probability that cell is occupied?

- Need sensor model to deal with uncertainty

- Let's look at the approach for a sonar sensor …

Modeling Common Sonar Sensor (from Murphy)



Region I: Probably occupied

Region II: Probably empty

Region III: Unknown

How to Convert to Numerical Values?

- Need to translate model (previous slide) to specific numerical values for each occupancy grid cell
  - *These values represent the probability that a cell is occupied (or empty), given a sensor scan (i.e., P(occupied | sensing))*

- Three methods:
  - *Bayesian*
  - *Dempster-Shafer Theory*
  - *HIMM (Histogrammic in Motion Mapping)*

- We'll cover:
  - *Bayesian*

- We won't cover:
  - *Dempster-Shafer*
  - *HIMM*

Bayesian: Most popular evidential method

- Approach:
  - *Convert sensor readings into probabilities*
  - *Combine probabilities using Bayes' rule:*

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

  - *That is,*

$$\text{Posterior} = \frac{\text{Likelihood} \times \text{Prior}}{\text{Normalizing constant}}$$

- Pioneers of approach:
  - *Elfes and Moravec at CMU in 1980s*

Review: Basic Probability Theory

- Probability function:
  - *Gives values from 0 to 1 indicating whether a particular event, H (Hypothesis), has occurred*

- For sonar sensing:
  - *Experiment:* *Sending out acoustic wave and measuring time of flight*
  - *Outcome:* *Range reading reporting whether the region being sensed is Occupied or Empty*

- Hypotheses (H) = {Occupied, Empty)

- Probability that H has really occurred:

  $0 < P(H) < 1$

- Probability that H has not occurred:

  $1 - P(H)$

Unconditional and Conditional Probabilities

- Unconditional probability: $P(H)$
  - *"Probability of* H*"*
  - *Only provides* a priori *information*
  - *For example, could give the known distribution of rocks in the environment, e.g., "x% of environment is covered by rocks"*
  - *For robotics, unconditional probabilities are not based on sensor readings*

- For robotics, we want: Conditional probability: $P(H \mid s)$
  - *"Probability of* H, *given* s*" (e.g., $P(Occupied \mid s)$, or $P(Empty \mid s)$)*
  - *These are based on sensor readings,* s

- Note: $P(H \mid s) + P(\text{not } H \mid s) = 1.0$

Probabilities for Occupancy Grids

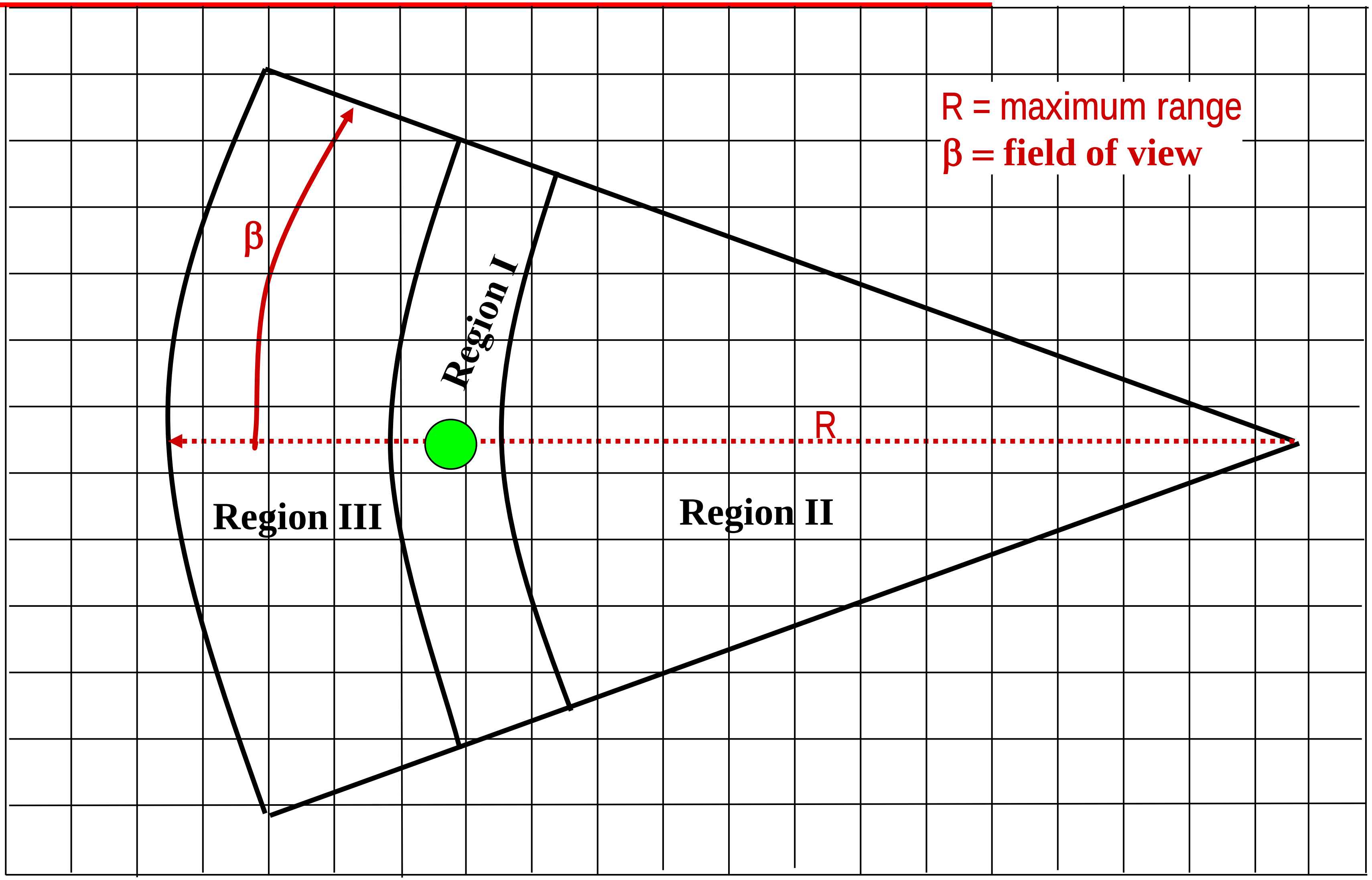
- For each grid[i][j] covered by sensor scan:
  - *Compute* P(Occupied | s) *and* P(Empty | s)

