Multiple View Geometry Applications to Robotic and Video Manipulation

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International Institute Of Information Technology

Advisor: Dr. C. V. Jawahar / P. J. Narayanan

Multiple View Geometry

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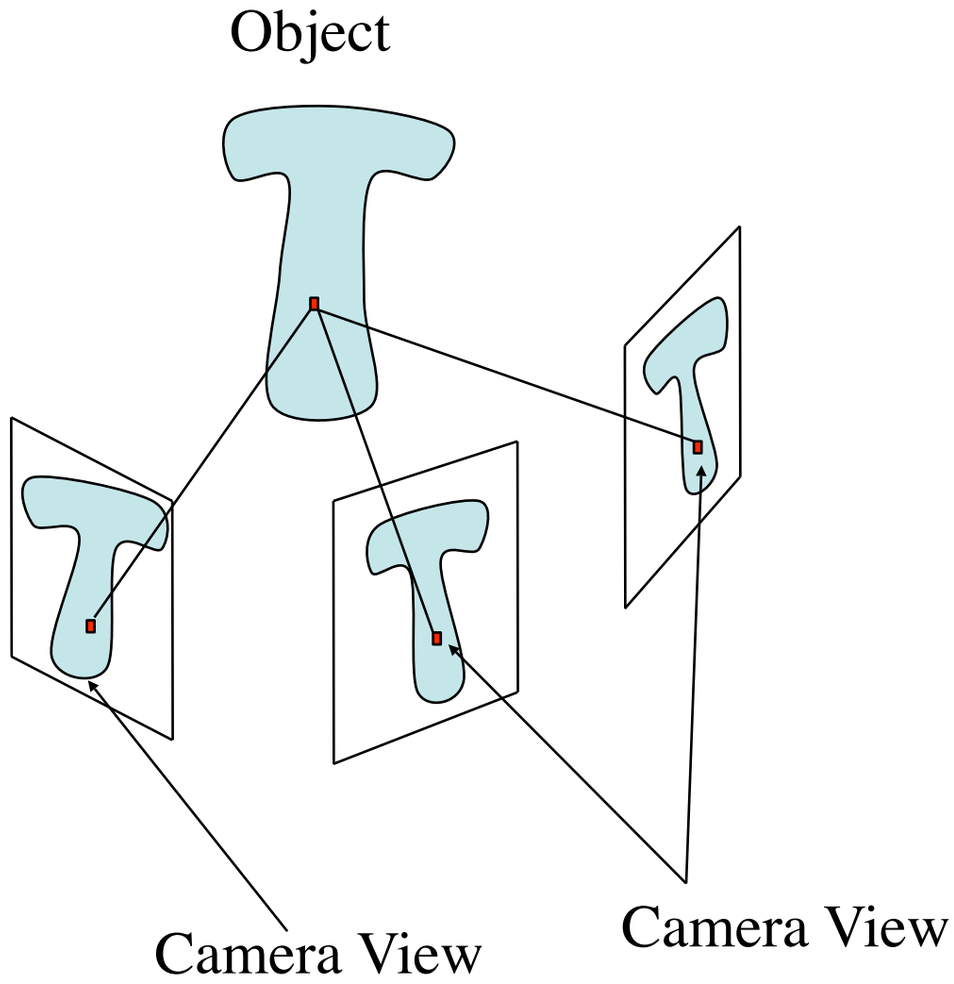
- As name states, geometry of multiple views!



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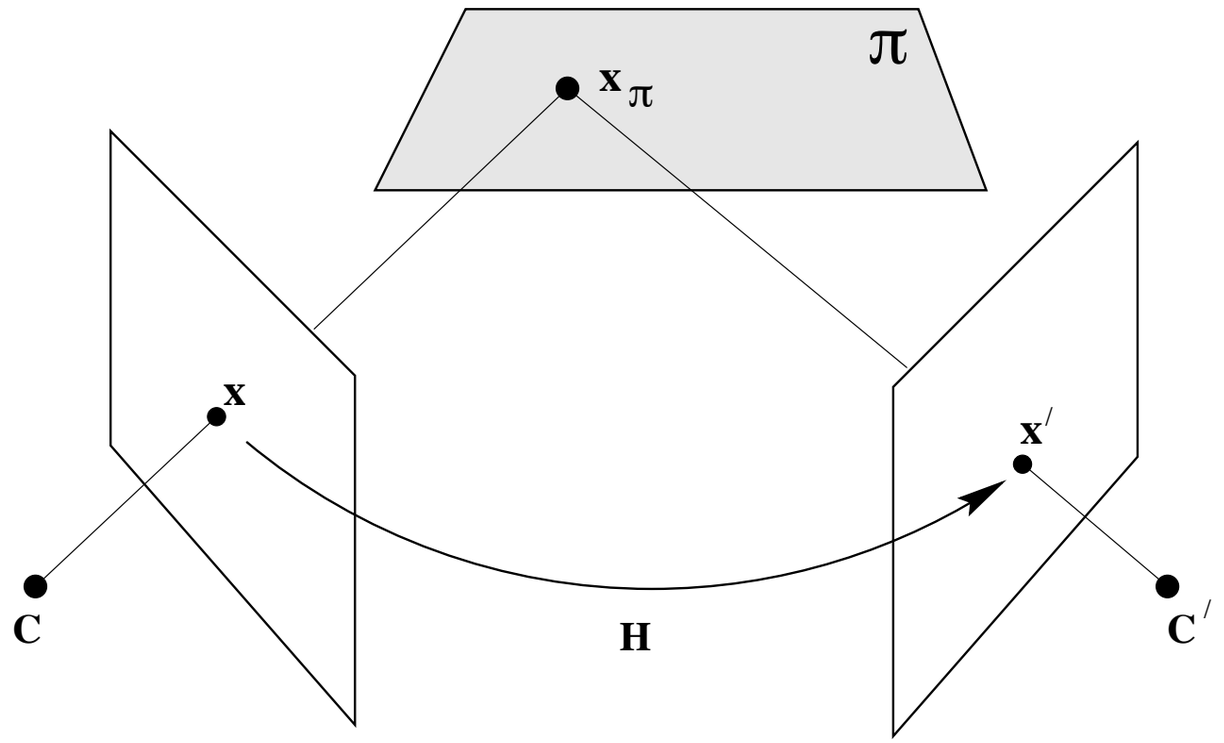

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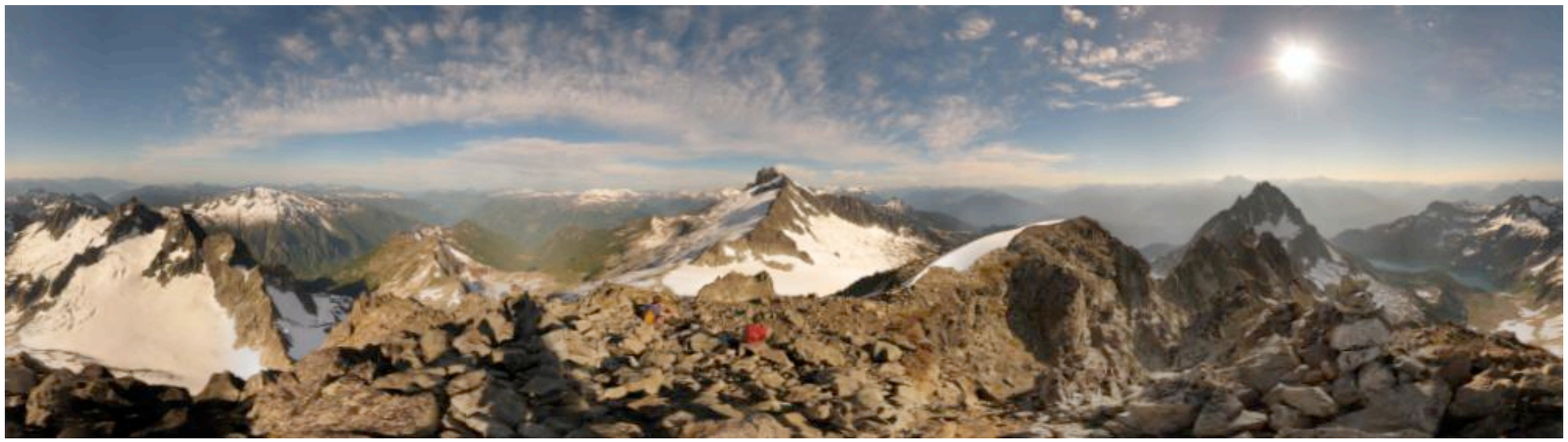

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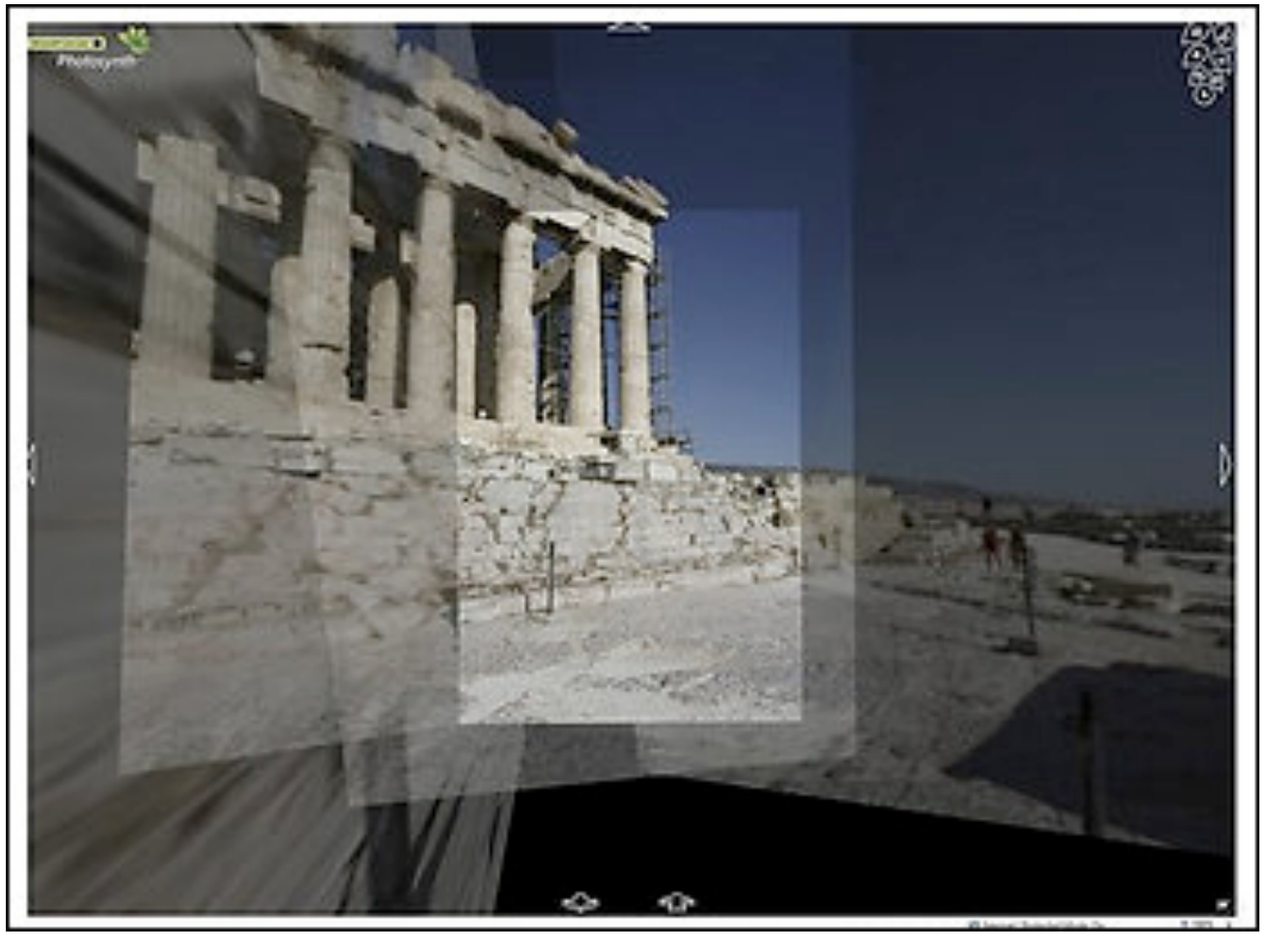

