Building Local Safety Maps for a Wheelchair Robot using Vision and Lasers

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Overall Goal

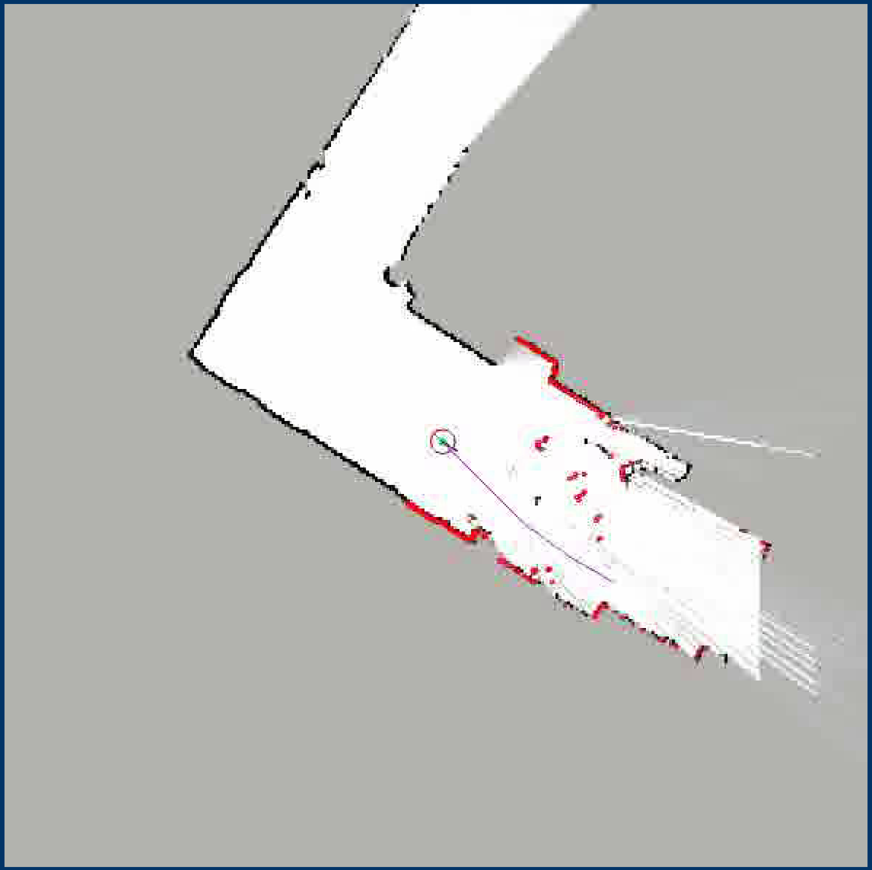
- Safe navigation of a wheelchair robot in a large scale urban environment
- This work addresses safety
- Approach: Use 2D local metrical maps to represent the navigability of the 3D environment

Safe Navigation for a Wheelchair Robot

- Why 2D local metrical maps are sufficient
  - For safety only local surroundings matter
  - Wheelchair moves on a 2-manifold

Safe Navigation for a Wheelchair Robot

- Advantages of using 2D local metrical maps
  - Computation stays bounded
  - Don't mix safety issues with global mapping issues



2D *scrolling* local metrical map constructed using lasers

Safe Navigation for a Wheelchair Robot

- Multimodal sensing is required
  - Sensors have limitations & strengths

2D lasers do not see table top but stereo does

Safe Navigation for a Wheelchair Robot

- Why multimodal sensing is required
  - Sensors have limitations & strengths

Lasers, stereo fail to distinguish sidewalk from mud, but color does

Safe Navigation for a Wheelchair Robot

- Why multimodal sensing is required
  - Sensors have limitations & strengths

Lasers, stereo do not detect glass but bump & sonar sometimes detect it

Approach

- Represent the environment using local 2D metrical maps annotated with safety information
  - called ***local safety maps***
- Use lasers (2D) & stereo to build safety maps of level environments (for now)
- Use an existing hybrid mapping framework to build global maps for large scale navigation
  - [Kuipers, et. al, ICRA ‘04]

Outline

- The environment and the local safety map
- Constructing the local safety map
- Results and conclusions

The Environment

- Wheelchair accessible urban environment
  - conforms to the Americans with Disabilities Act
- Environment has pedestrians and low speed traffic
  - e.g. a University campus

Urban Environment: Features relevant to safety

Fixed obstacles

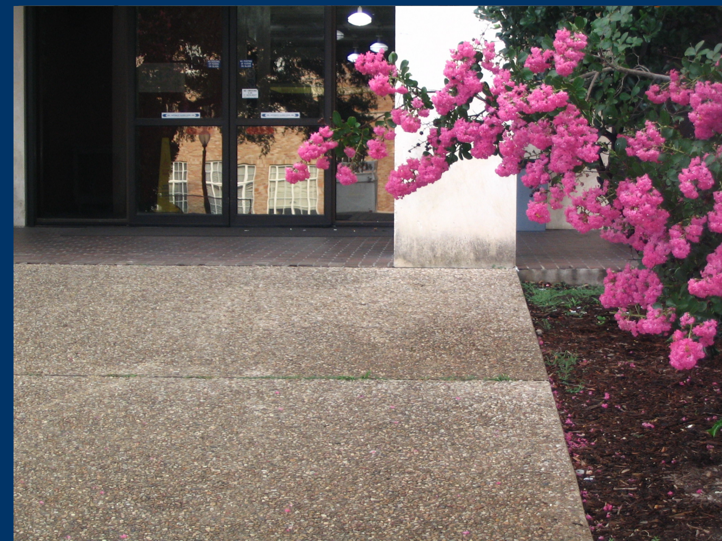
Overhangs

Drop-offs

Inclines

Urban Environment: Features relevant to safety

Fixed obstacles



Overhangs

Drop-offs

Inclines

Urban Environment: Features relevant to safety

Narrow regions

Dynamic obstacles

Rough/uneven surfaces

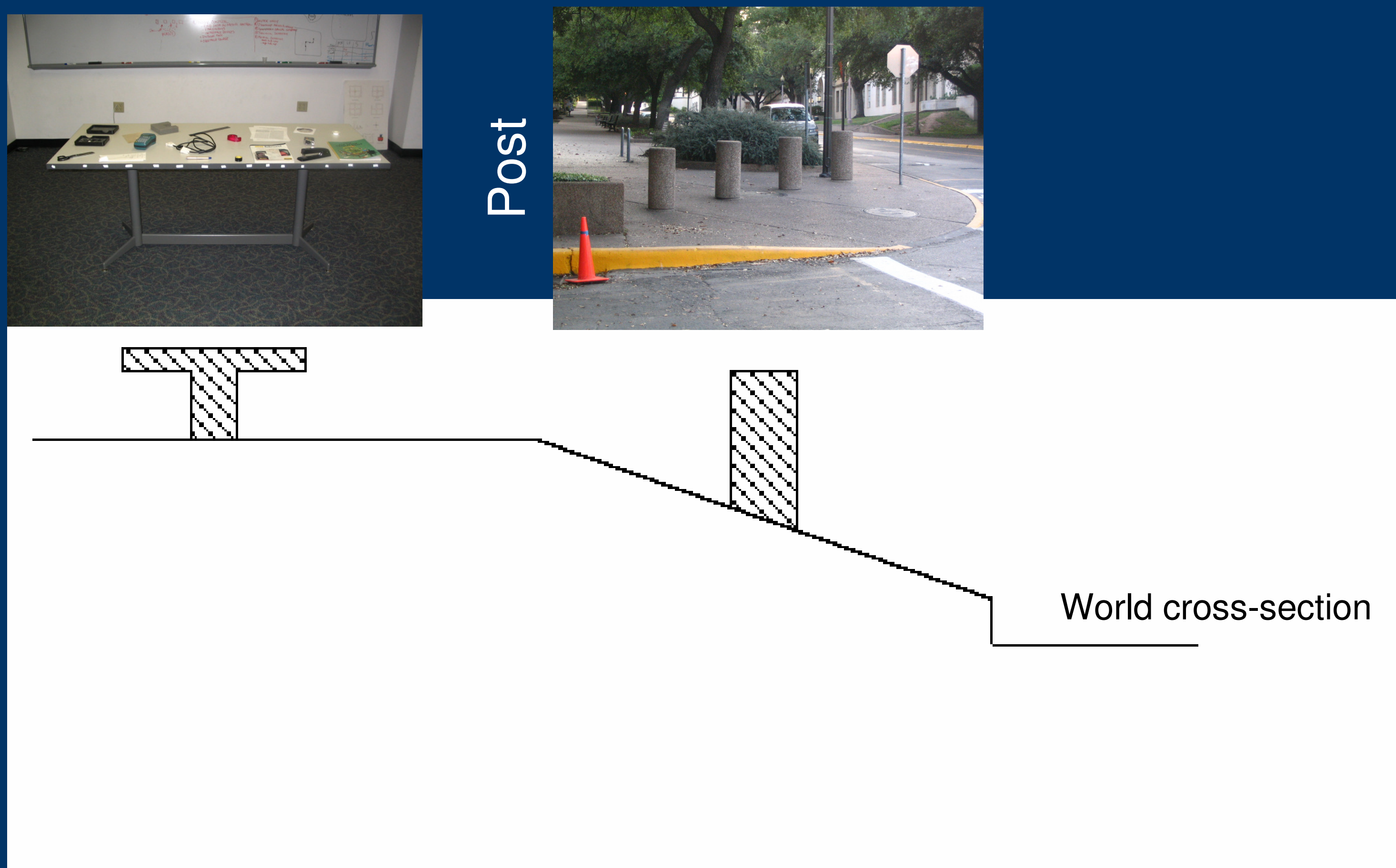
Invisible obstacles

Safety Classification

- Obstacles *("Can't go there")*
  - fixed, dynamic, etc
- Hazards *("Shouldn't go there")*
  - overhangs, drop offs, etc
- Caution areas *("Slow down")*
  - inclines, narrow regions, etc
- Unknown areas *("Stop, look, & listen")*
  - insufficient data
- Safe areas *("Full speed ahead")*