- For each grid element, grid[i][j], store tuple of the two probabilities:

```
typedef struct {
    double occupied;  // i.e., P(occupied | s)
    double empty;     // i.e., P(empty | s)
  } P;

P occupancy_grid[ROWS][COLUMNS];
```

Recall: Modeling Common Sonar Sensor to get P(s | H)



Region I: Probably occupied   Region II: Probably empty   Region III: Unknown

Converting Sonar Reading to Probability: Region I

- Region I:

The nearer the grid element to the origin of the sonar beam, the higher the belief

The closer to the acoustic axis, the higher the belief

$$P(\text{Occupied}) = \frac{\frac{R-r}{R} + \frac{\beta-\alpha}{\beta}}{2} \quad x\ Max_{occupied}$$

We never know with certainty

where r is distance to grid element that is being updated

α is angle to grid element that is being updated

$Max_{occupied}$ = highest probability possible (e.g., 0.98)

P(Empty) = 1.0 – P(Occupied)

Converting Sonar Reading to Probability: Region II

- Region II:

The nearer the grid element to the origin of the sonar beam, the higher the belief

The closer to the acoustic axis, the higher the belief

$$P(\text{Empty}) = \frac{\frac{R-r}{R} + \frac{\beta-\alpha}{\beta}}{2}$$

P(Occupied) = 1.0 – P(Empty)