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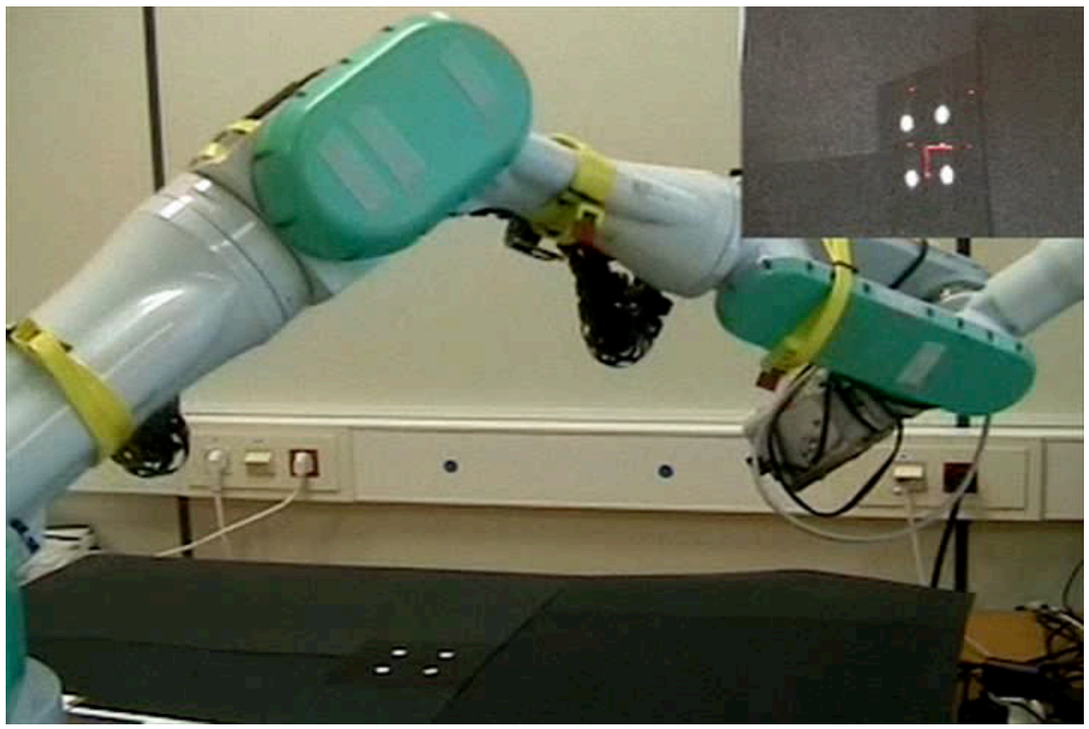

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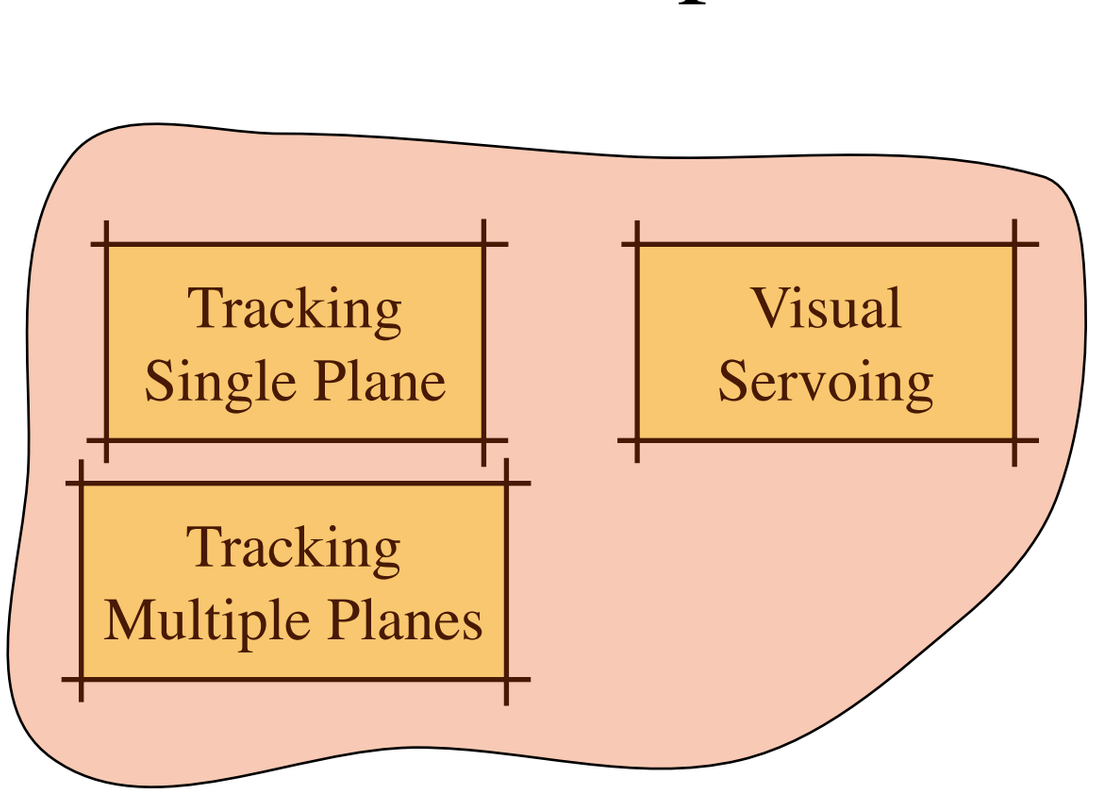

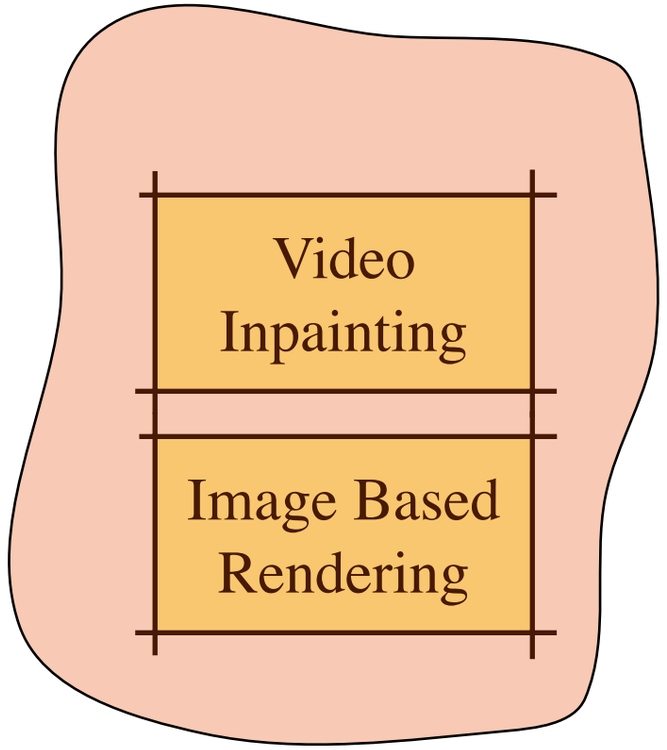

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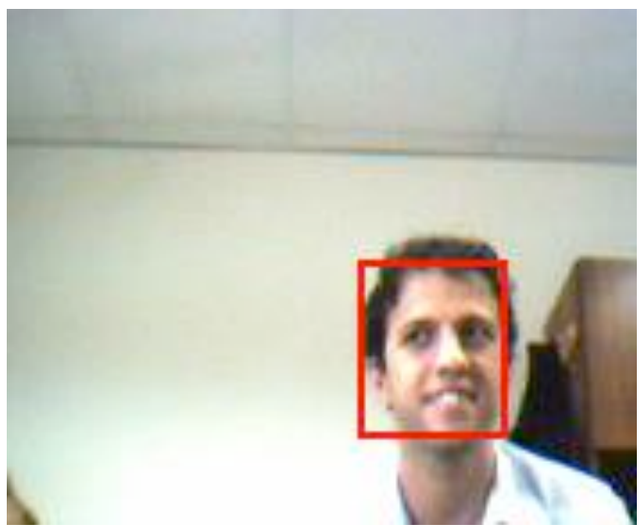

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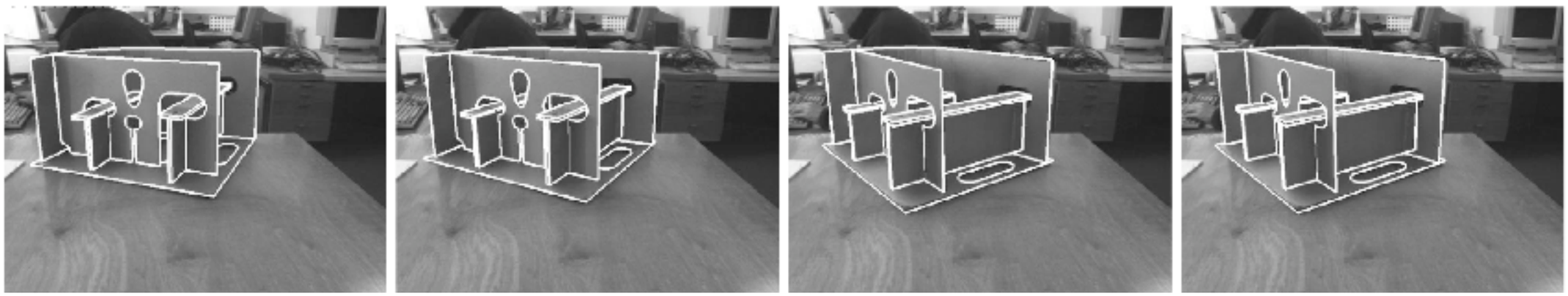

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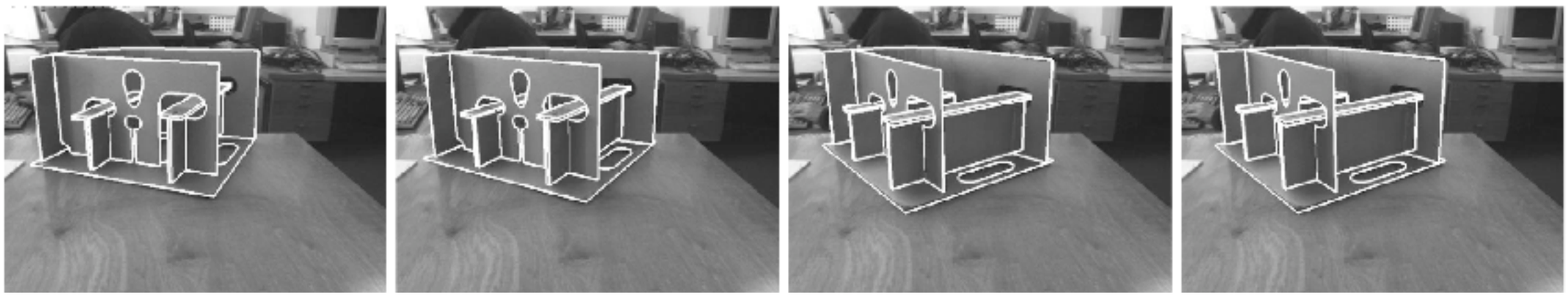

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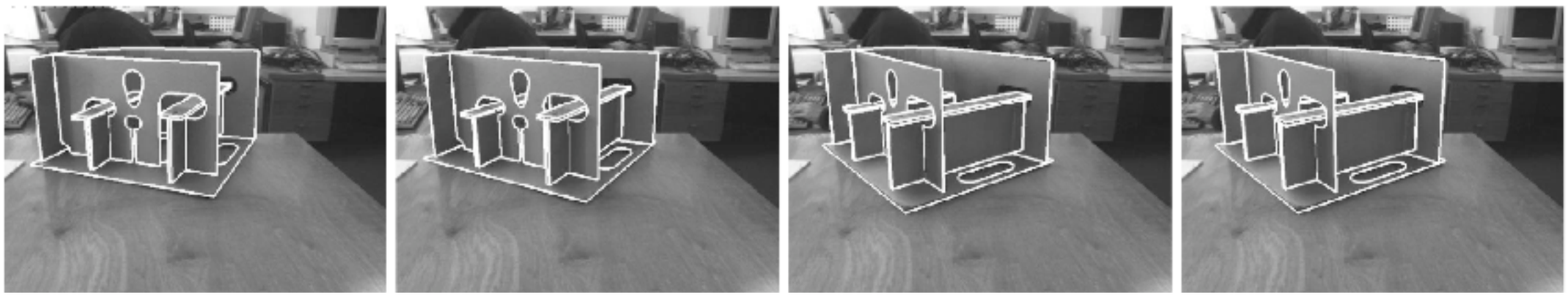

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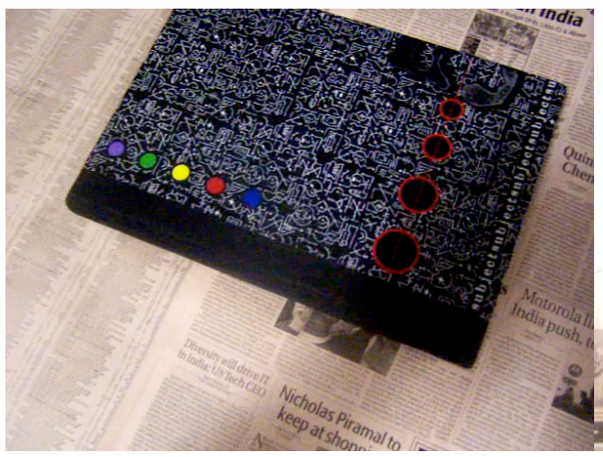