The Local Safety Map

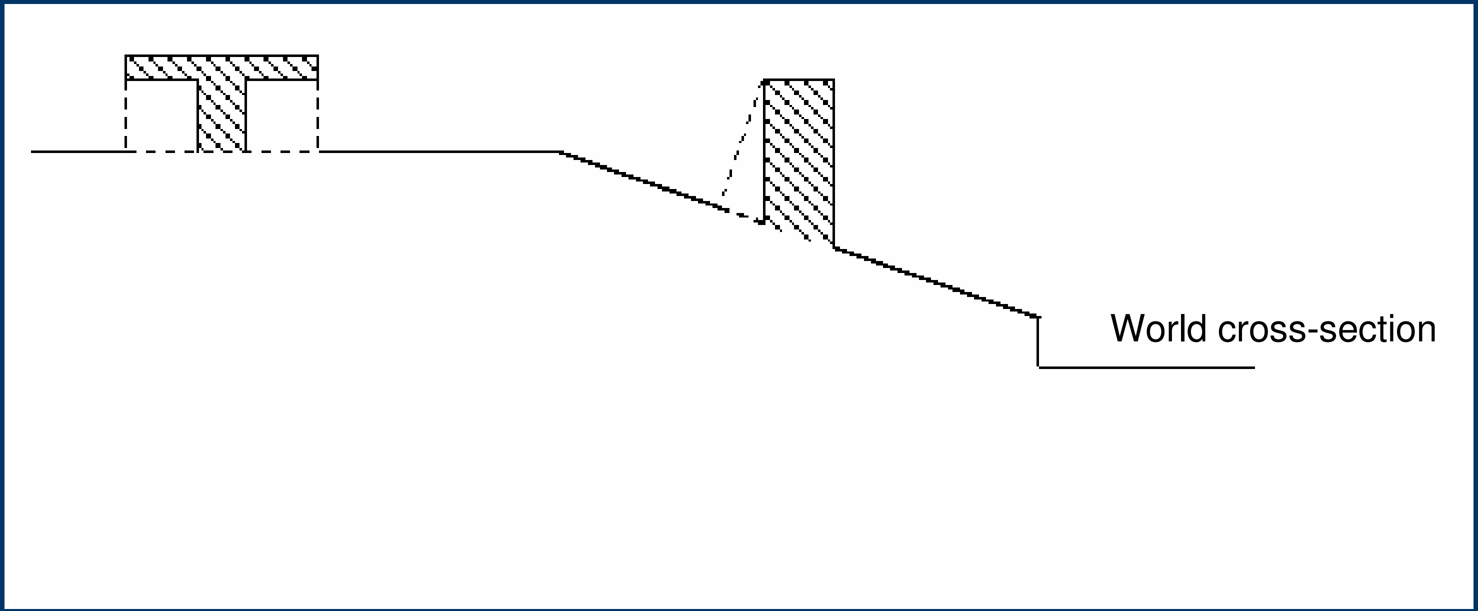
Table



safety map = f (agent, environment)

The Local Safety Map

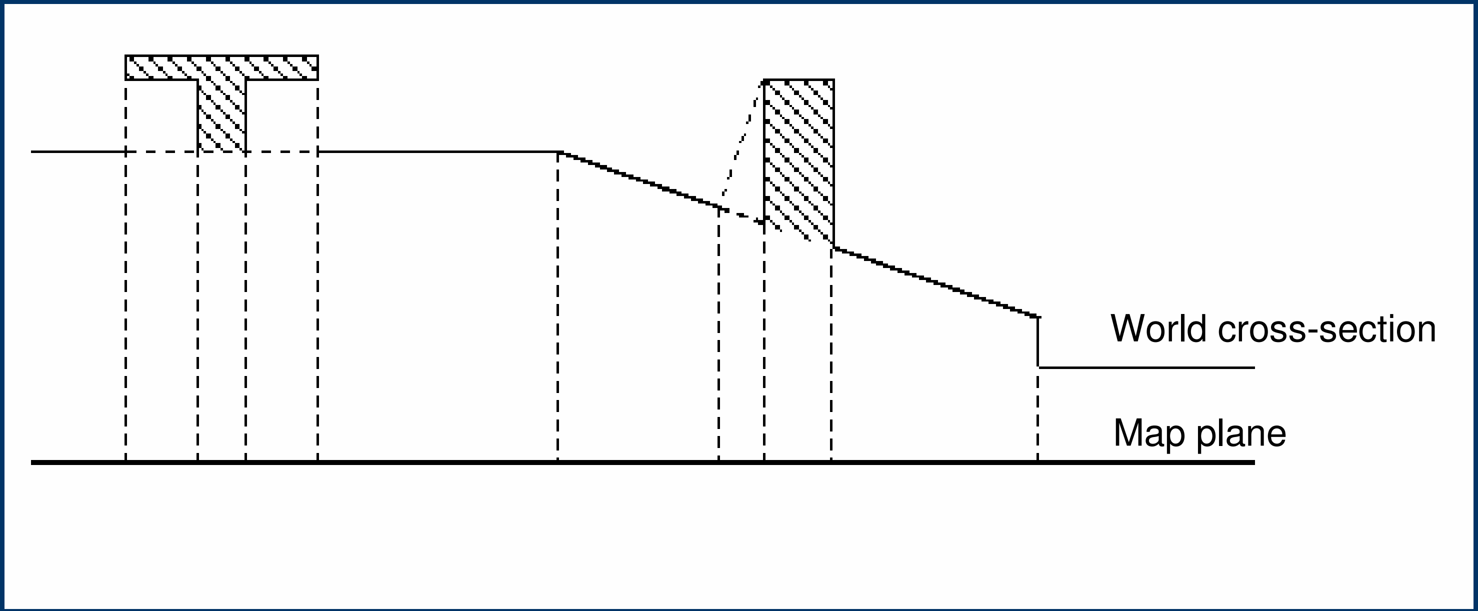
Project objects/features perpendicular to local ground plane



safety map = f (agent, environment)

The Local Safety Map

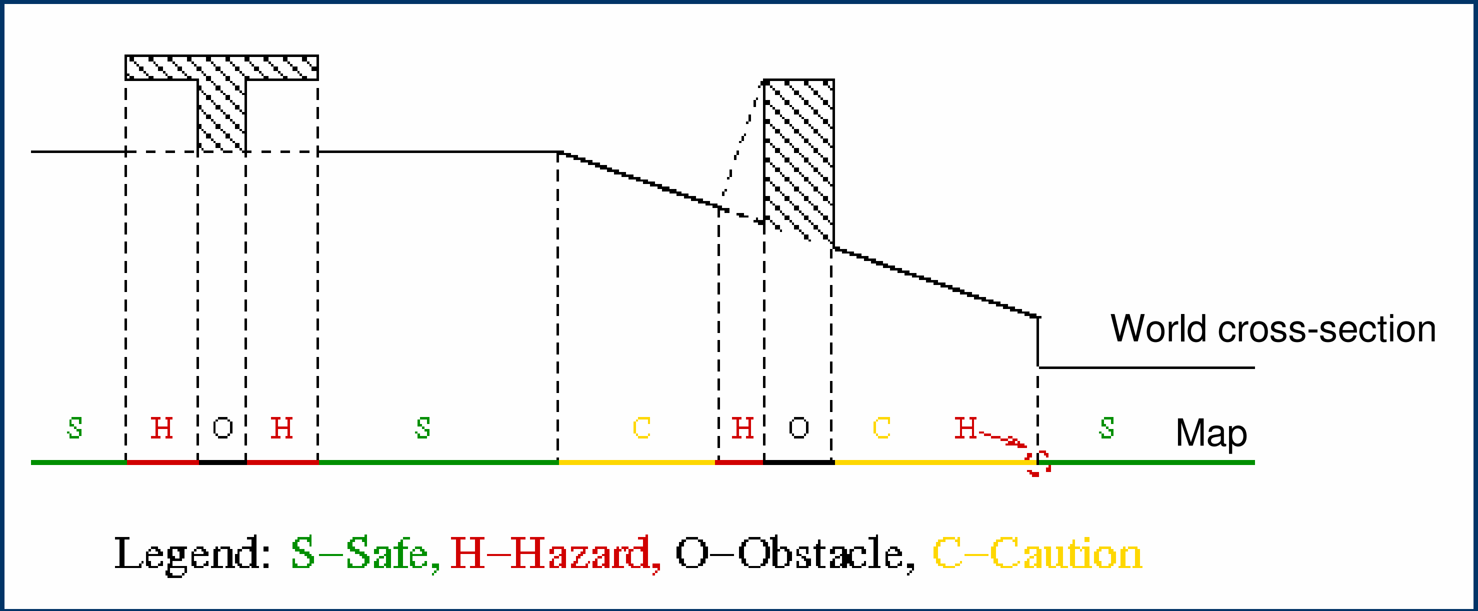
Project further to the map plane to define distinct regions



safety map = f (agent, environment)

The Local Safety Map

Classify regions to get safety map



safety map = f (agent, environment)

The Local Safety Map: Example

Green – Safe

Black – Obstacle

Red – Hazard

Gray – Unknown

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Constructing the Local Safety Map

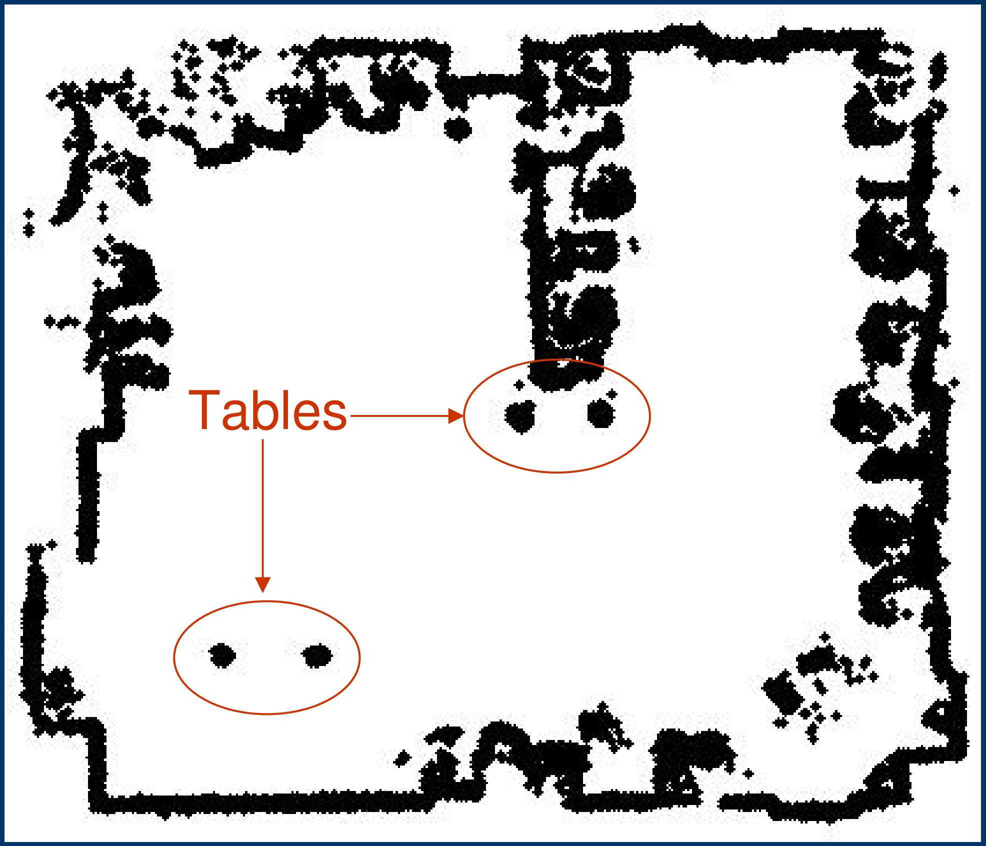
1. Use lasers for localization with respect to the local surroundings