where r *is distance to grid element being updated,*

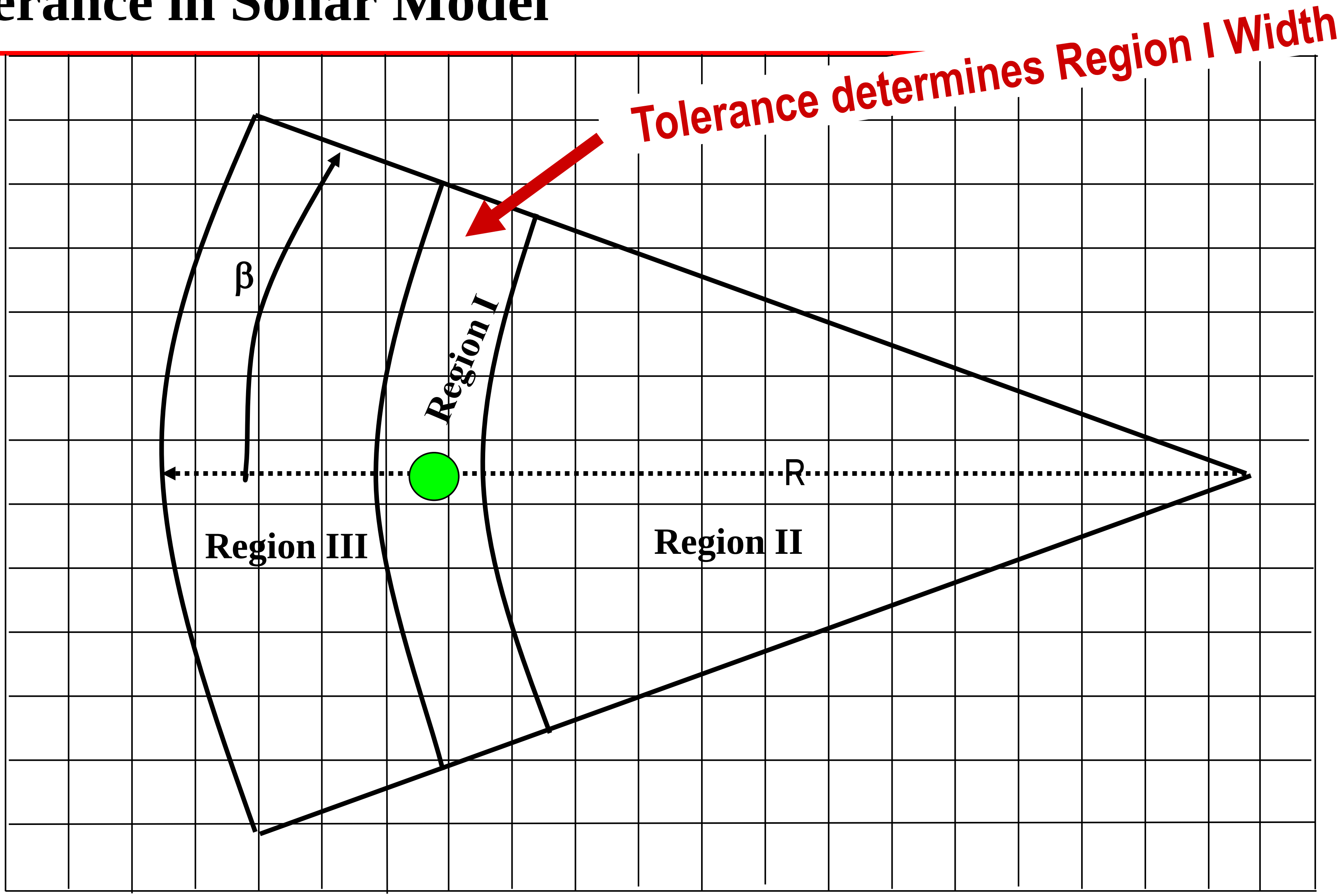
α is angle to grid element being updated

Note that here, we allow probability of being empty to equal 1.0

Sonar Tolerance

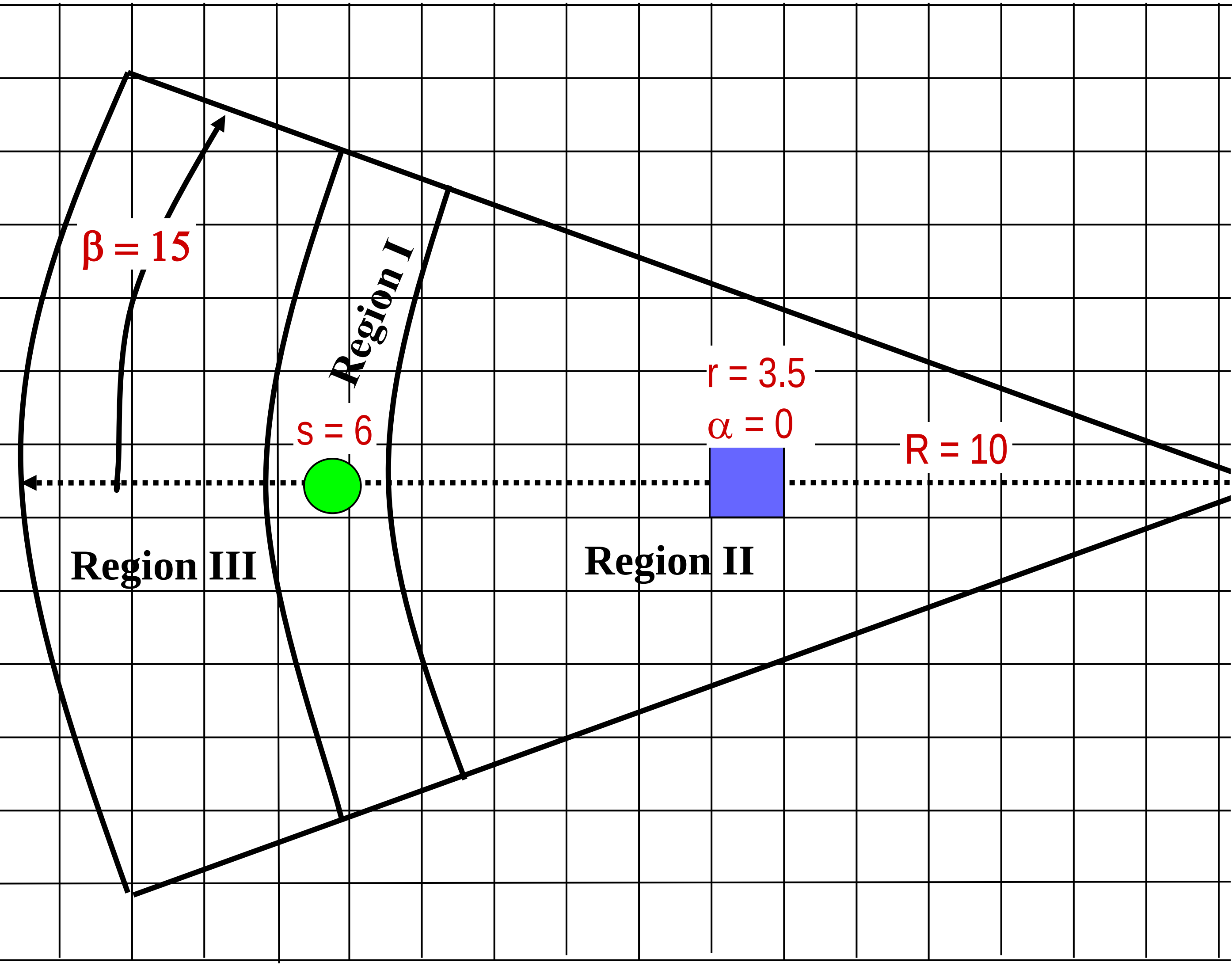
- Sonar range readings have resolution error
- Thus, specific reading might actually indicate range of possible values
- E.g., reading of 0.87 meters actually means within (0.82, 0.92) meters
  - *Therefore,* tolerance *in this case is 0.05 meters.*
- Tolerance gives width of Region I