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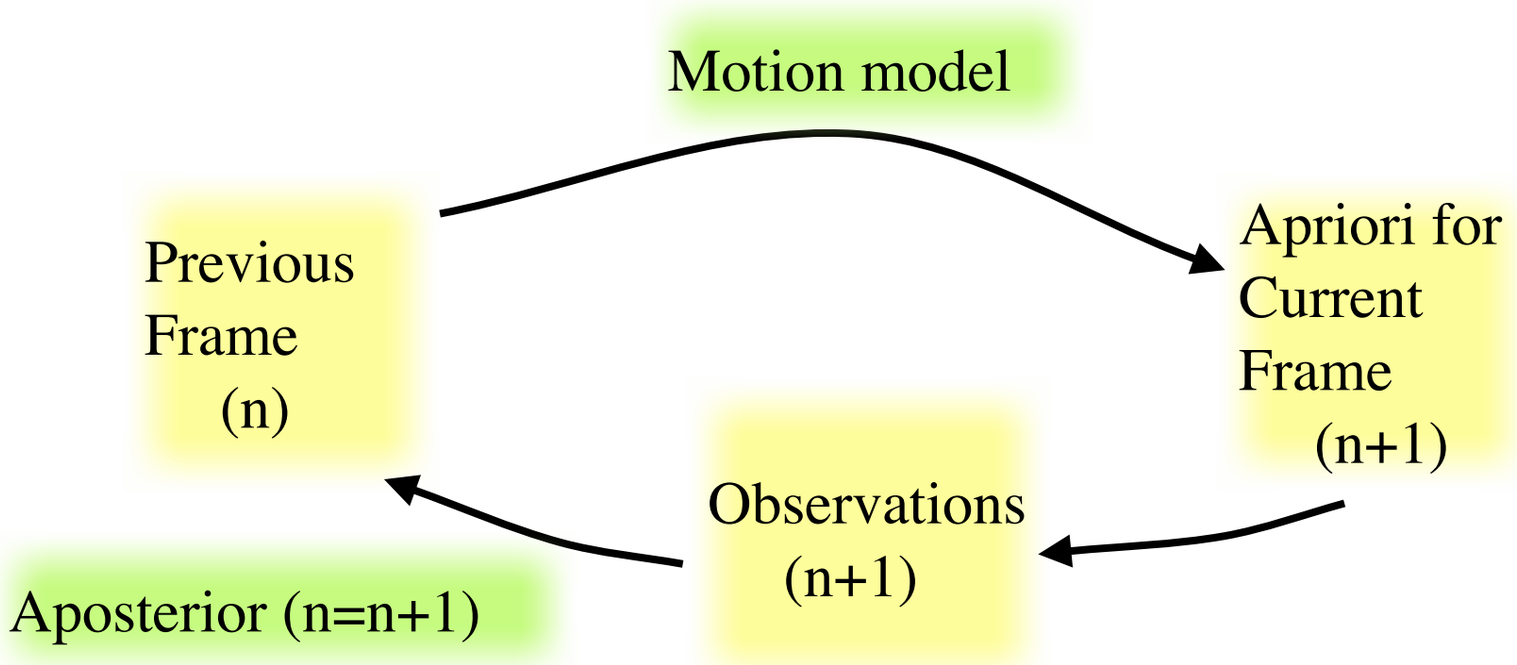

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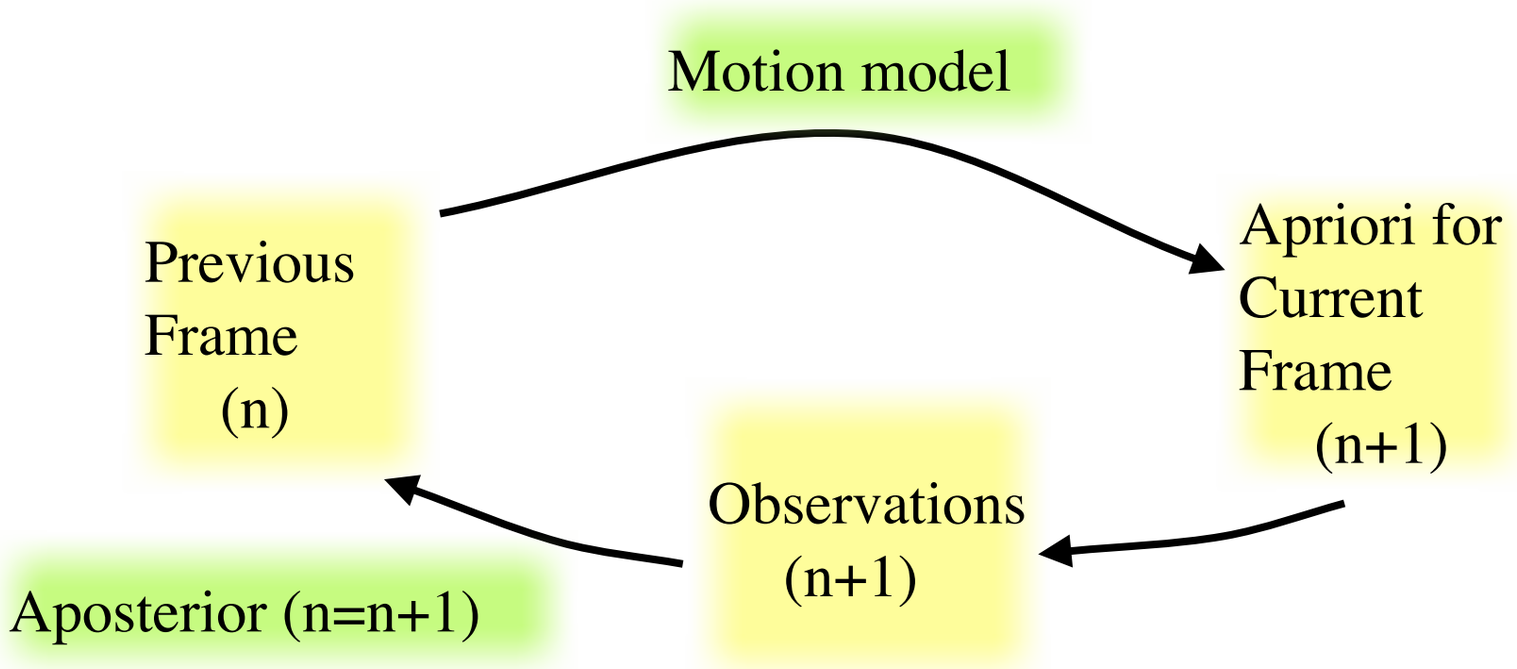

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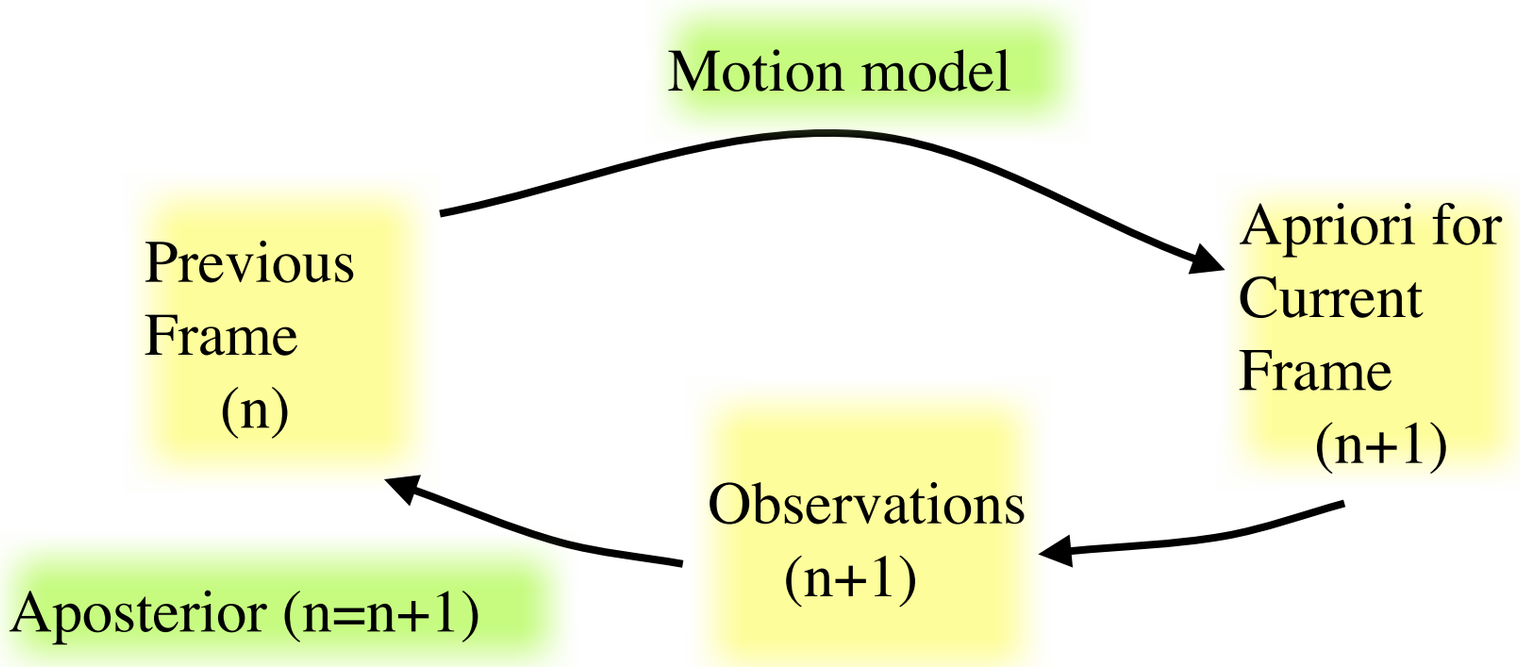

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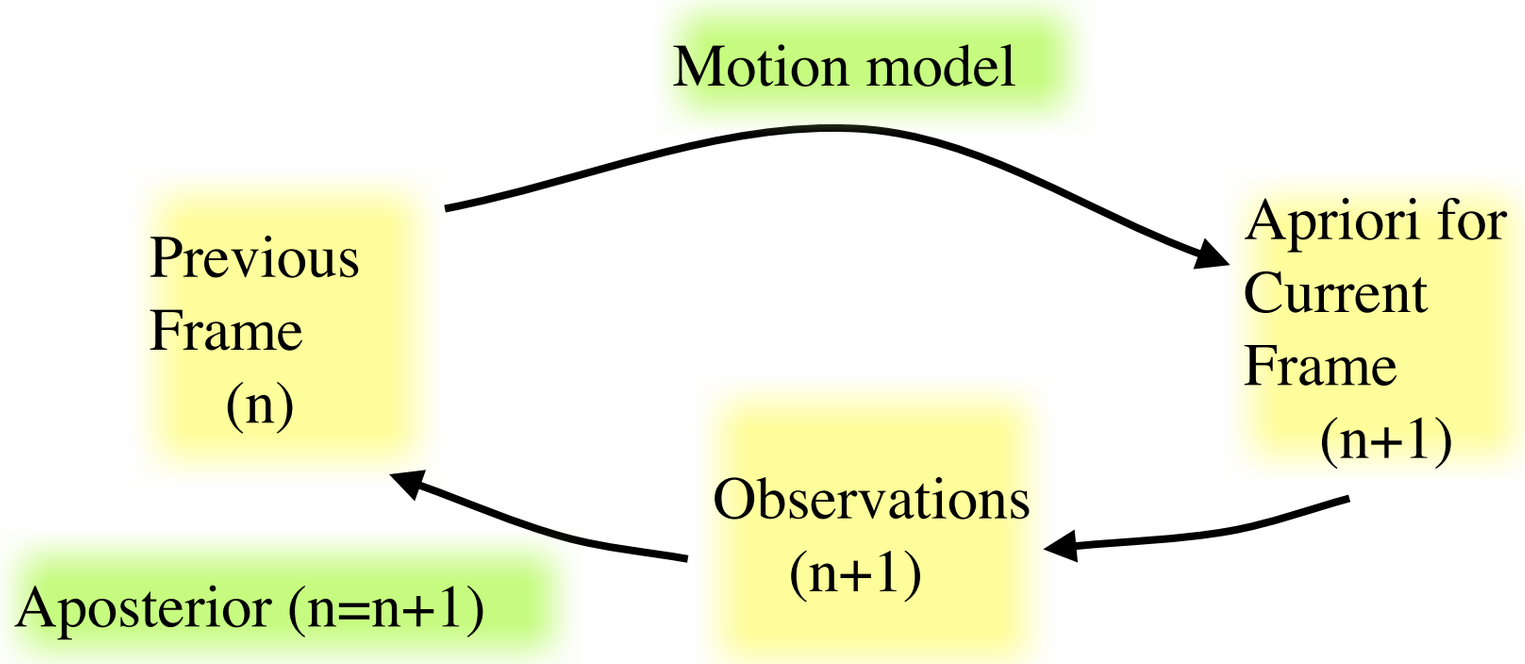