2. Build geometric models of the local surroundings using lasers and stereo

3. Construct safety map by projecting the models onto the ground plane & classifying projected regions

Lasers: Localization & 2D metric map

- Standard particle filter based SLAM algorithm
  - Accurate 3 dof localization
  - 2D occupancy grid map



Stereo: 3D point cloud

1. 3D point landmarks obtained in robot's egocentric reference frame using
   - dense (correlation-based) stereo or,
   - feature-based stereo (SIFT [Lowe, IJCV, '04])
2. Landmark locations transformed from egocentric to local map reference frame using laser localization
3. Observed landmarks matched to existing landmarks using a Bayesian method
4. Landmark locations updated and tracked using Kalman filters

Bayesian Data Association

- For each existing landmark, L_P,
  - find the current observation, L_{O^*}, that maximizes the probability that the observation and landmark match:

$$L_{O^*} = \underset{L_O}{\arg\max}\ p\,(L_O = L_P \mid X_O, X_P, V_O, V_P)$$

  - where, the probability of a match is computed based on the observation's and landmark's
    - locations (X_O , X_P), and
    - visual properties (V_O , V_P)

Bayesian Data Association

- For Gaussian error models:

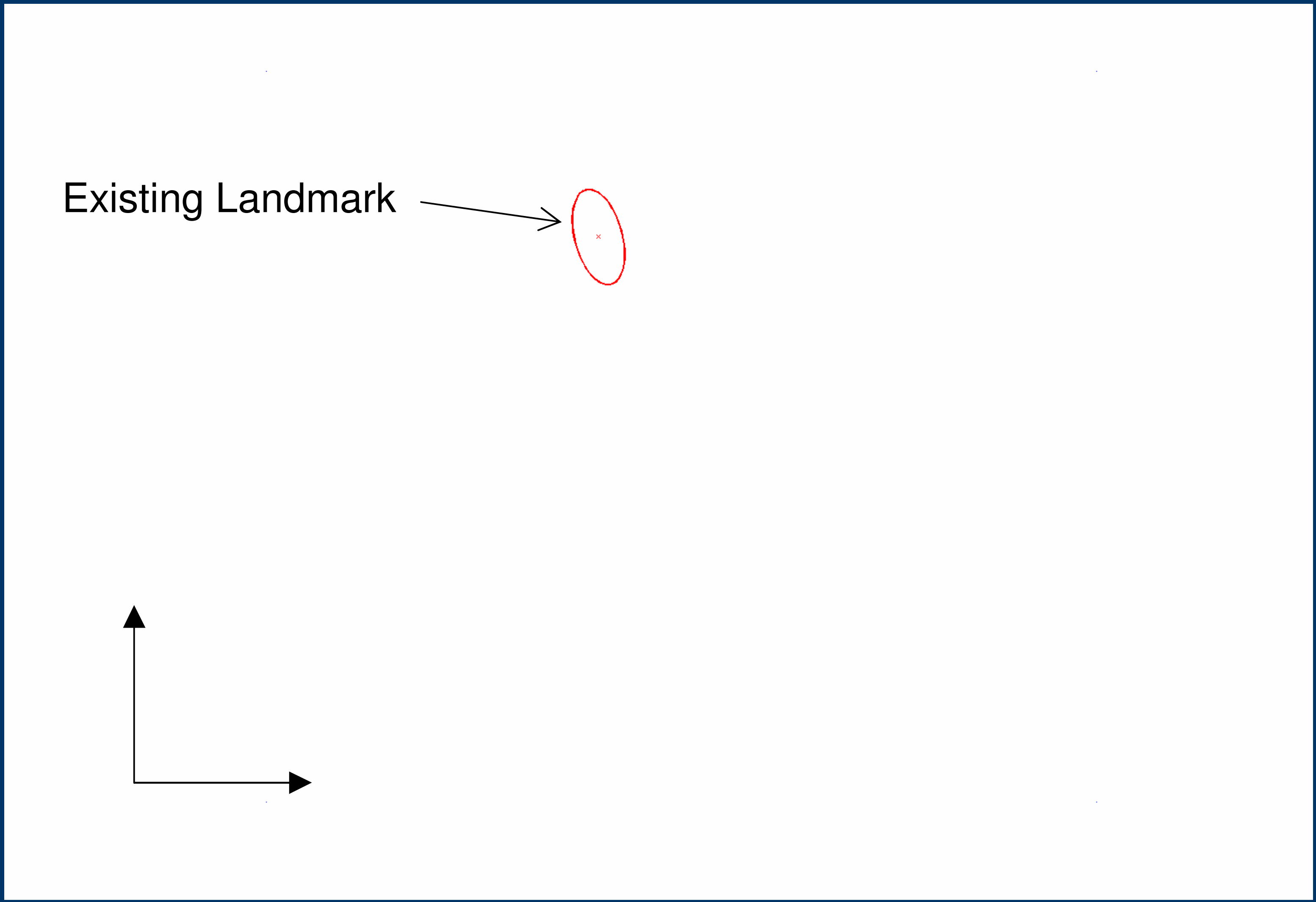
  maximizing matching probability = minimizing (square of) the Mahalanobis distance

$$L_{O^*} = \underset{L_O}{\arg\min}\ (X_O - X_P)^T(\Sigma_O + \Sigma_P)^{-1}(X_O - X_P) + (V_O - V_P)^T\Sigma^{-1}(V_O - V_P)$$

- Also use Mahalanobis distance for identifying new landmarks and eliminating false observations

- Previous work: [Reid, TAC, '79], [Dissanayake, et. al, TRA, '01]

Bayesian Data Association



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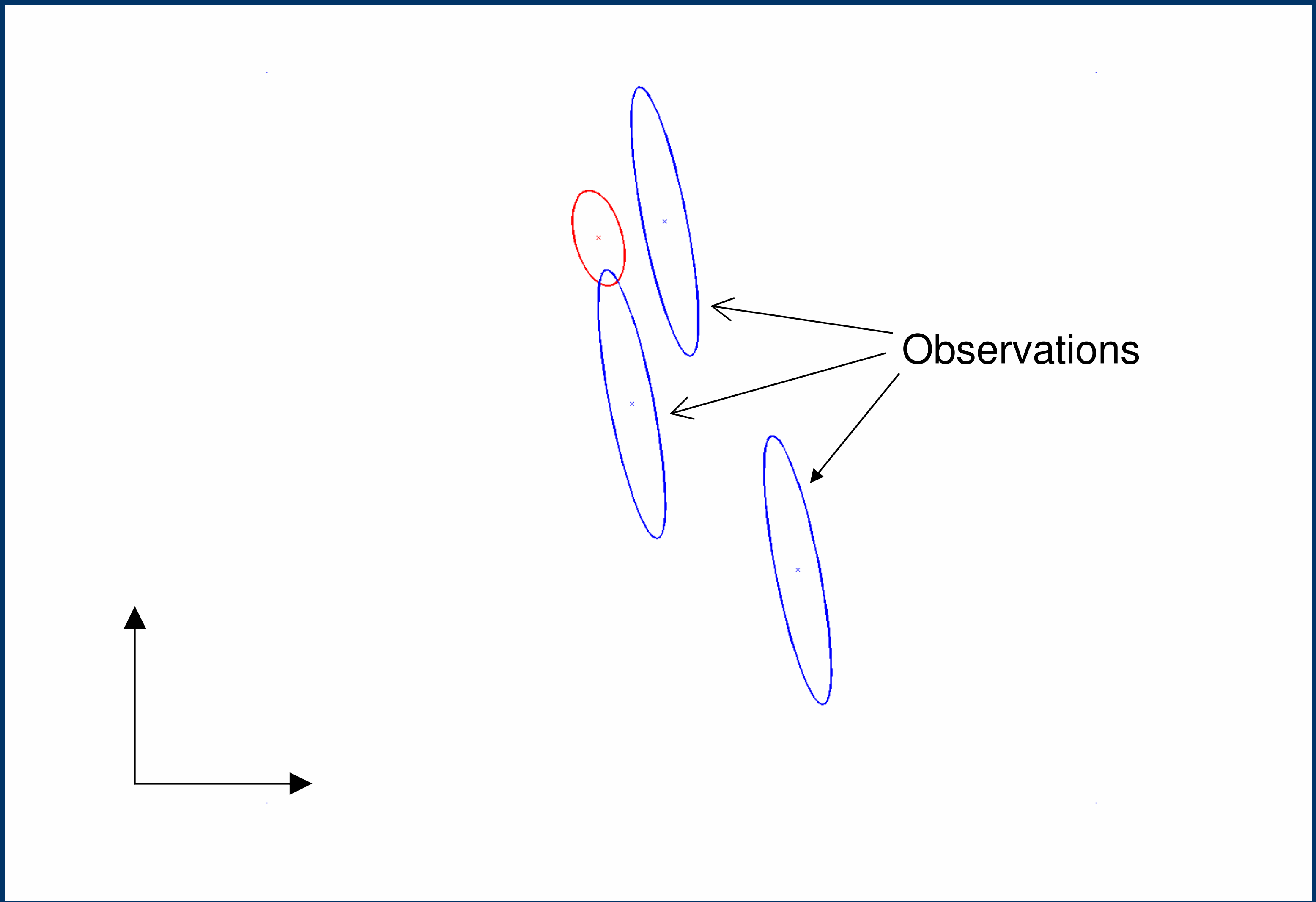