Tolerance in Sonar Model



Region I: Probably occupied Region II: Probably empty Region III: Unknown

Example: What is value of grid cell ■ ? (assume tolerance = 0.5)



Which region?

3.5 < (6.0 – 0.5) ➔ Region II

$$P(Empty) = \frac{\frac{10 - 3.5}{10} + \frac{15 - 0}{15}}{2}$$

$= 0.83$

P(Occupied) = (1 – 0.83) = 0.17

But, not yet there – need P(H|s), not P(s|H)

- Note that previous calculations gave: $P(s \mid H)$, not $P(H \mid s)$
- Thus, use Bayes Rule:

$$\mathrm{P(H \mid s)} = \frac{P(s \mid H)\, P(H)}{P(s \mid H)\, P(H) + P(s \mid not\ H)\, P(not\ H)}$$

$$\mathrm{P(H \mid s)} = \frac{P(s \mid Empty)\, P(Empty)}{P(s \mid Empty)\, P(Empty) + P(s \mid Occupied)\, P(Occupied)}$$

- $P(s \mid Occupied)$ and $P(s \mid Empty)$ are known from sensor model
- $P(Occupied)$ and $P(Empty)$ are unconditional, prior probabilities (which may or may not be known)
  - *If not known, okay to assume* P(Occupied) = P(Empty) = *0.5*

Returning to Example

- Let's assume we're on Mars, and we know that *P(Occupied)* = 0.75
- Continuing same example for cell …
- $P(Empty \mid s{=}6) = \dfrac{P(s \mid Empty)\, P(Empty)}{P(S \mid Empty)\, P(Empty) + P(s \mid Occupied)\, P(Occupied)}$

$$= \frac{0.83 \times 0.25}{0.83 \times 0.25 + 0.17 \times 0.75}$$

$$= 0.62$$

- $P(Occupied \mid s{=}6) = 1 - P(Empty \mid s{=}6) = 0.38$

- *These are the values we store in our grid cell representation*

Updating with Bayes Rule

- How to fuse multiple readings obtained over time?
- First time:
  - *Each element of grid initialized with* a priori *probability of being occupied or empty*
- Subsequently:
  - *Use Bayes' rule iteratively*
  - *Probability at time* t_{n-1} *becomes prior and is combined with current observation at* t_n *using recursive version of Bayes rule*:

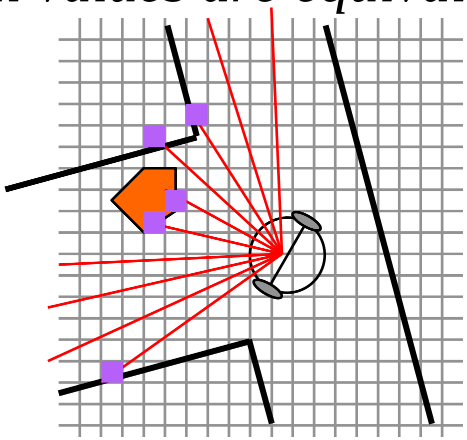
$$P(H \mid s_n) = \frac{P(s_n \mid H)\, P(H \mid s_{n-1})}{P(s_n \mid H)\, P(H \mid s_{n-1}) + P(s_n \mid \text{not } H)\, P(\text{not } H \mid s_{n-1})}$$

Now, back to: Vector Field Histogram (VFH)

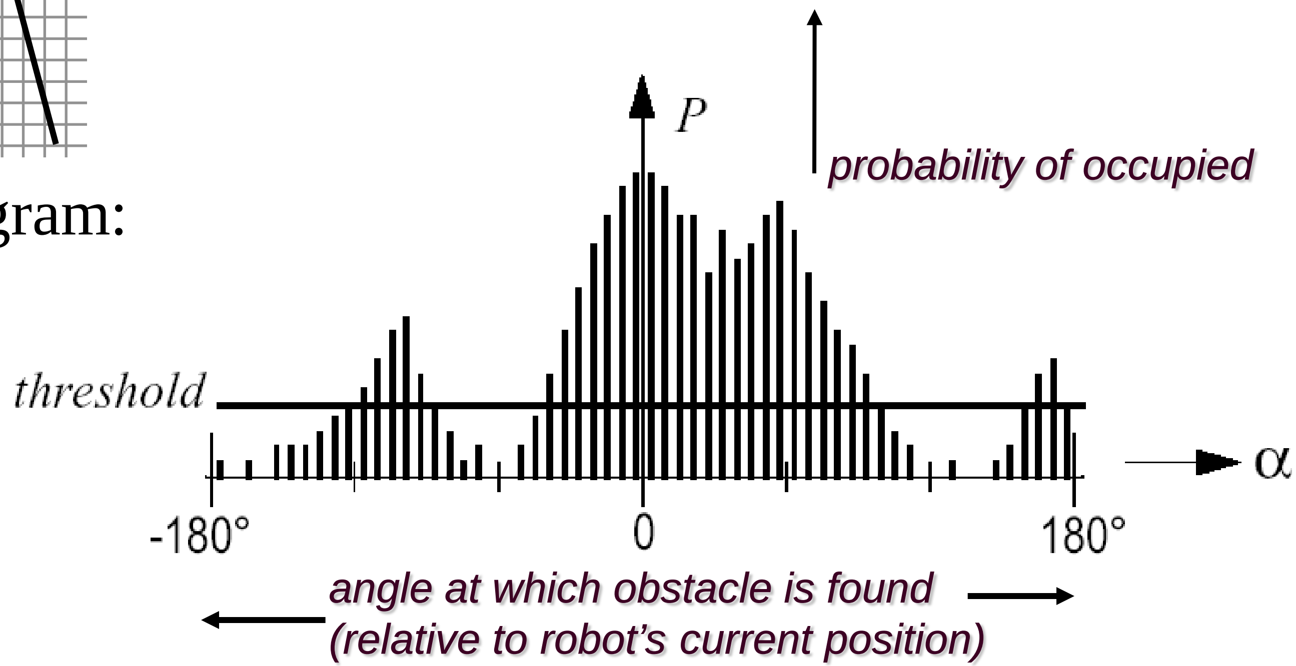
- Environment represented in a grid (2 DOF)

Koren & Borenstein, ICRA 1990

  - *cell values are equivalent to the probability that there is an obstacle*



- Generate polar histogram:



Now, back to: Vector Field Histogram (VFH)

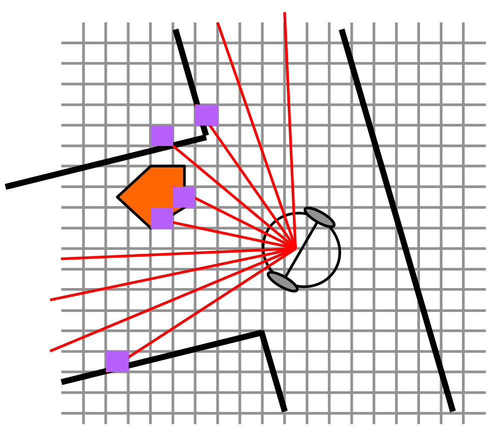
- From histogram, calculate steering direction: *Koren & Borenstein, ICRA 1990*
  - ➢ *Find all openings large enough for the robot to pass through*
  - ➢ *Apply cost function G to each opening*