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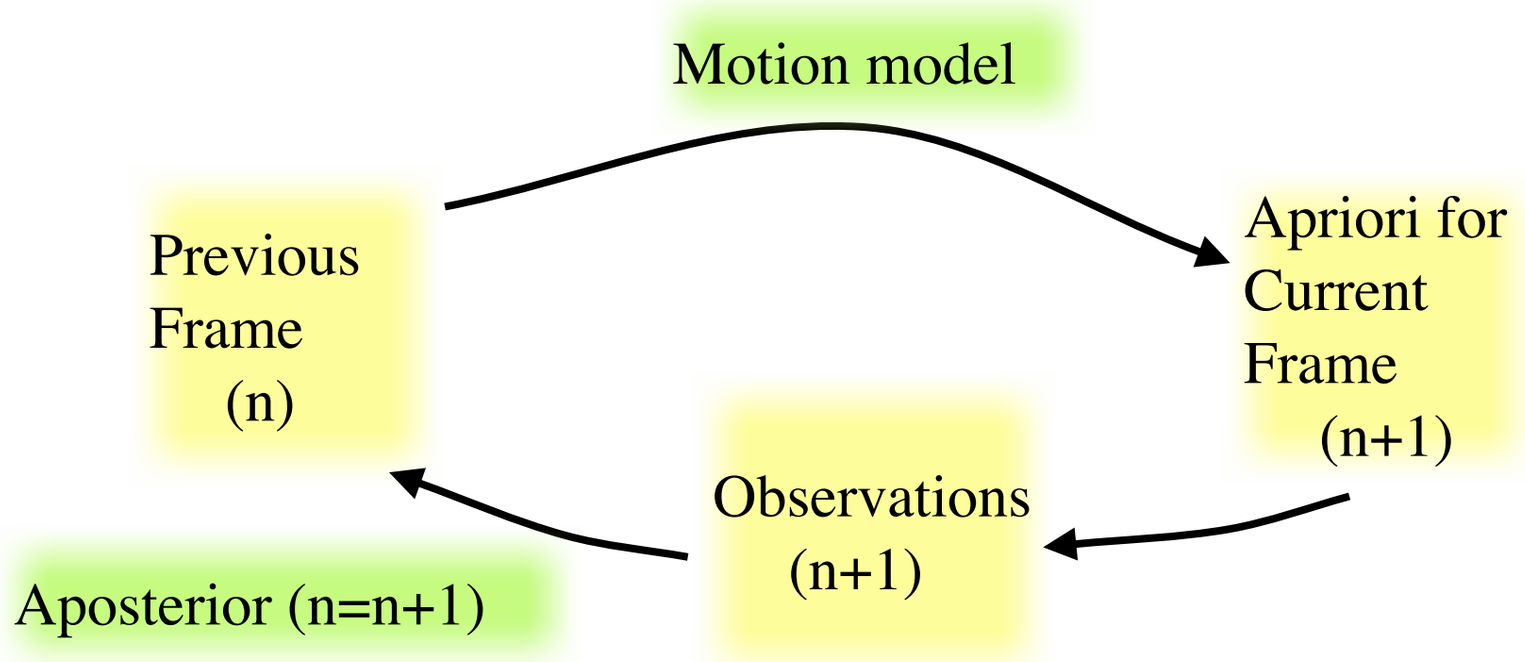

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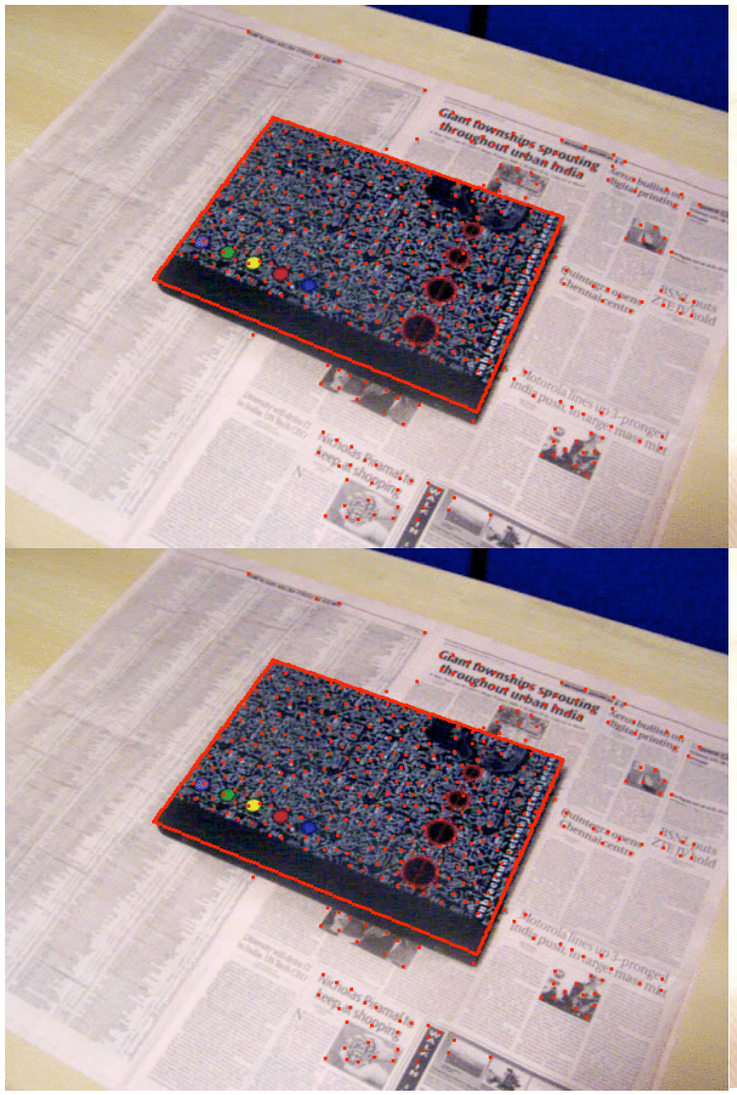
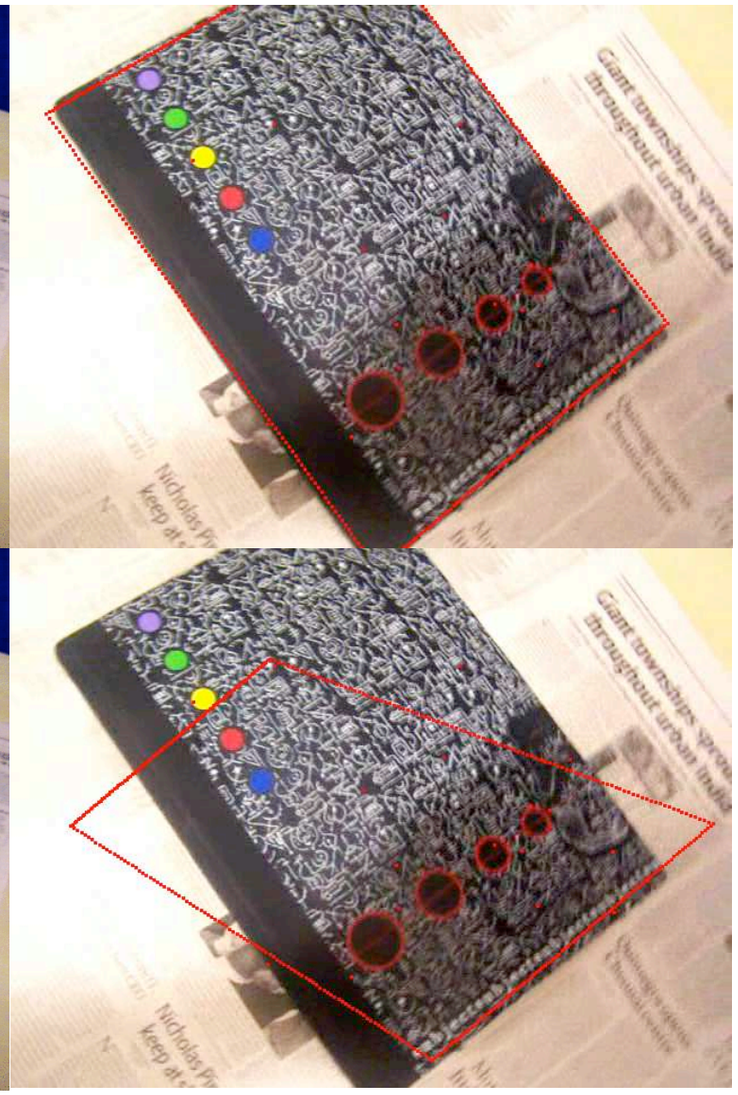
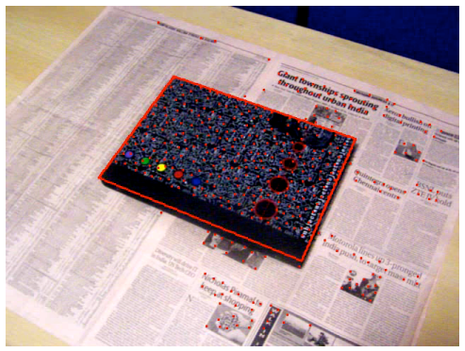
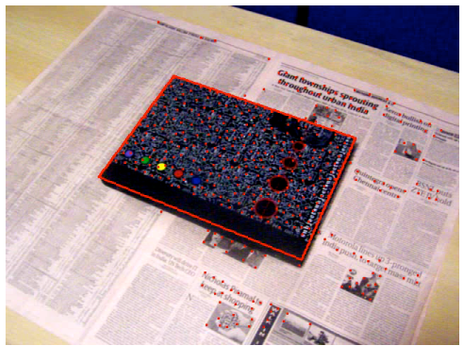
Important Differences and Choices!

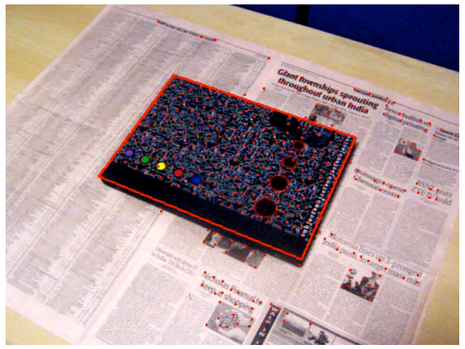
Tracking: Results











Tracking: Results

Tracking: Summary

- Tracking as pre-requisite.
- 2D + 3D tracking.
- Illumination and Occlusion handling.
- Globally optimal initialization.
- Two complementary algorithms.

Visual Servoing: Past Work

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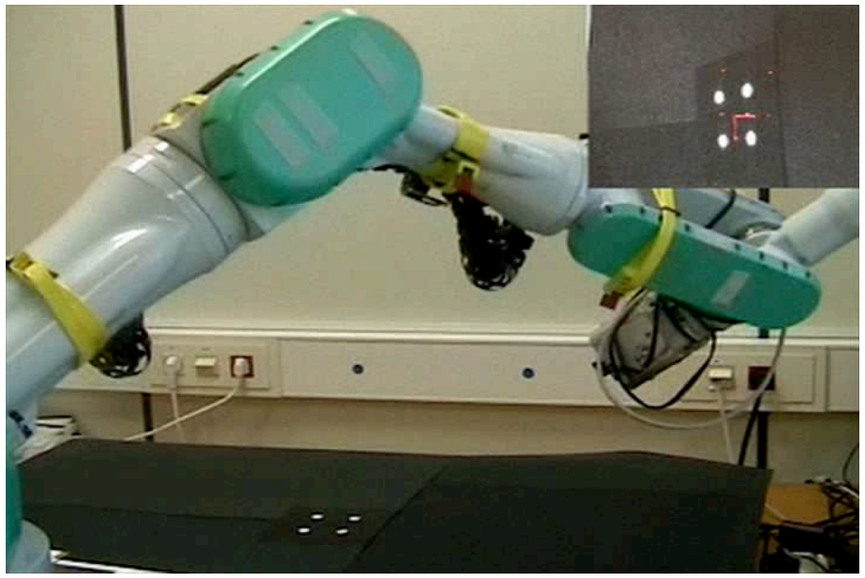