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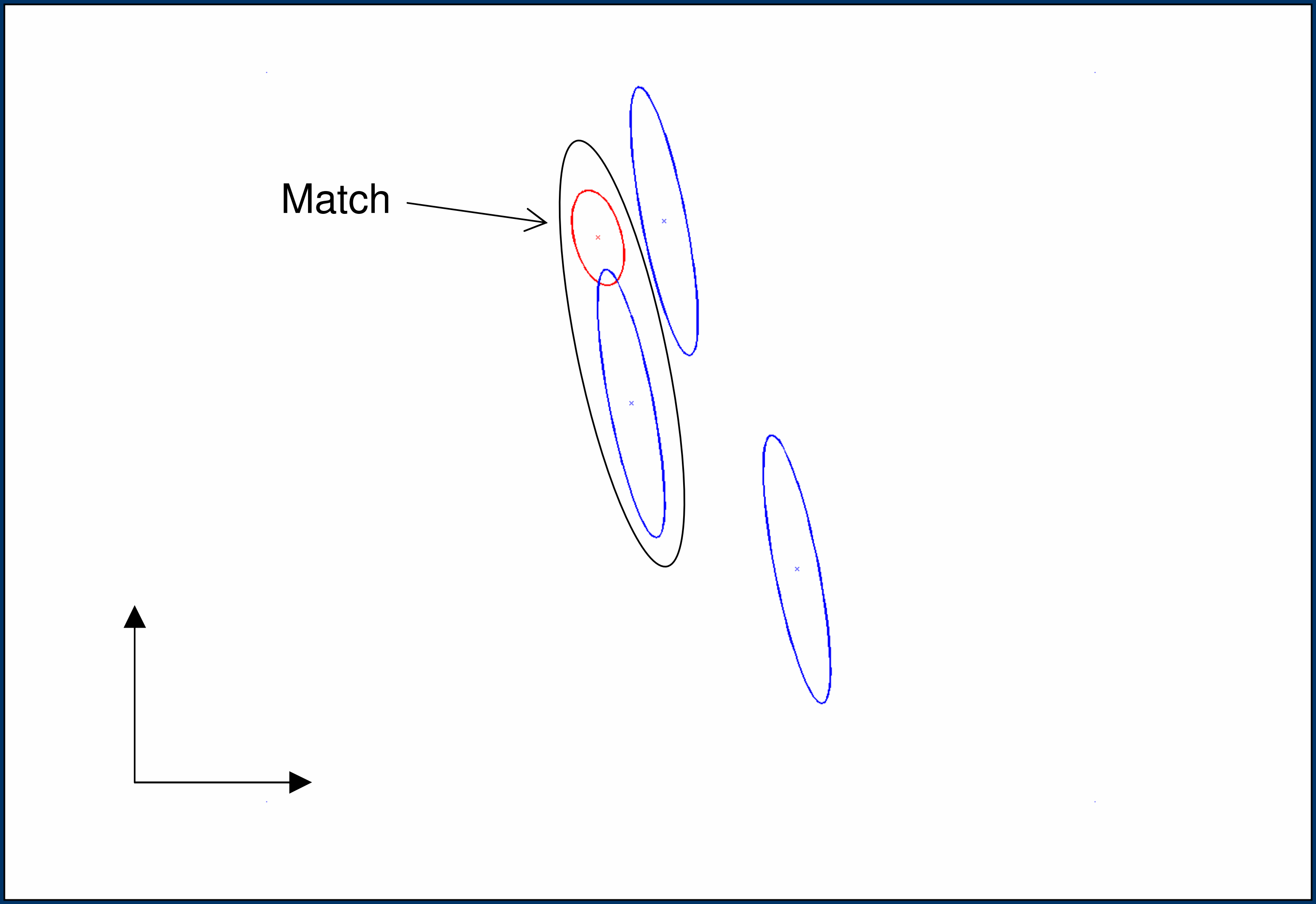
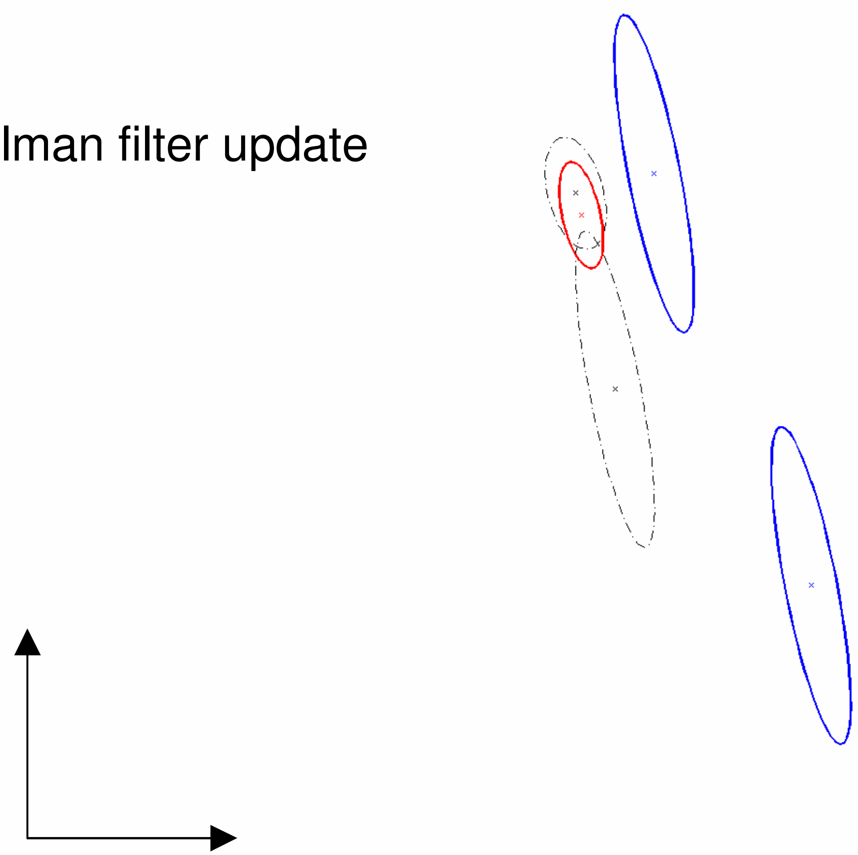
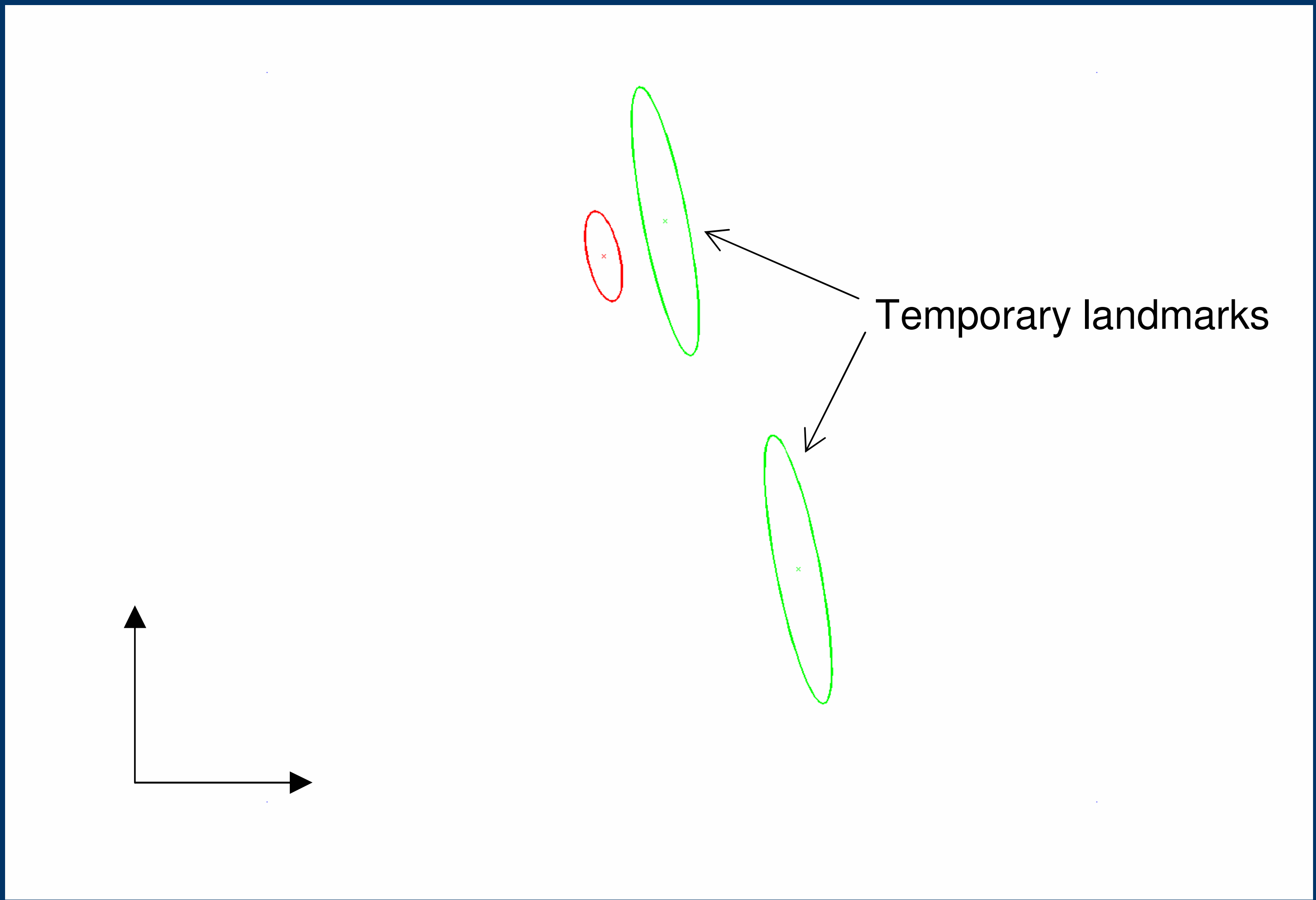