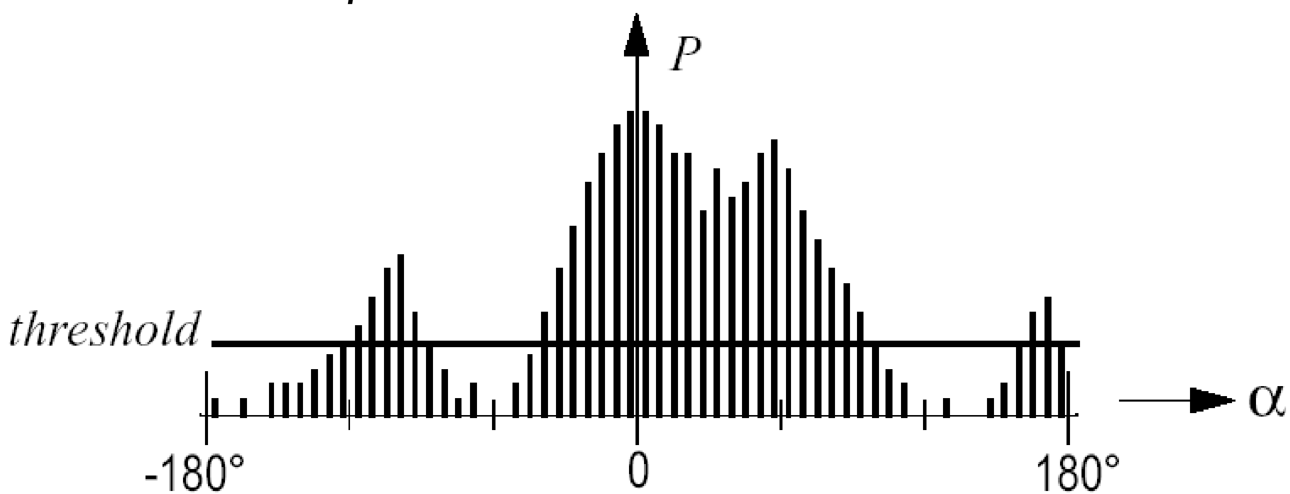
$$G = a \cdot \text{target\_direction} + b \cdot \text{wheel\_orientation} + c \cdot \text{previous\_direction}$$

where:

- o *target_direction = alignment of robot path with goal*
- o *wheel_orientation = difference between new direction and current wheel orientation*
- o *previous_direction = difference between previously selected direction and new direction*

- ➢ *Choose the opening with lowest cost function value*





VFH Limitations

Borenstein et al.

- Limitation if narrow areas (e.g. doors) have to be passed
- Local minimum might not be avoided
- Reaching of the goal cannot be guaranteed
- Dynamics of the robot not really considered