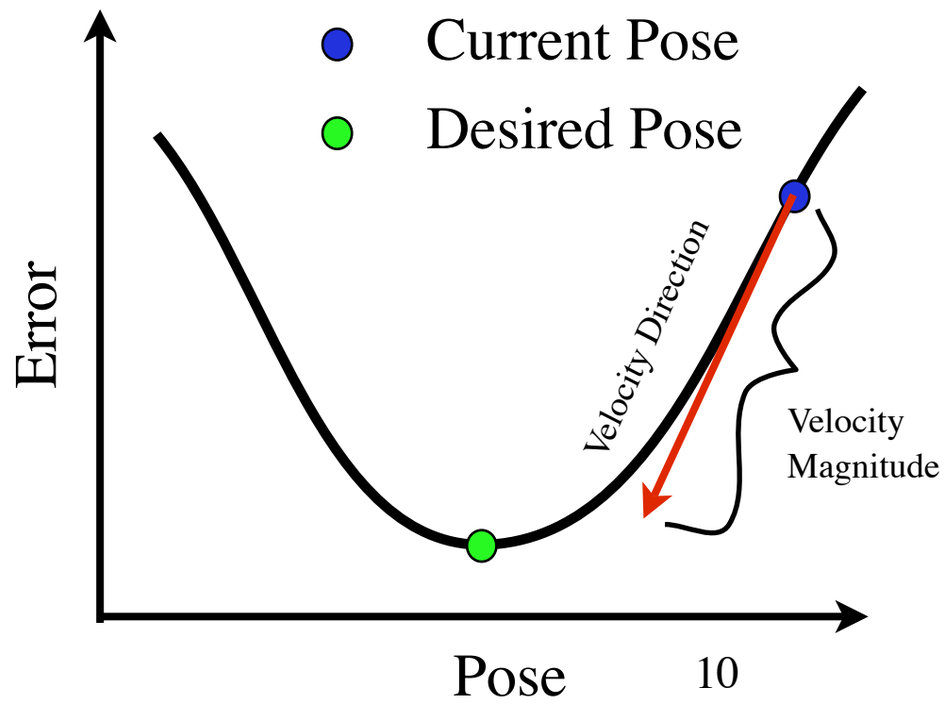

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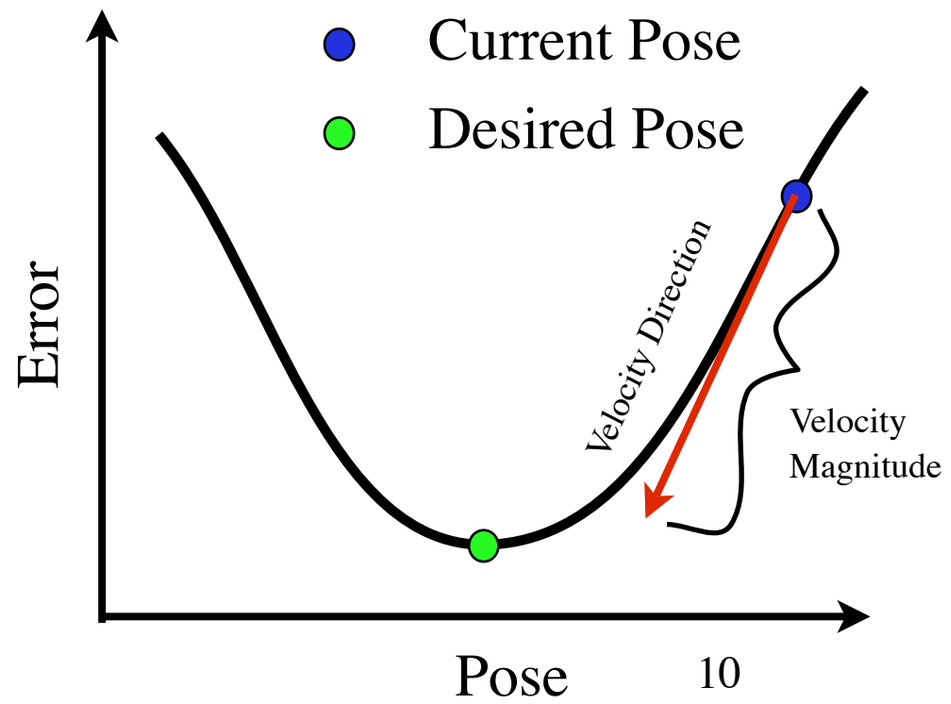

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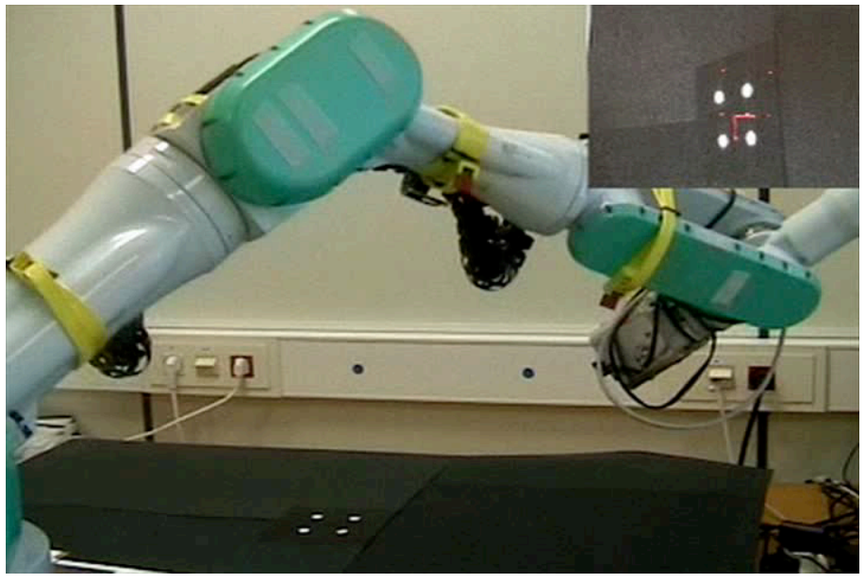

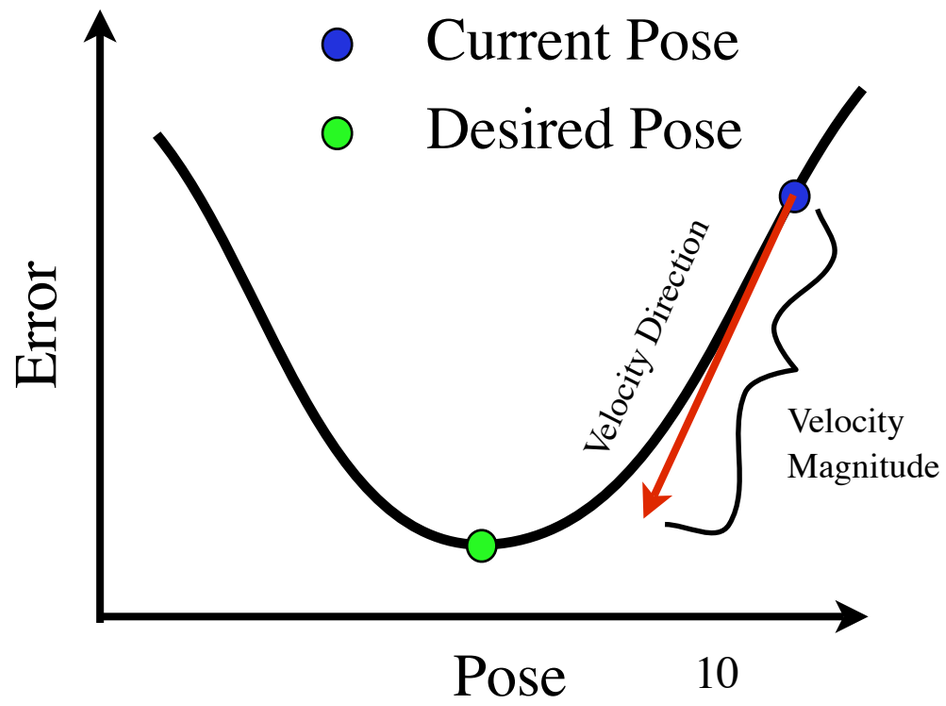

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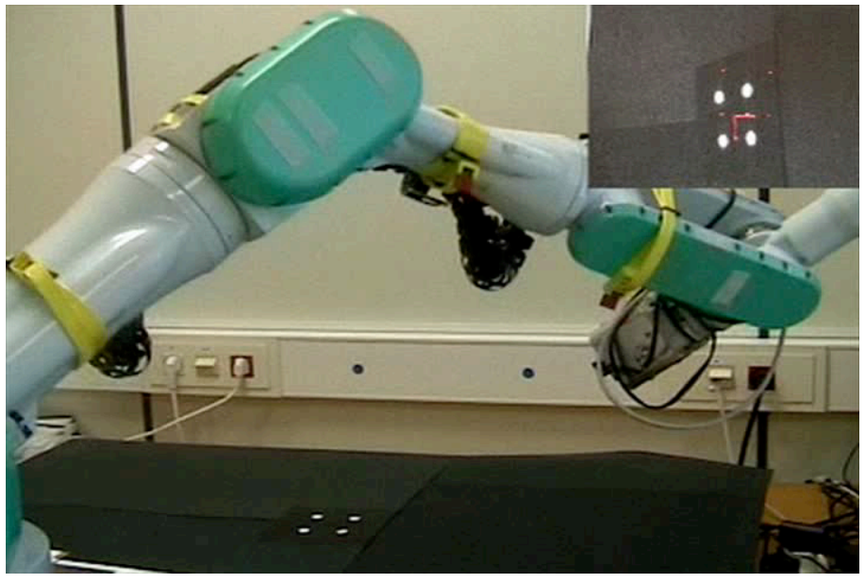

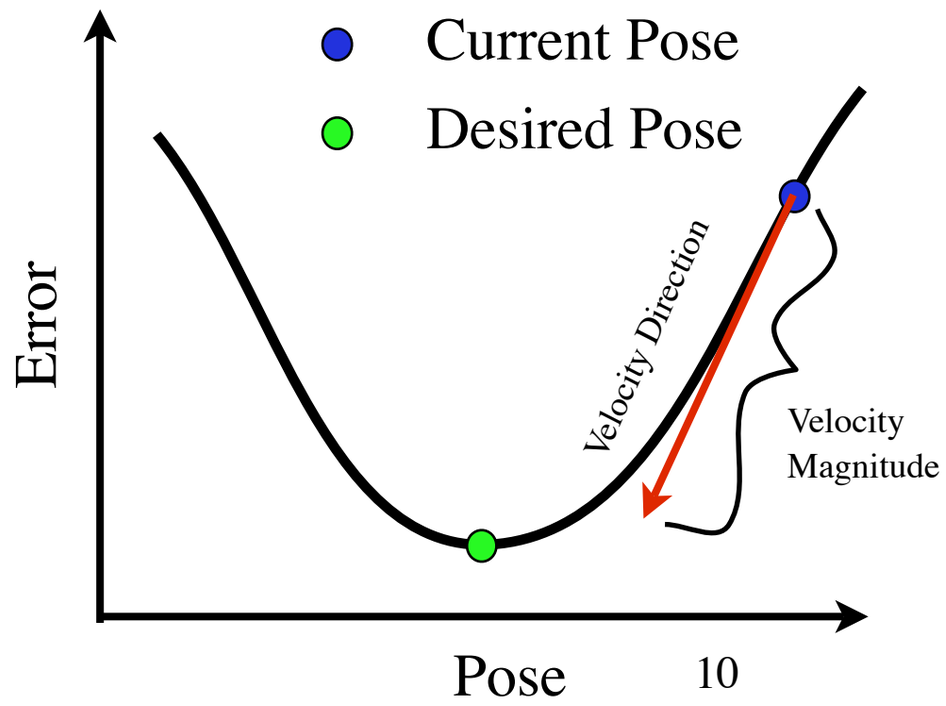

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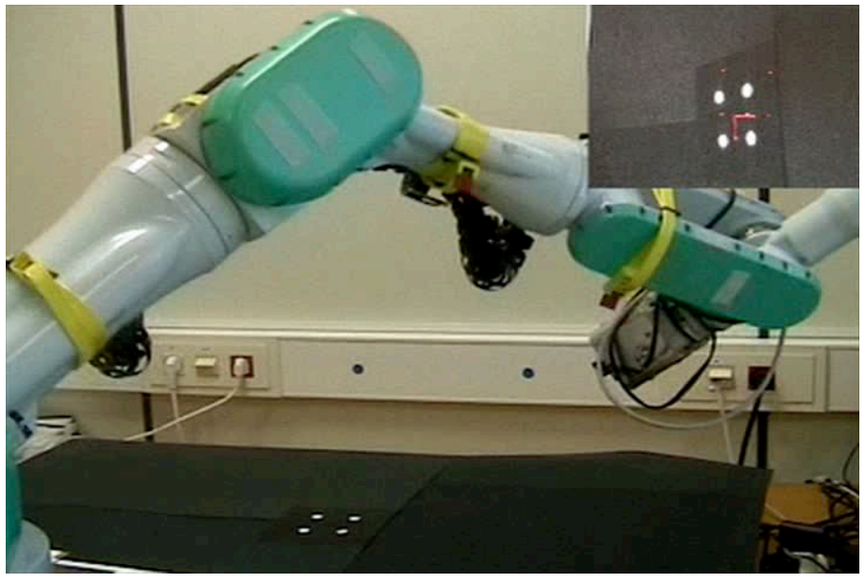