Bayesian Data Association

Kalman filter update



Bayesian Data Association



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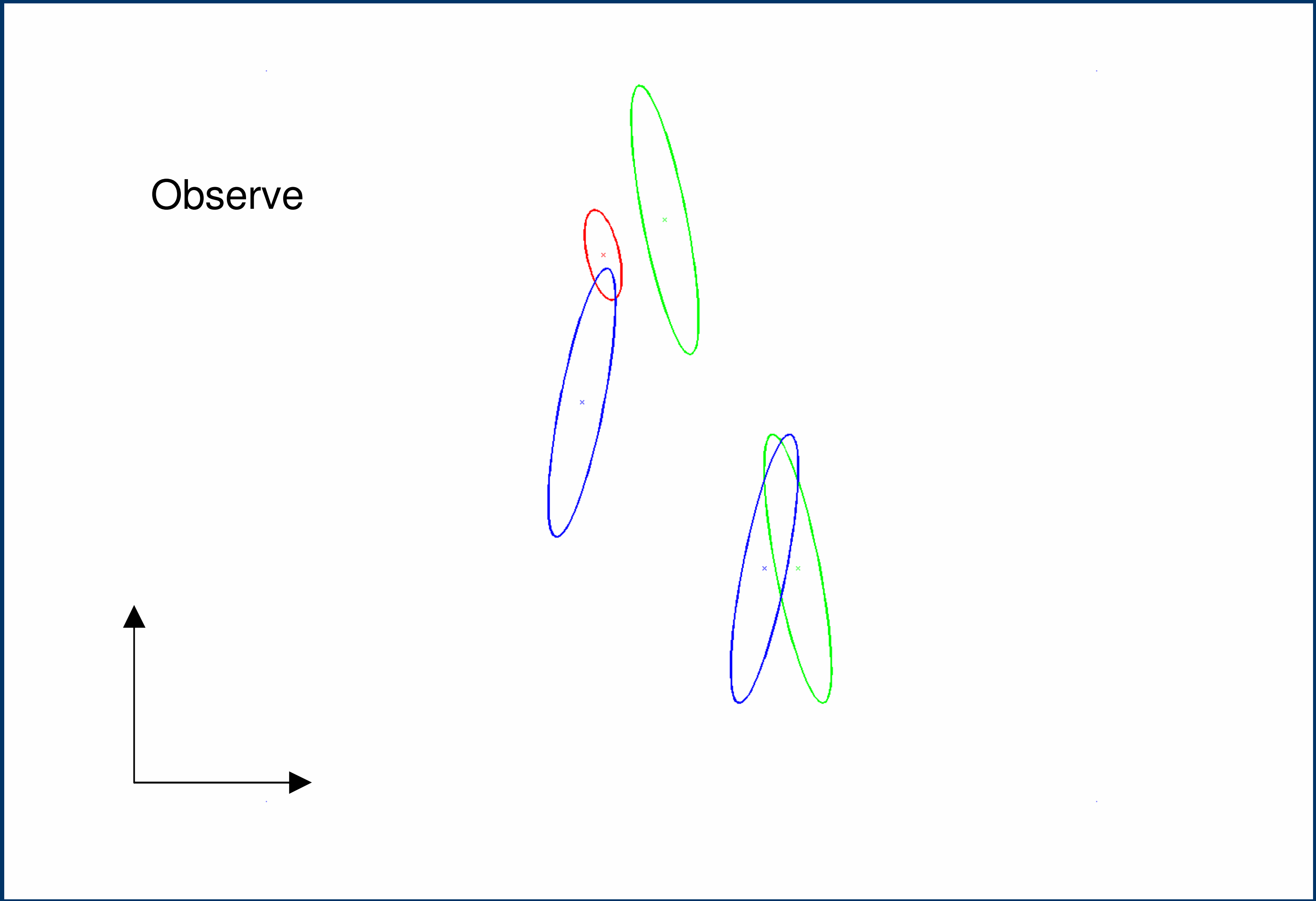

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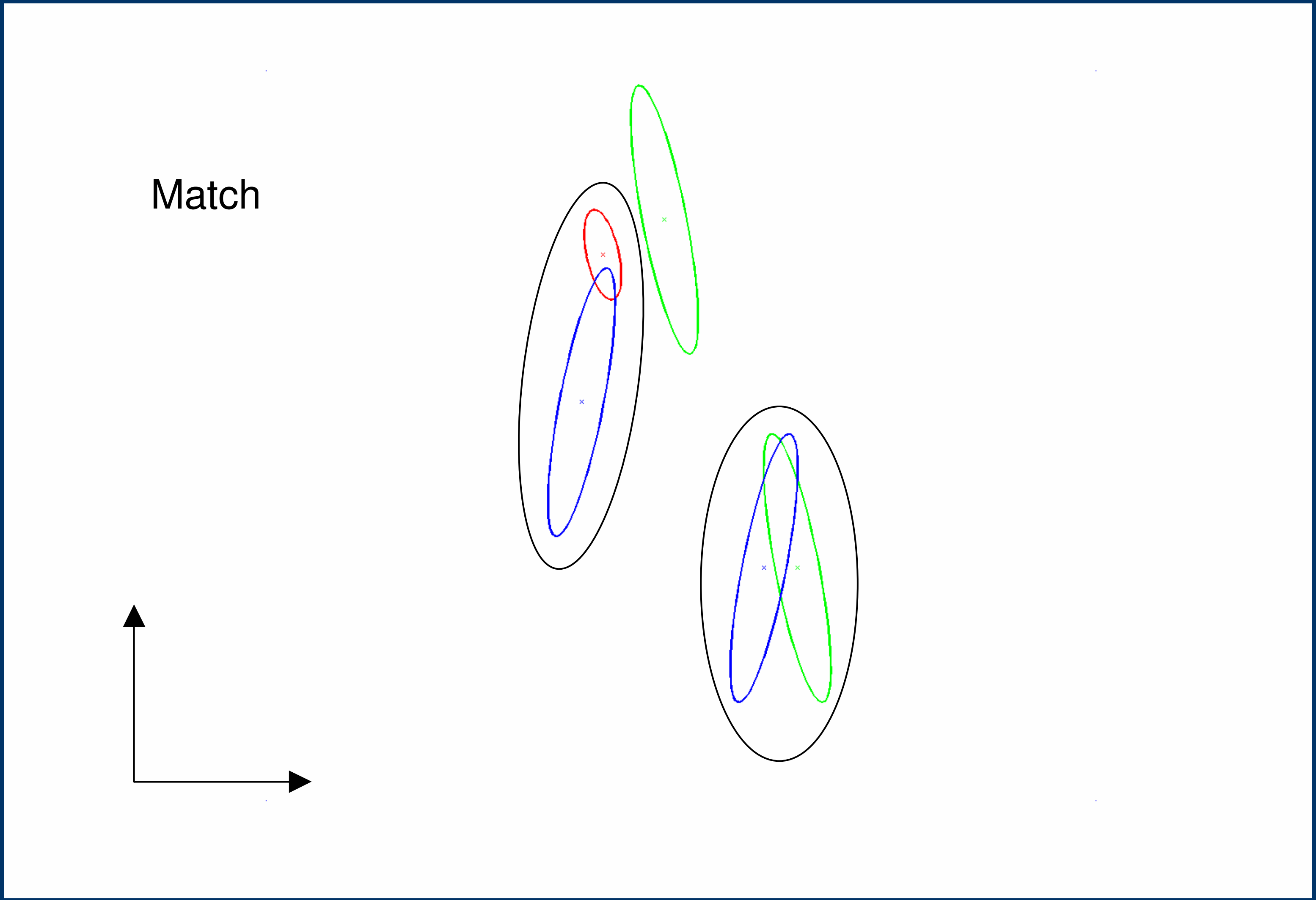

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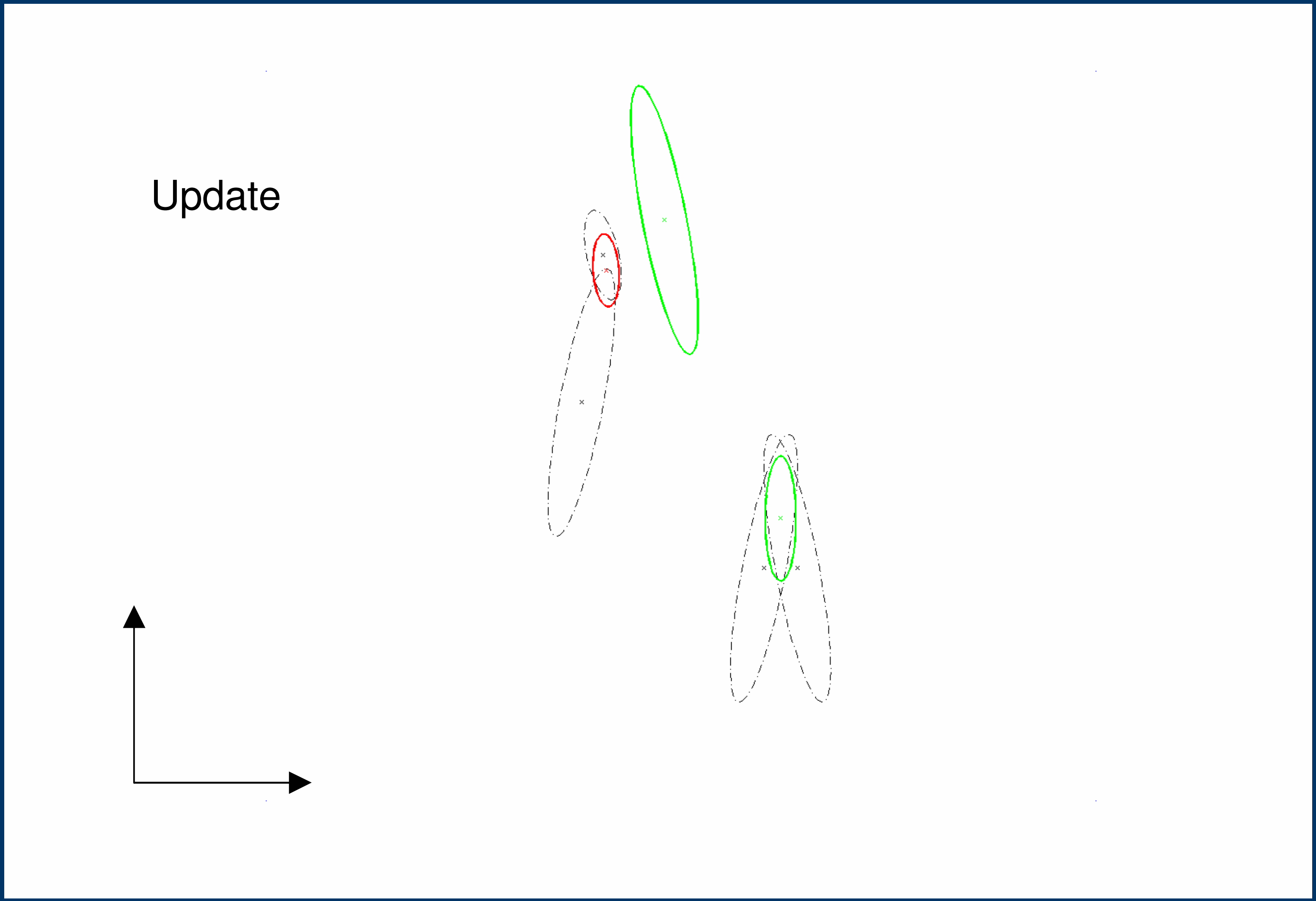