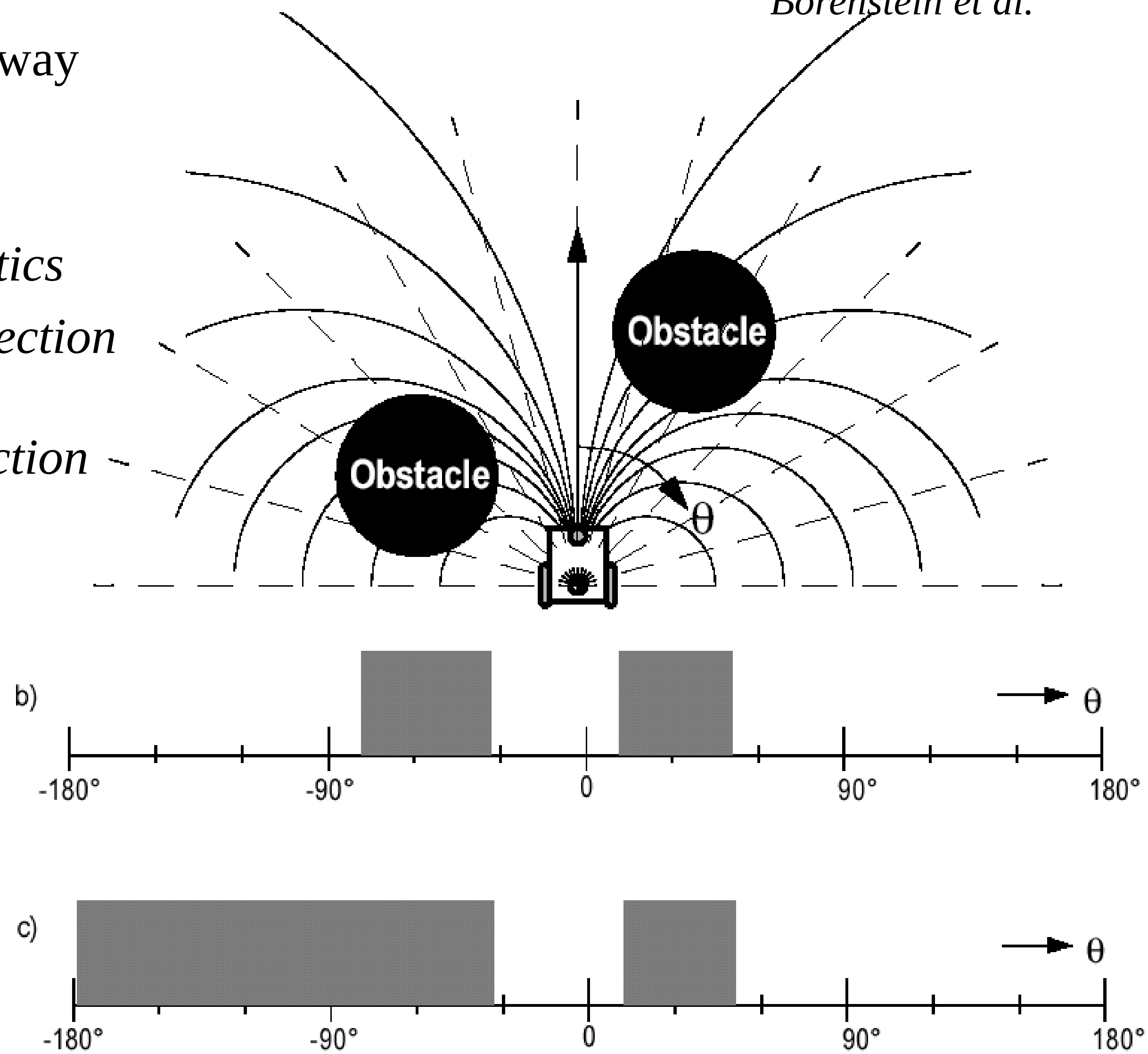
Movie

- VFH in action on Pioneer robot (Tracking_VFH_2x)

Obstacle Avoidance: **Vector Field Histogram + (VFH+)**

Borenstein et al.

- Accounts also in a very simplified way for the moving trajectories
  - *robot can move on arcs*
  - *arcs take into account kinematics*
  - *obstacles blocking a given direction also block all the trajectories (arcs) going through this direction*

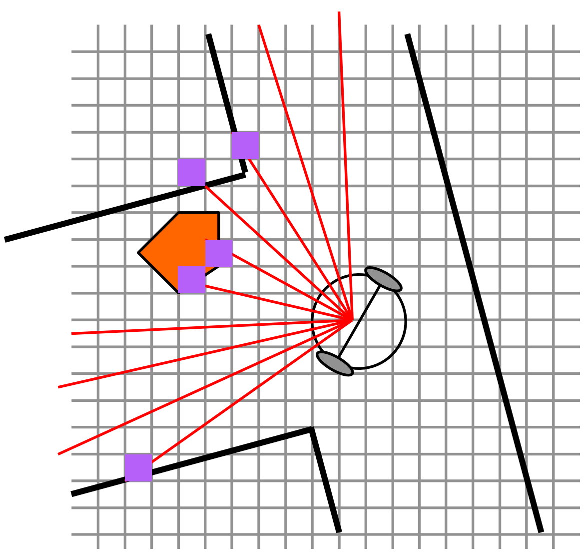


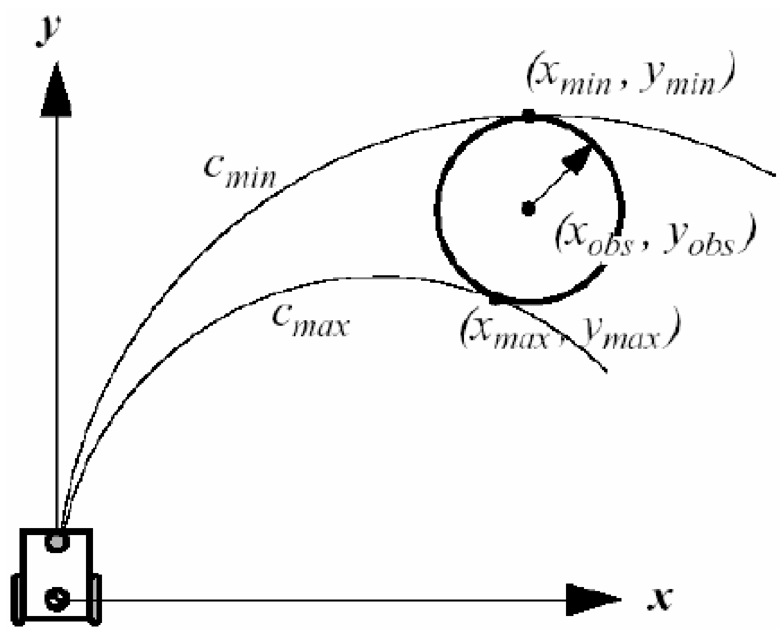
Caprari et al. 2002

Obstacle Avoidance: Basic Curvature Velocity Methods (CVM)

Simmons et al.