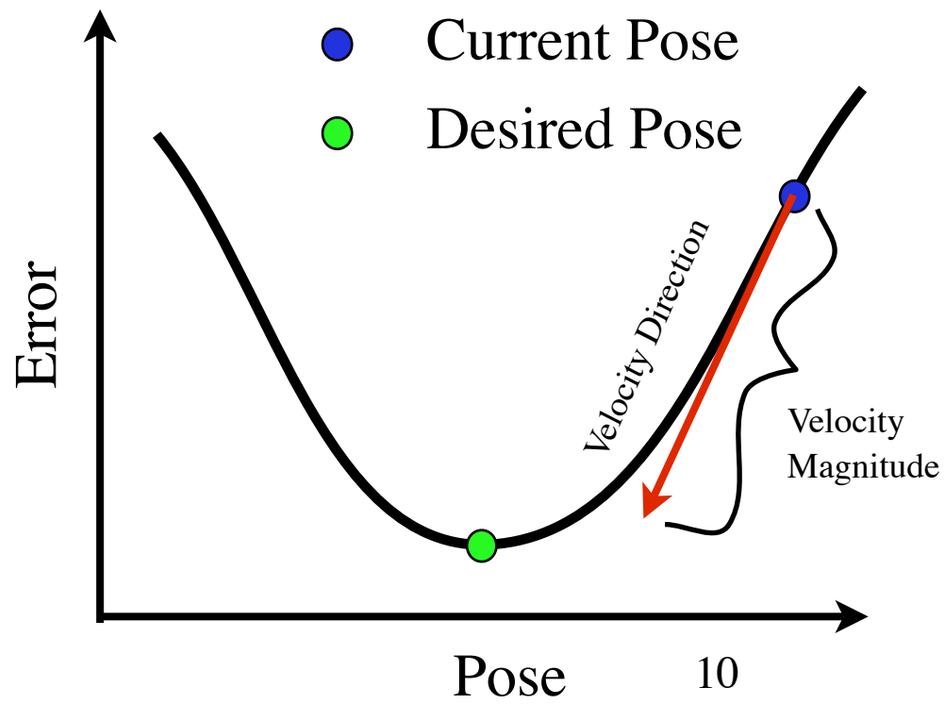

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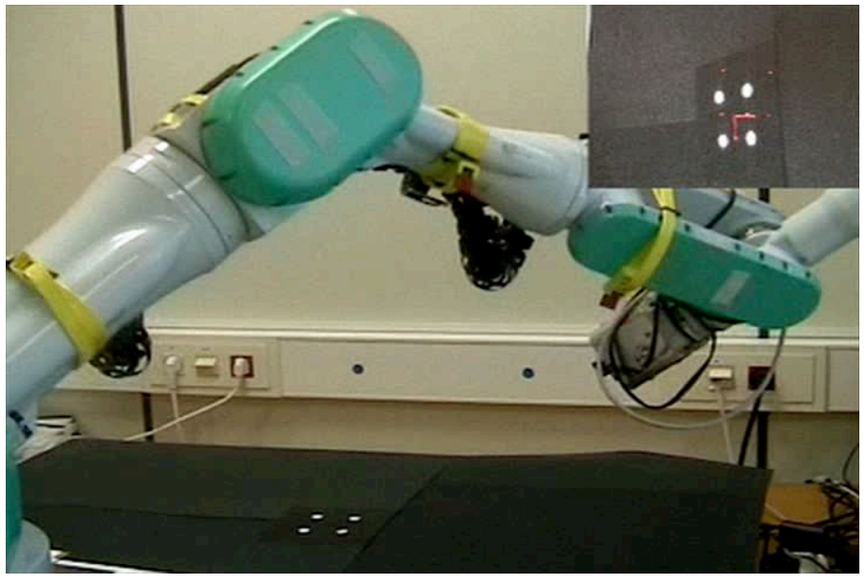
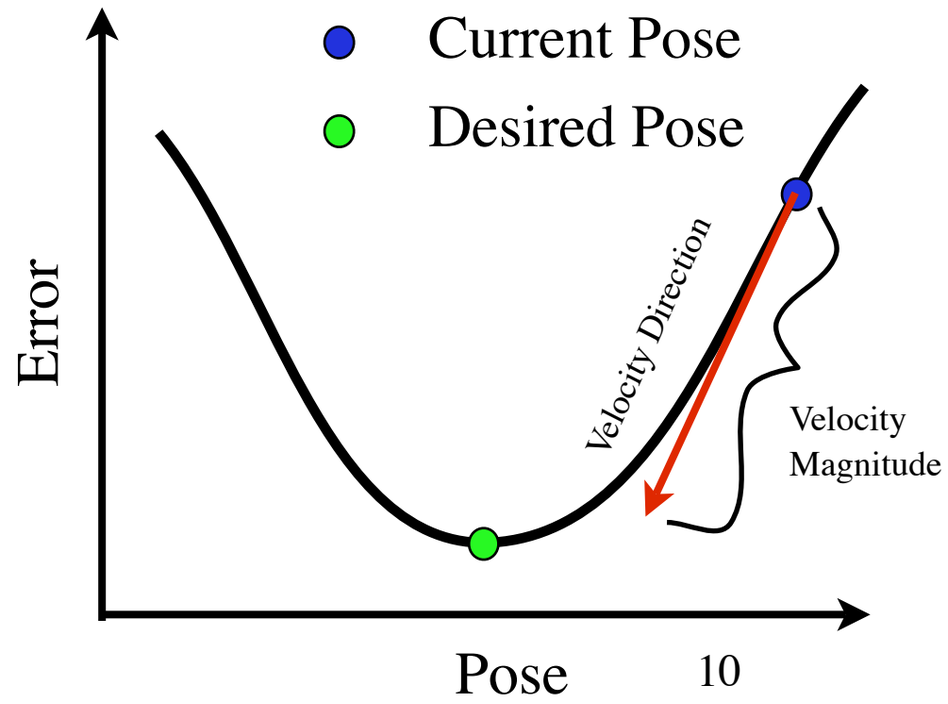
Introduce Fourier techniques in Servoing, shows promise.





Servoing Algorithms

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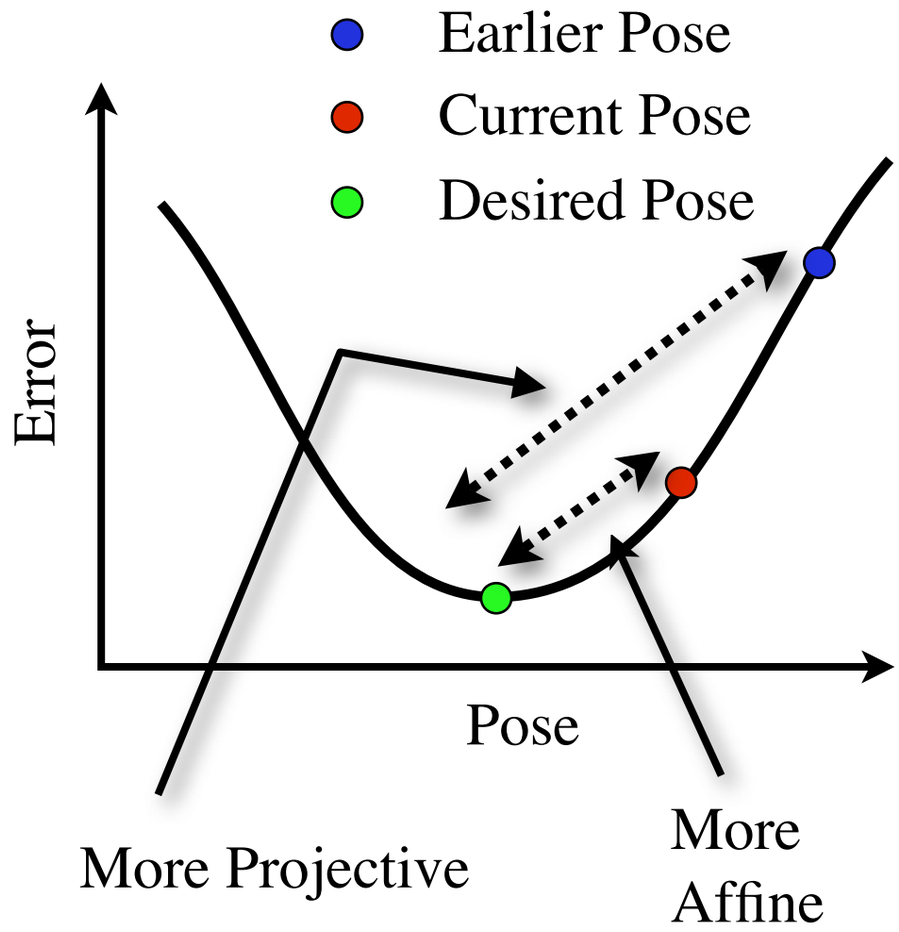
- Correspondence-less transformation estimation.



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- Correspondence-less transformation estimation.
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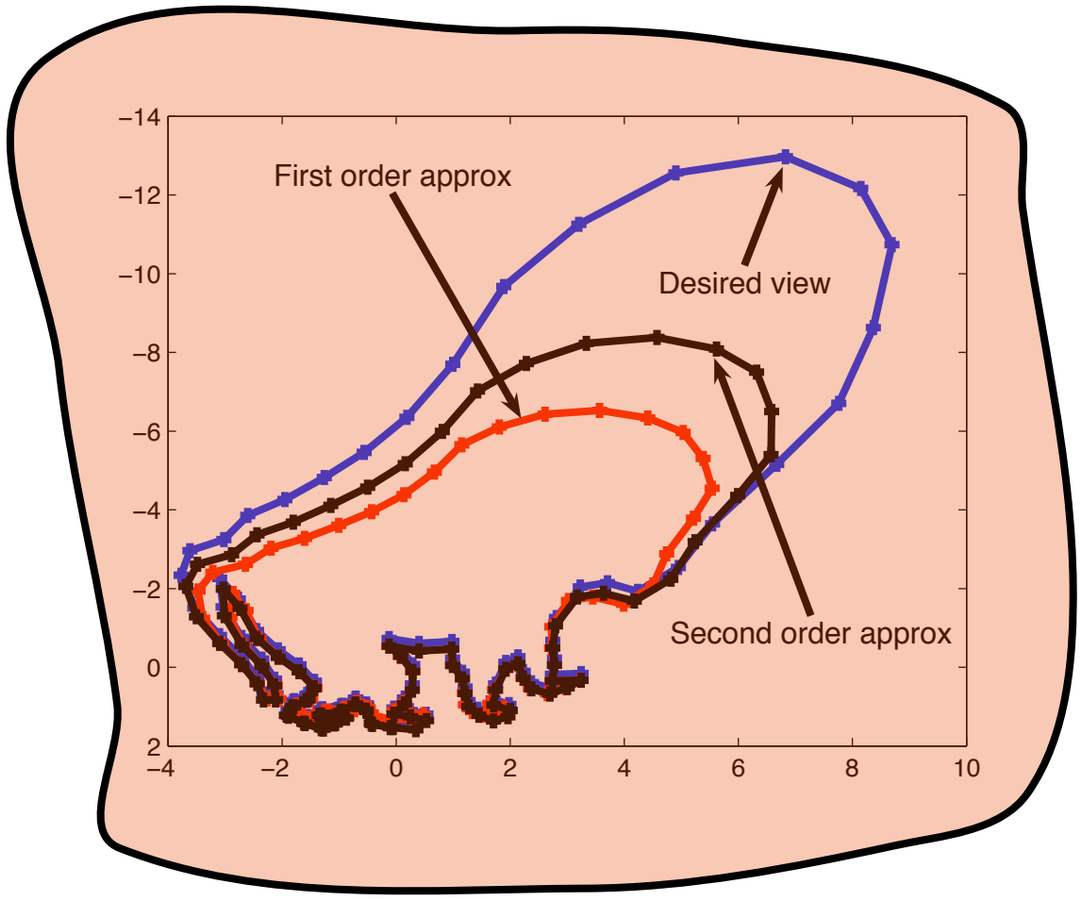
Fourier Transform



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- Incorporate path planning output in servoing.

Results

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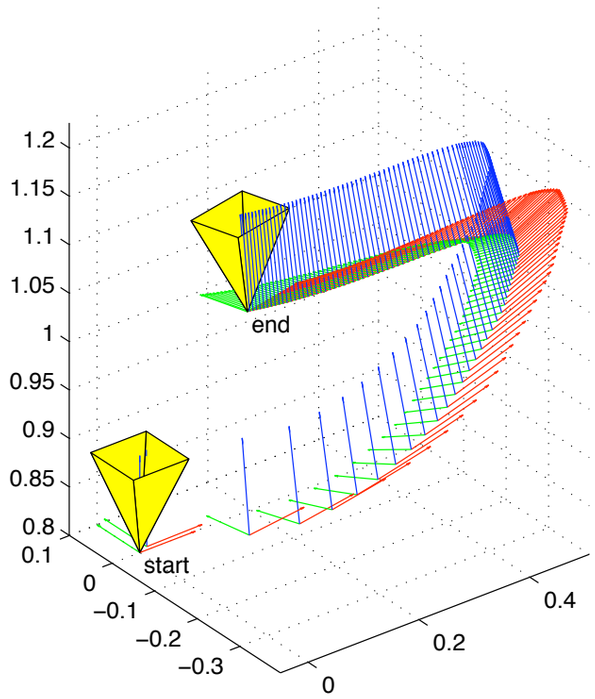
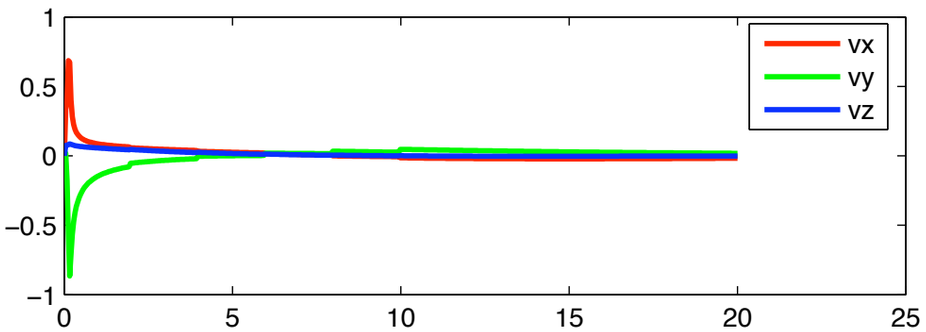
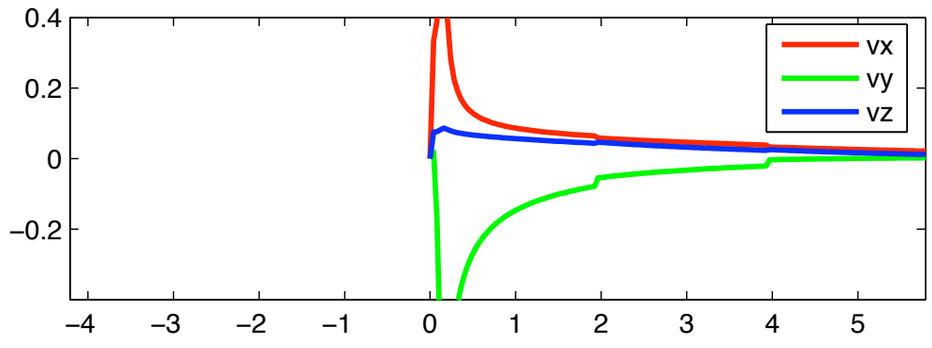
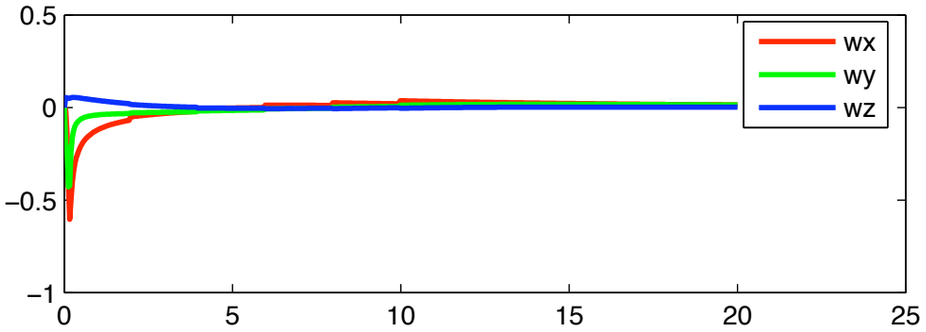
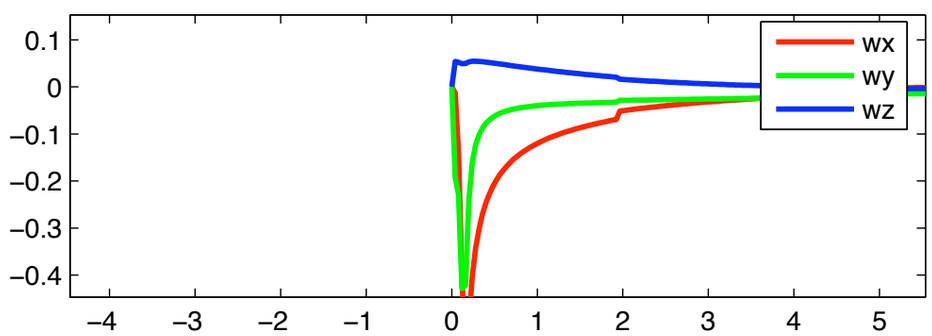
- Correspondence-less servoing.