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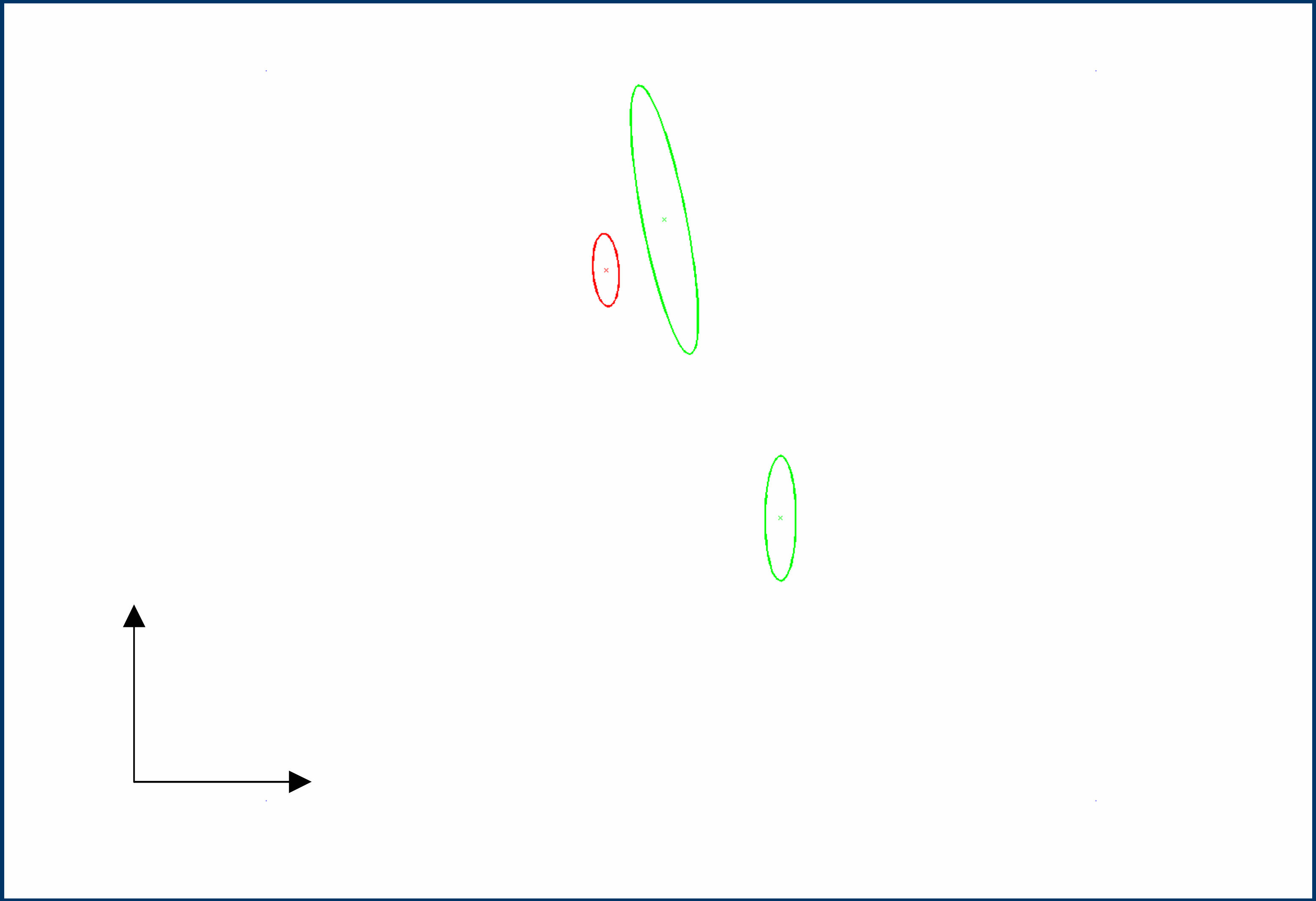

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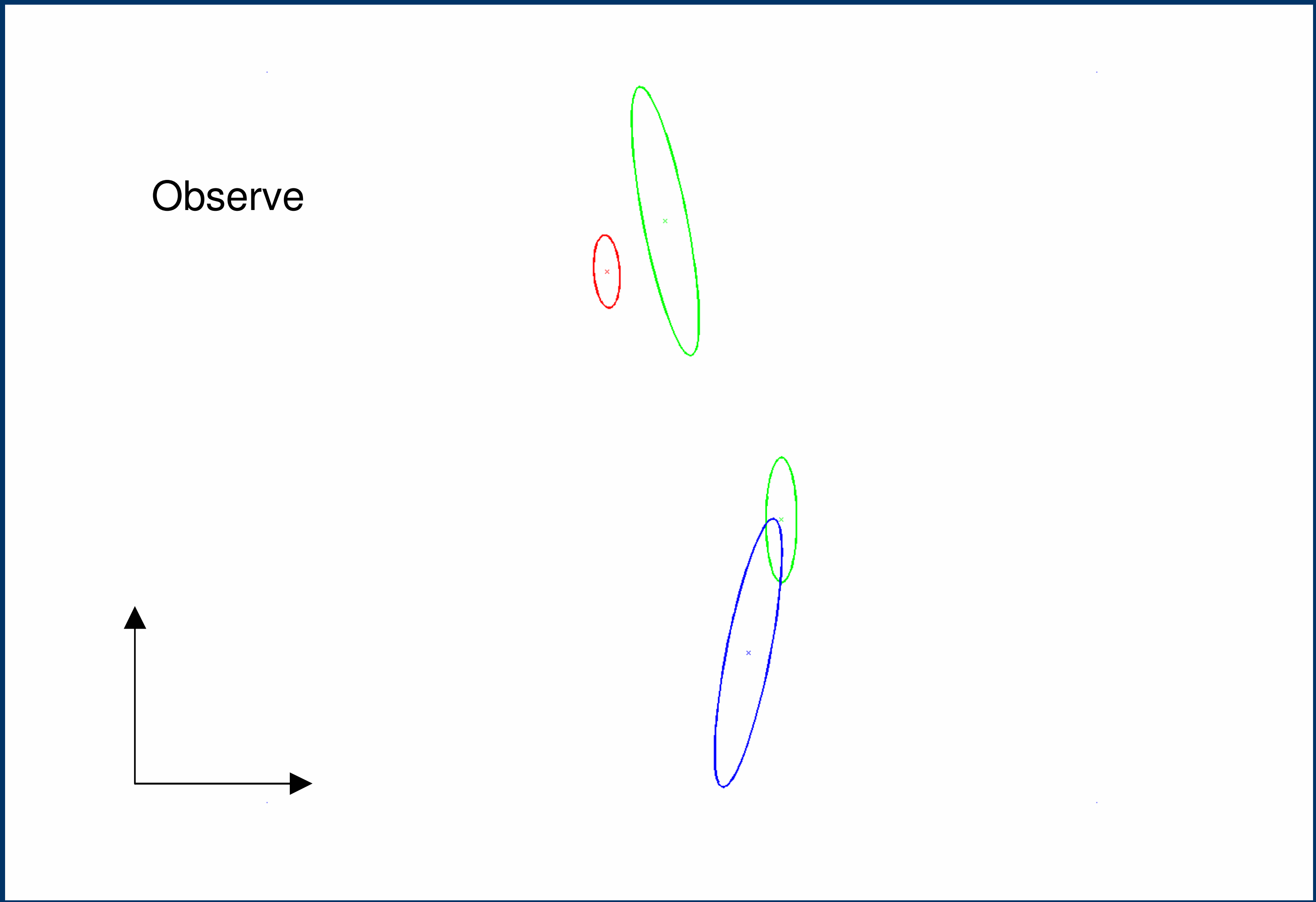

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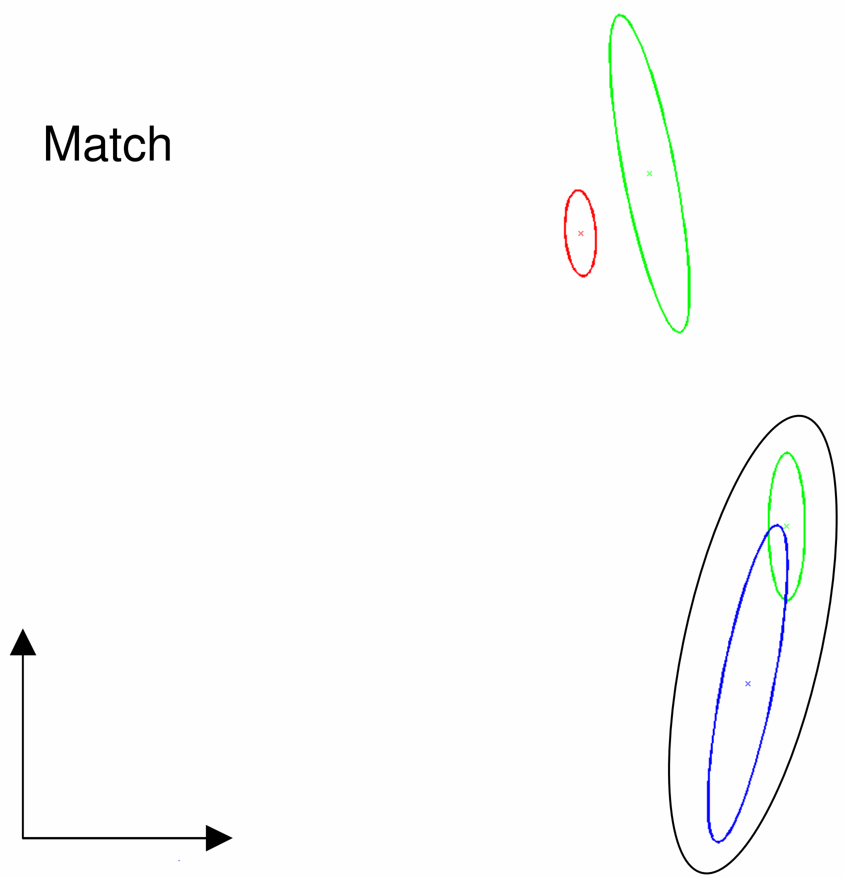