- Adding *physical constraints* from the robot and the environment on the *velocity space* (v, ω) of the robot
  - *Assumption that robot is traveling on arcs ($c = \omega / v$)*
  - *Constraints: $-v_{max} < v < v_{max}$ $-\omega_{max} < \omega < \omega_{max}$*
  - *Obstacle constraints: Obstacles are transformed in velocity space*
  - *Objective function used to select the optimal speed*



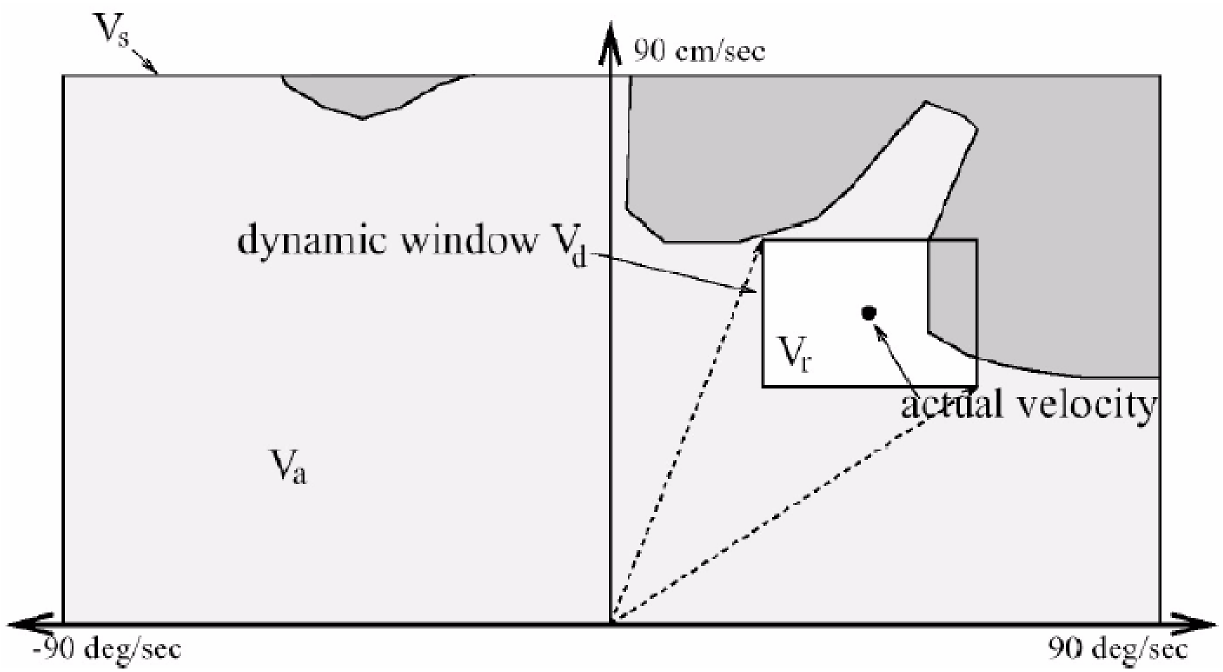


Obstacle Avoidance: **Dynamic Window Approach**

Fox and Burgard, Brock and Khatib

- The kinematics of the robot is considered by searching a well chosen velocity space
  - *velocity space -> some sort of configuration space*
  - *robot is assumed to move on arcs*
  - *ensures that the robot comes to stop before hitting an obstacle*
  - *objective function is chosen to select the optimal velocity*

$$O = a \cdot heading(v, \omega) + b \cdot velocity(v, \omega) + c \cdot dist(v, \omega)$$



- *heading* = progress toward goal
- *velocity* = forward velocity of robot (encourages fast movements)
- *dist* = distance to closest obstacle in trajectory

Obstacle Avoidance: Global **Dynamic Window Approach**

- Global approach:
  - *This is done by adding a minima-free function named NF1 (wave-propagation) to the objective function* O *presented above.*
  - *Occupancy grid is updated from range measurements*