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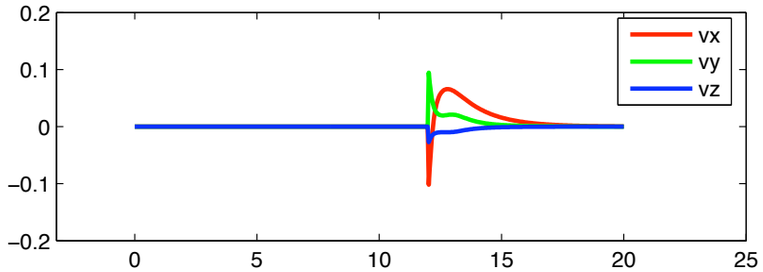
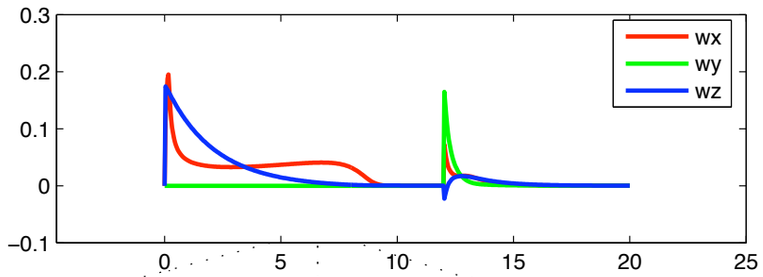
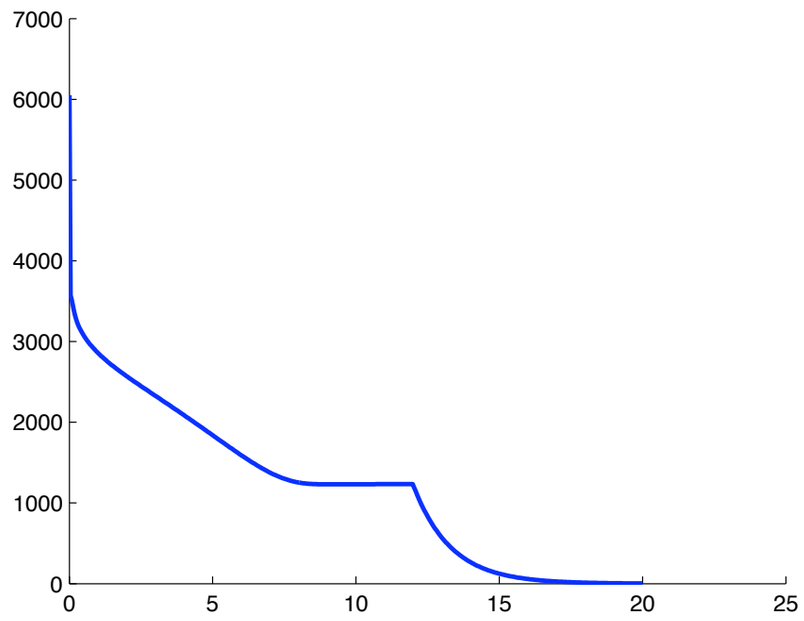
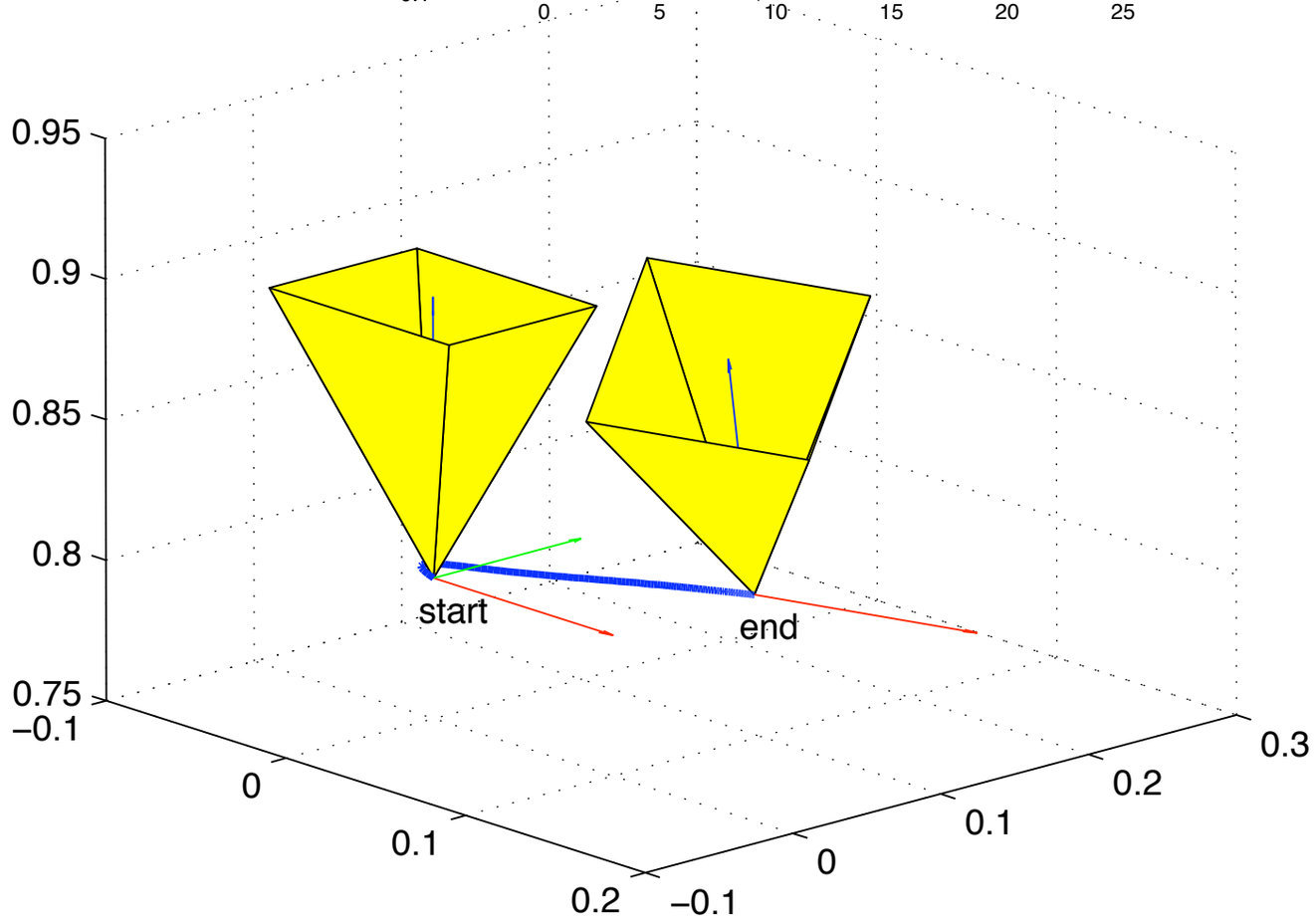
- Straight Cartesian path.









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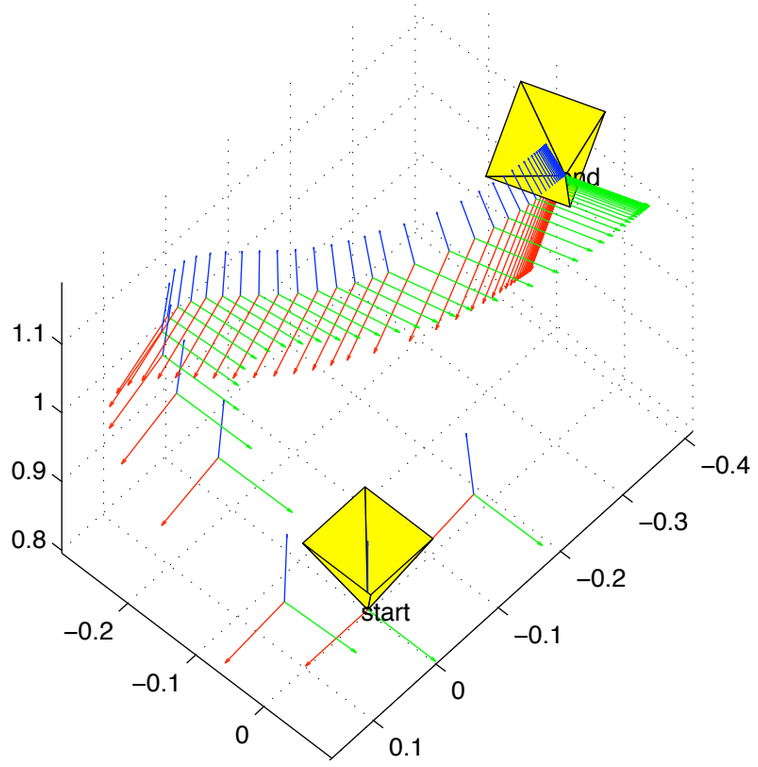

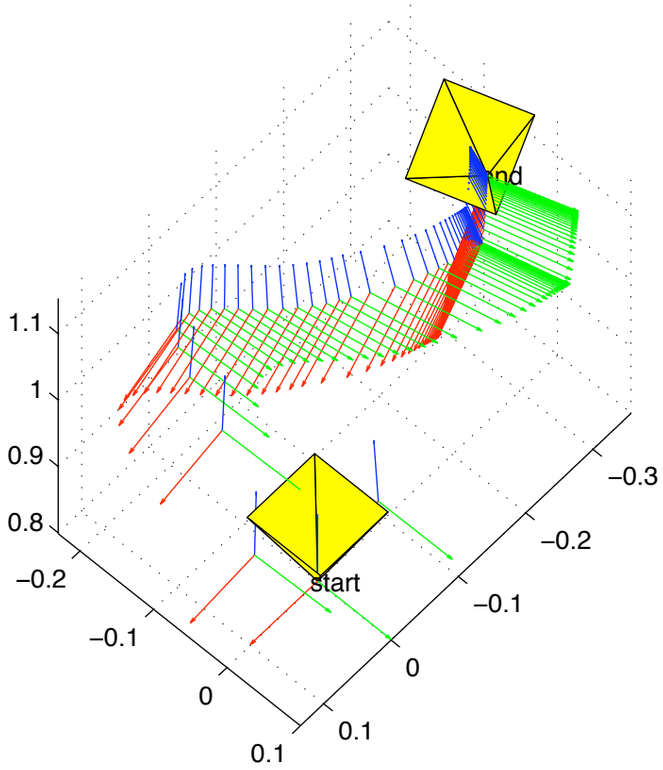

Servoing: Summary

- Fourier Visual Servoing.
- Traditional IBVS errors.
- Has potential for further growth.
- Path planning algorithms.