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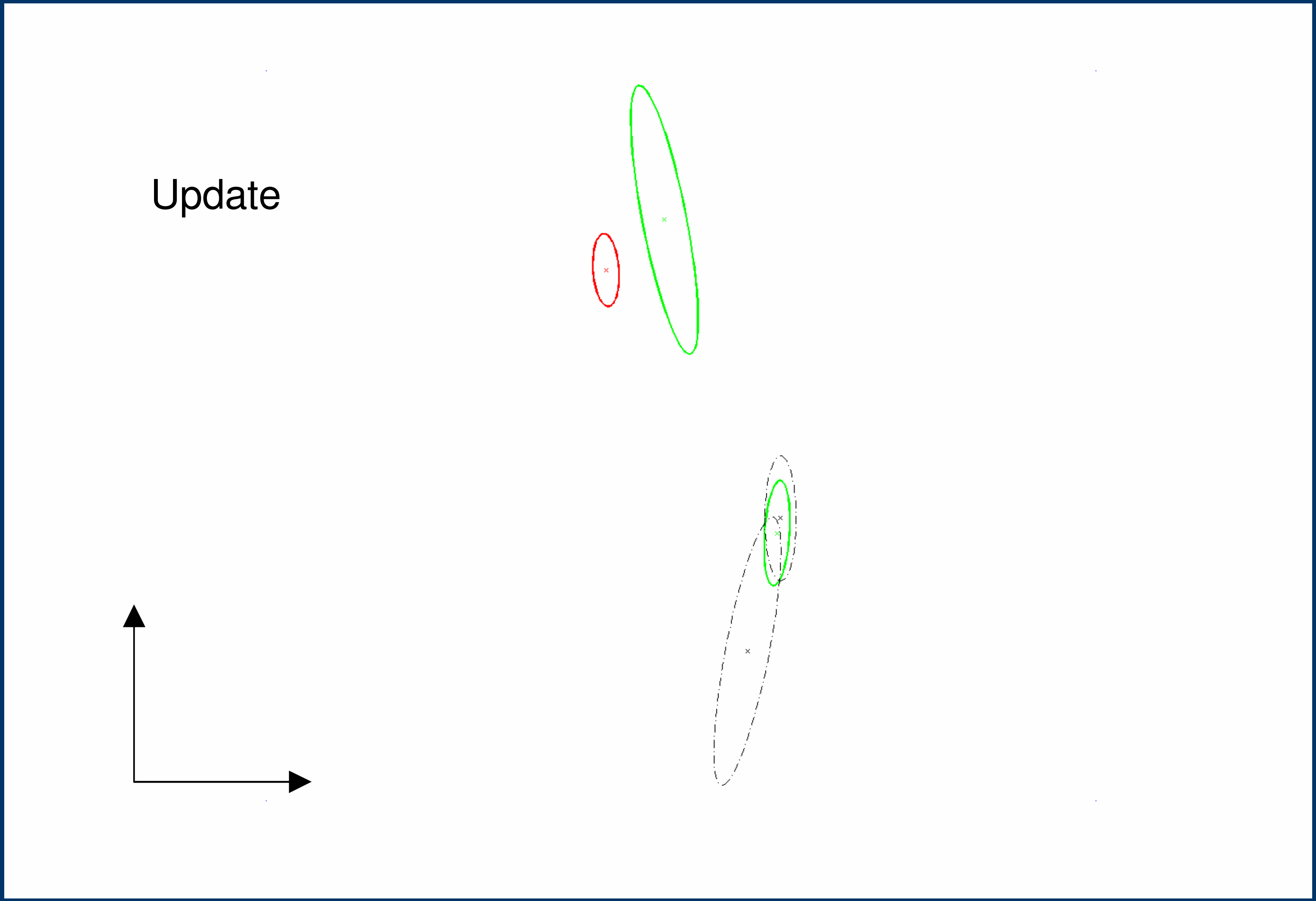

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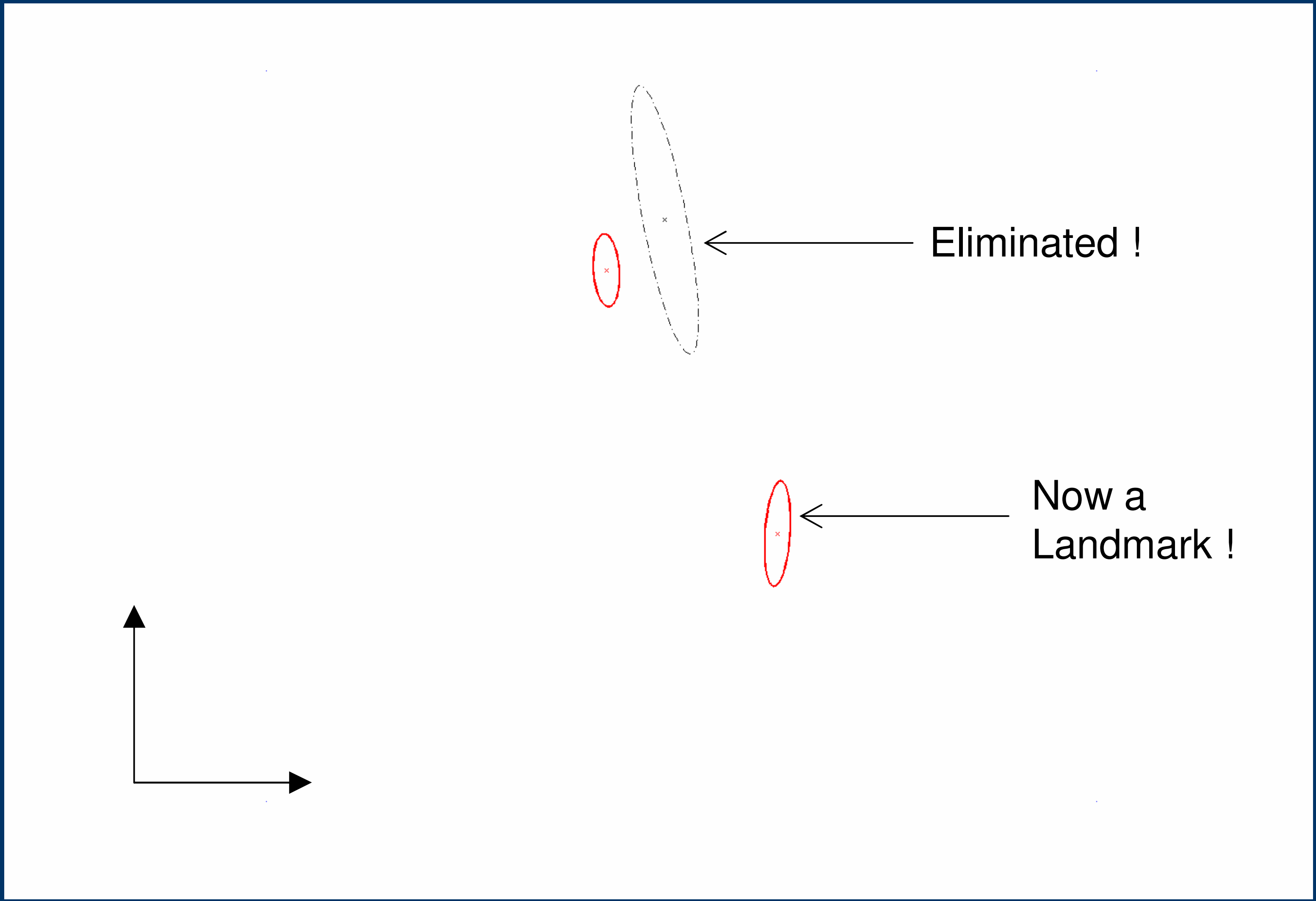
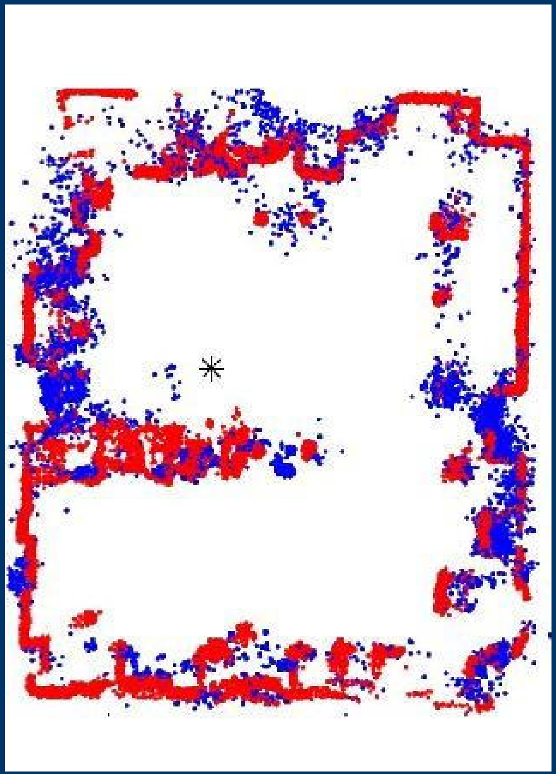


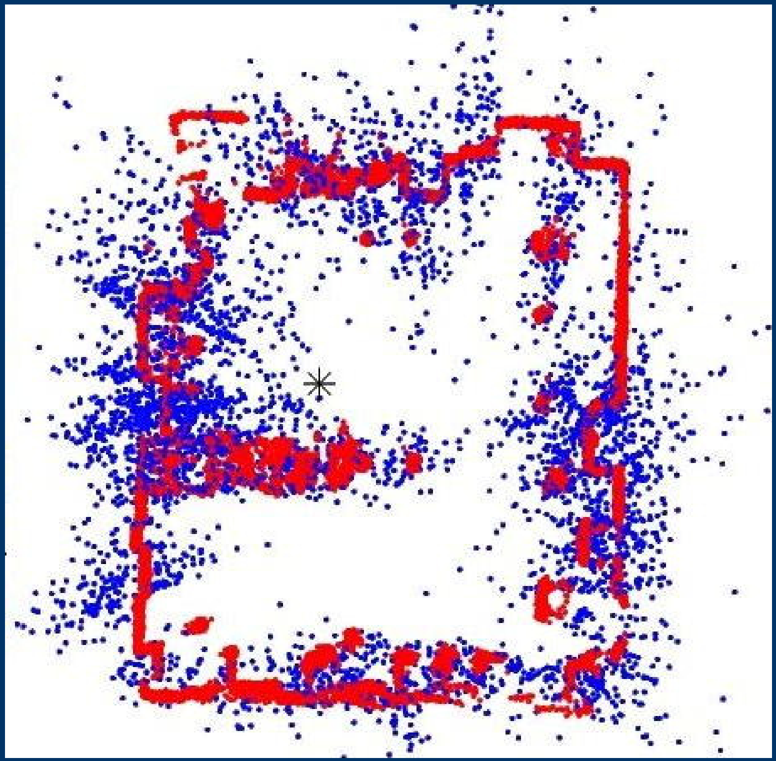
Mahalanobis Distance Removes False Observations

Stereo 3D point cloud (in blue) constructed using 2 different metrics overlaid on a 2D laser map (in red)

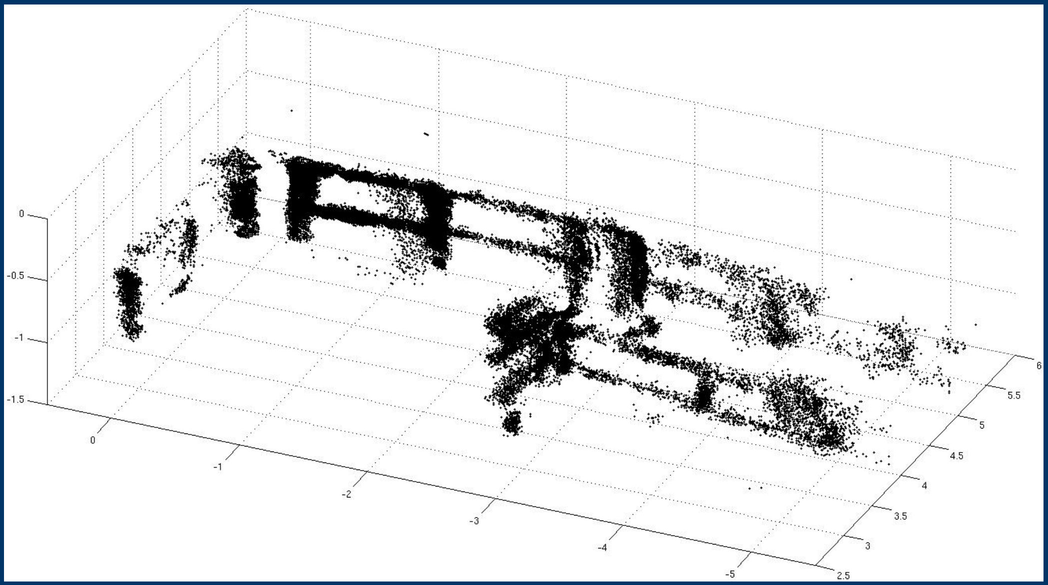
Mahalanobis distance



Euclidean distance



Stereo: Good 3D models obtained



Current Rules for Obtaining the Safety Map

- Project geometric model onto the ground plane
- Classify projected regions in the plane as
  - an obstacle
    - if detected by stereo to be above the ground plane, and
    - if detected by lasers
  - a hazard (overhang)
    - if detected by stereo to be above the ground plane, and
    - if invisible to lasers
  - safe
    - if detected by stereo to be on the ground plane or if not detected at all, and
    - if invisible to lasers
  - unknown
    - if not detected by lasers and stereo

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Results: Safety maps of the lab

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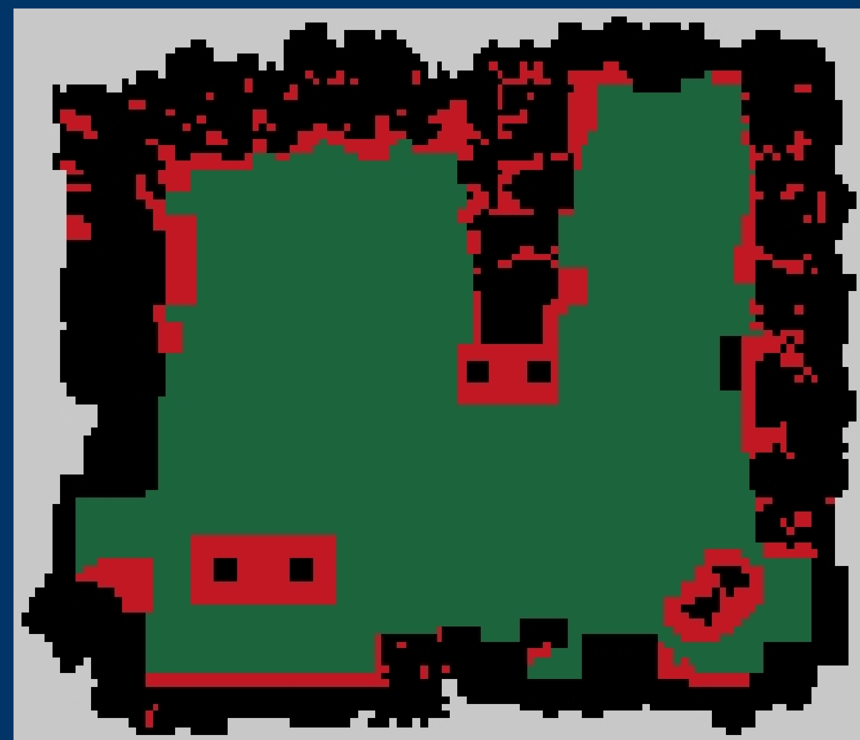
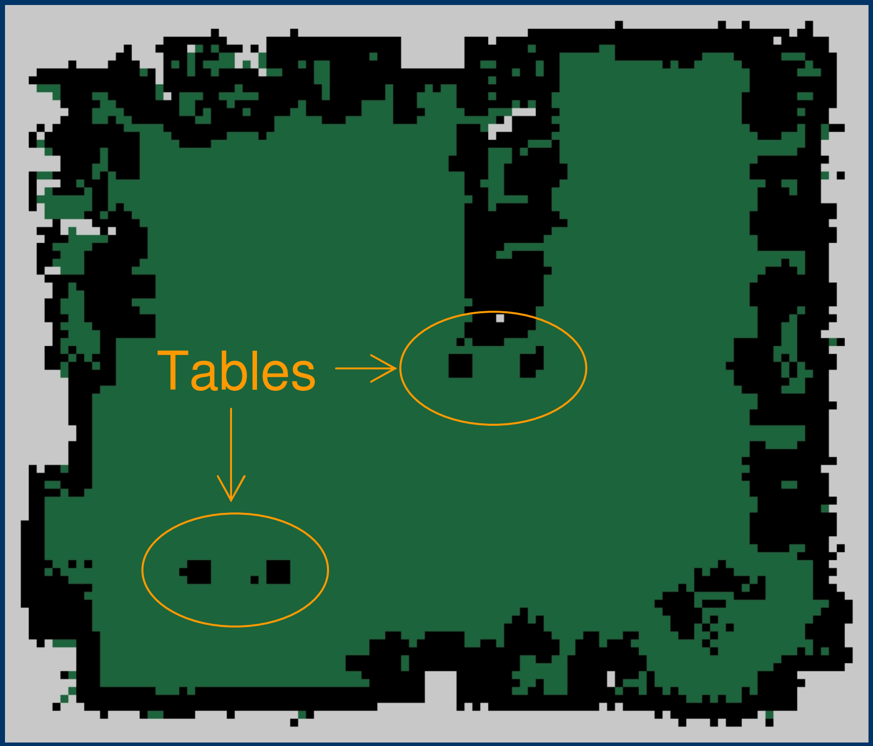


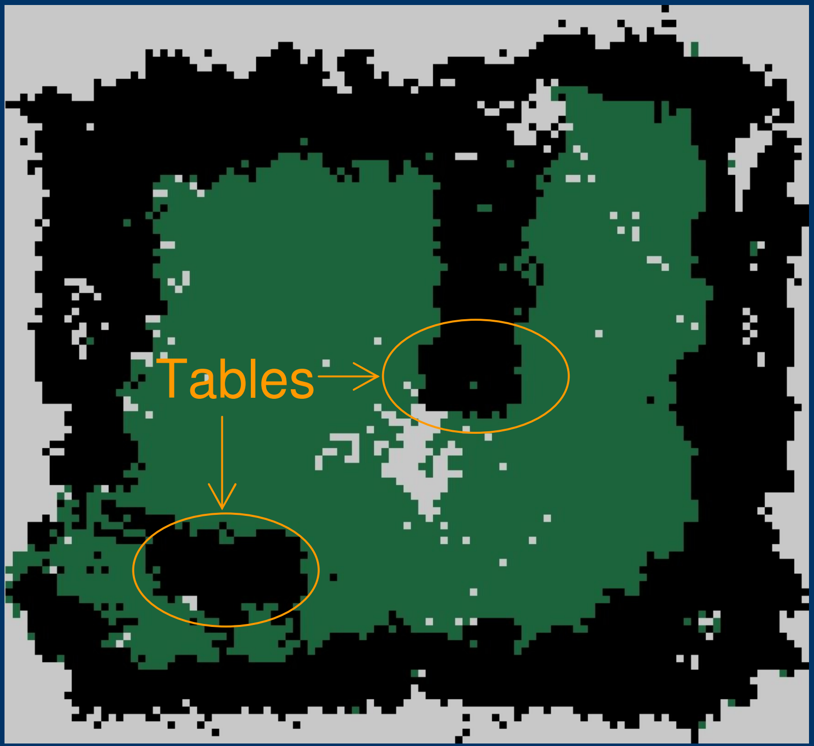
Made using lasers & stereo

Manually annotated

Legend: Safe, **Obstacle**, Hazard, Unknown

Results: Safety maps of the lab





Made using only lasers

Made using only stereo

Legend: Safe, **Obstacle**, Hazard, Unknown

Evaluating the Safety Maps: Precision & Recall

- **Precision**: Ratio of all cells marked safe by the robot, that are actually safe
  - *Precision = #TP / (#TP + #FP)*

- **Recall**: Ratio of all cells that are actually safe, that are marked safe by the robot
  - *Recall = #TP / (#TP + #FN)*

- **F**: Combined measure of precision & recall
  - *F = 2 x #TP / (2 x #TP + #FP + #FN)*

- *Where,*
  - TP (True Positive): cell marked safe and is actually safe
  - FP (False Positive): cell marked safe but is actually unsafe
  - FN (False Negative): cell marked unsafe but is actually safe

Evaluating the Safety Maps: Results

- Laser map
  - Very high recall (~1): safe areas rarely marked as unsafe
  - Low precision: overhangs not detected
- Stereo map
  - High precision (~0.95) : most objects detected
  - Low recall due to noise
- Laser & stereo map
  - Improves stereo recall
  - Improves laser precision
  - Has highest F measure

Conclusions

- 2D local safety maps are sufficient for safe navigation for a wheelchair robot
- Multimodal sensing is necessary for constructing the local safety maps
- Mahalanobis distance is an effective metric for dense stereo data association

Future Work

- Using other visual cues, in addition to stereo, to learn safety classification
  - e.g., color and texture
    - [Ulrich & Nourbakhsh, AAAI `00]
    - [Saxena, Chung, & Ng, NIPS `05]
- Extending to non-level (inclined) environments
  - 6 dof localization using lasers and vision
- Auto-calibrating the sensors against each other
- Optimizing for real-time performance

Thank you

Questions?

http://www.cs.utexas.edu/~qr/robotics