Inpainting & IBR: Past Work

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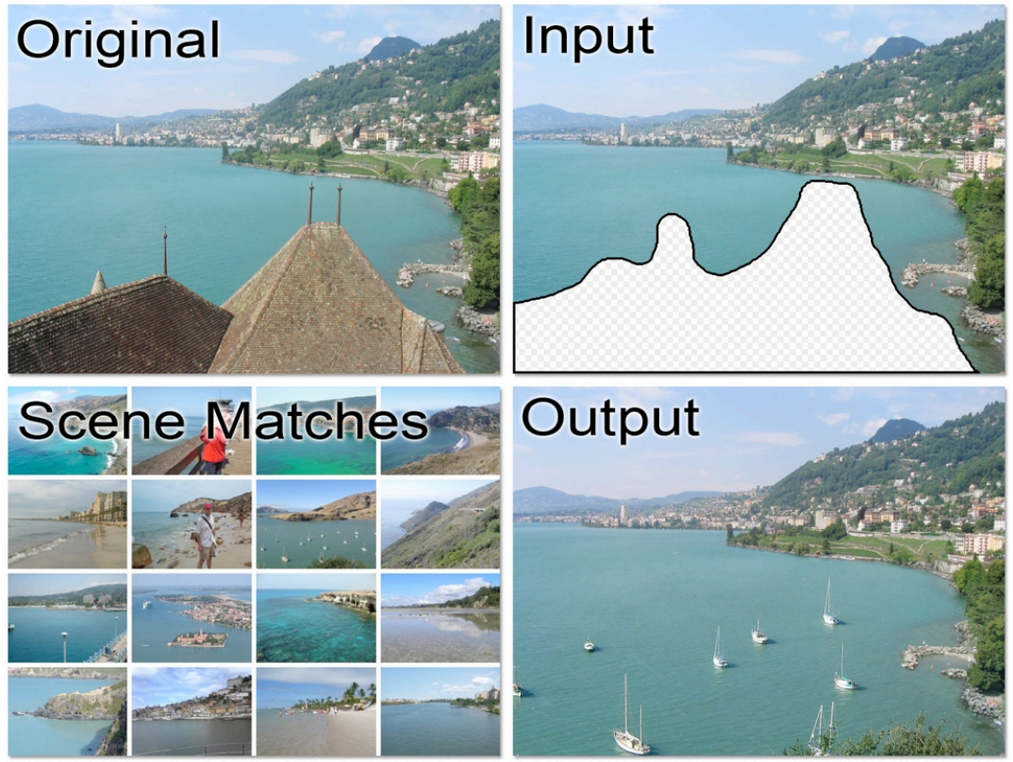
- Inpainting as “hole-filling”. [Efros et. al 2007] [Wexler et al. 2007]



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Approaches

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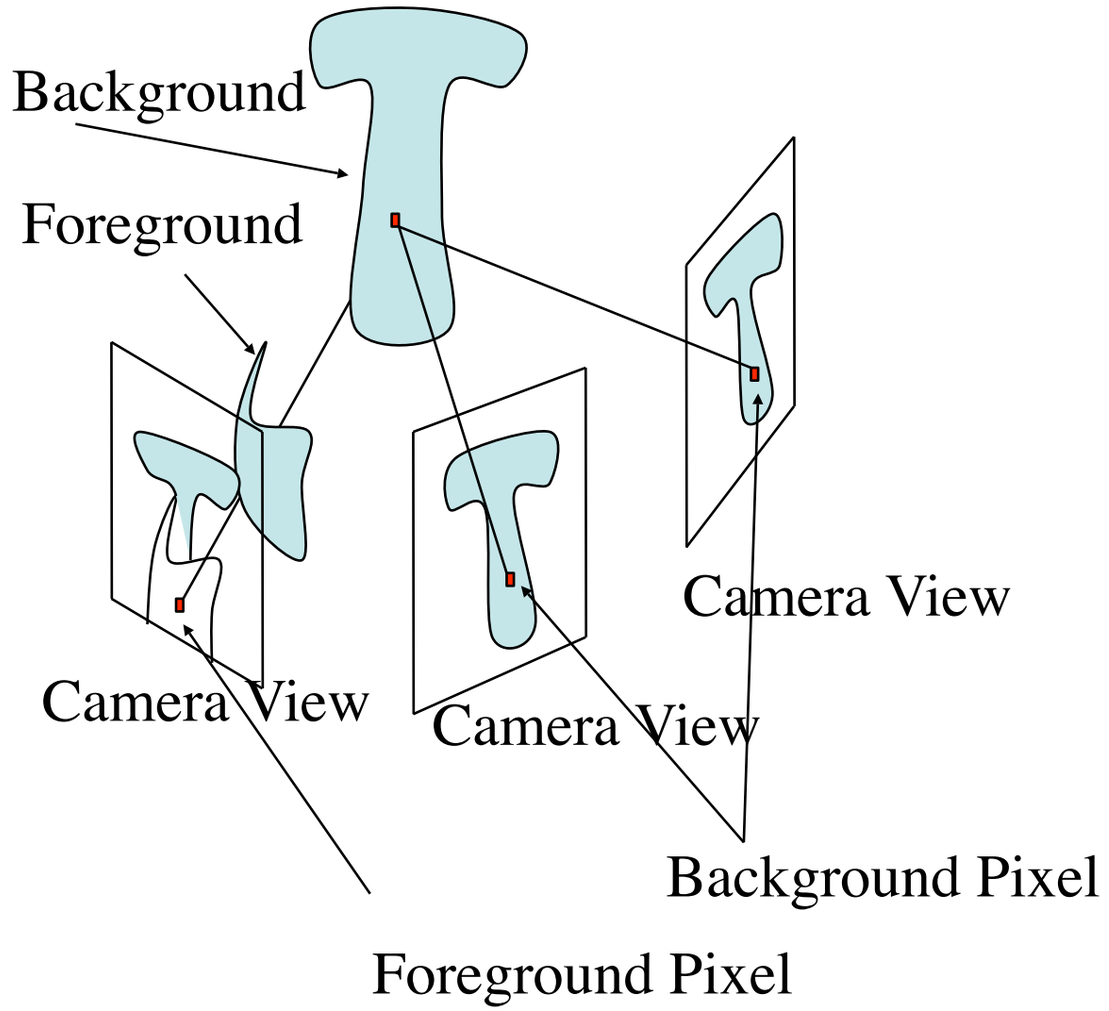

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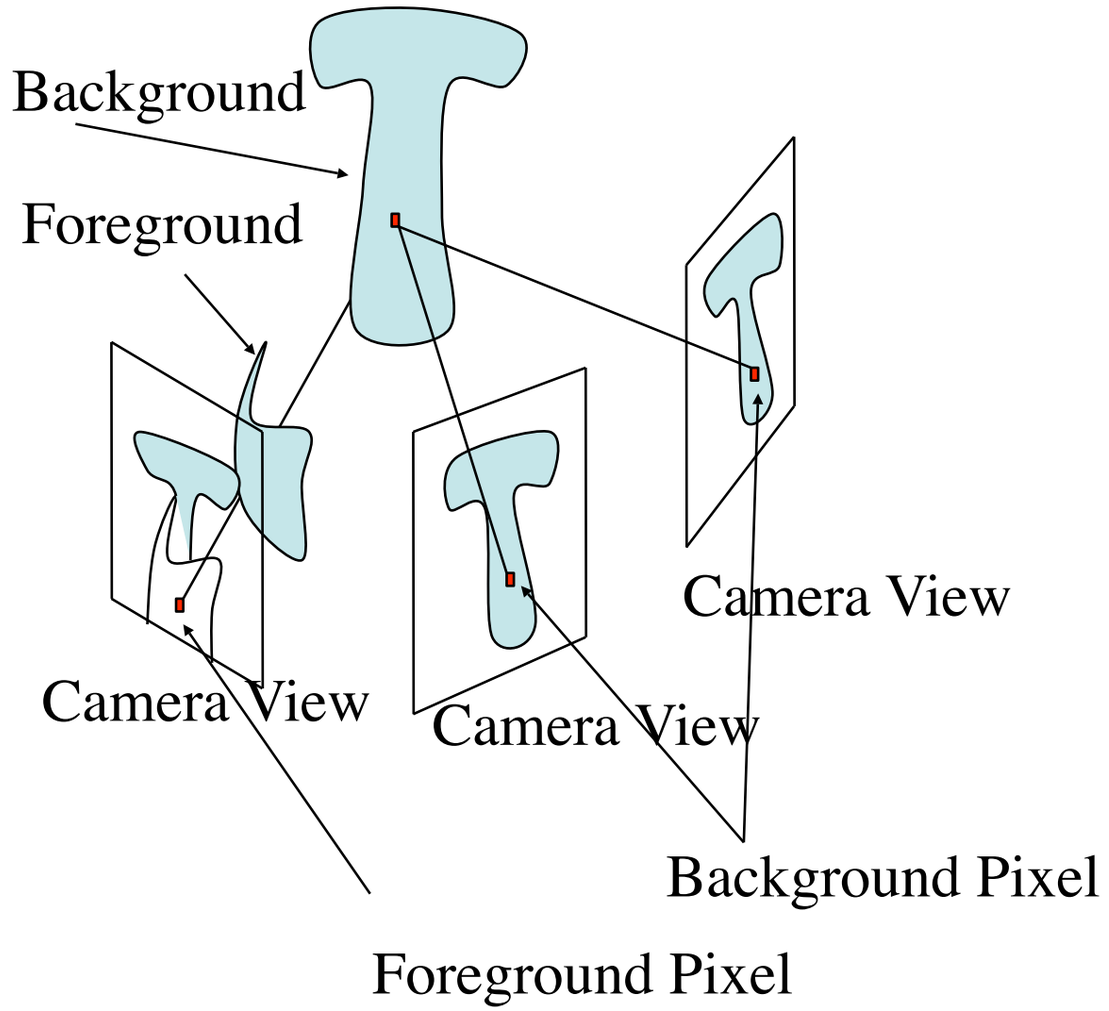

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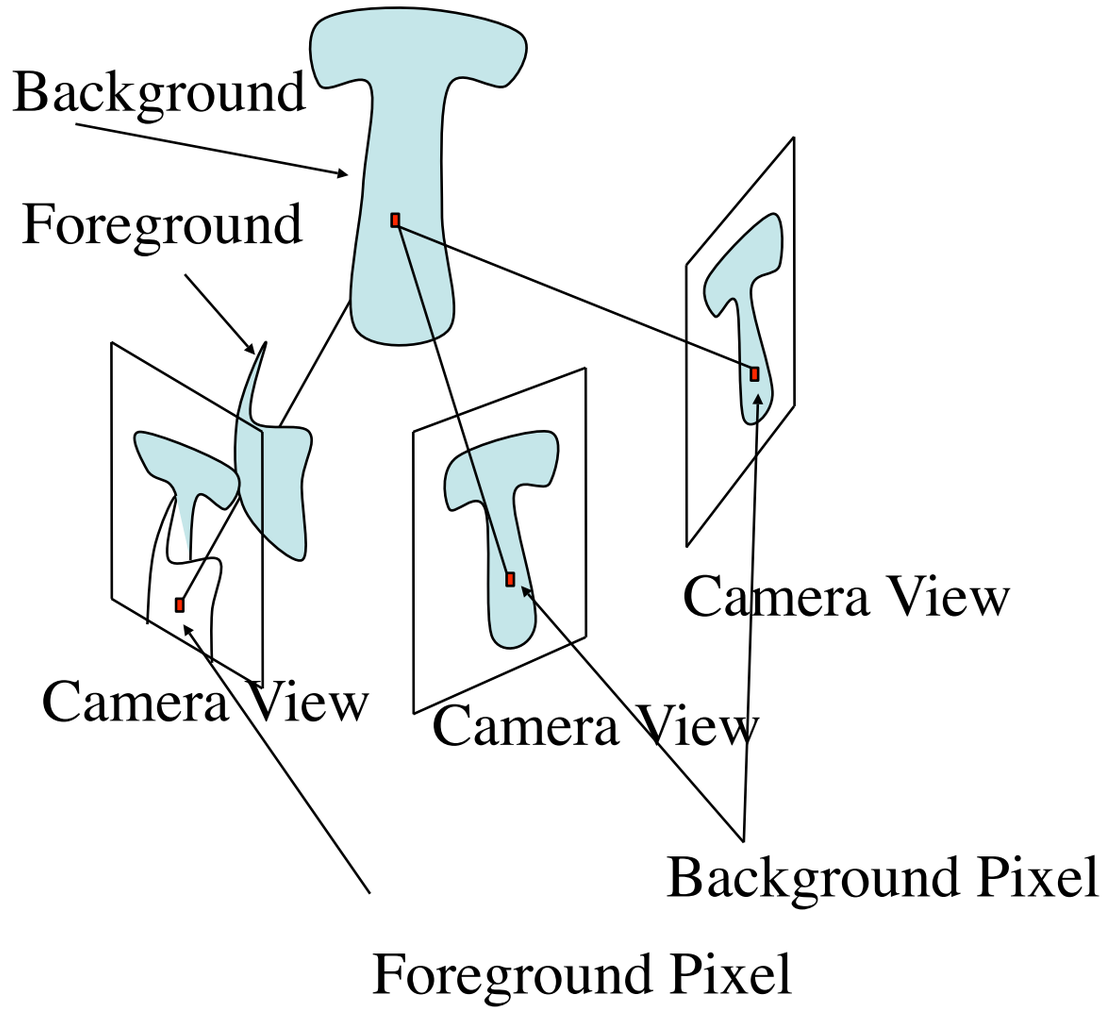

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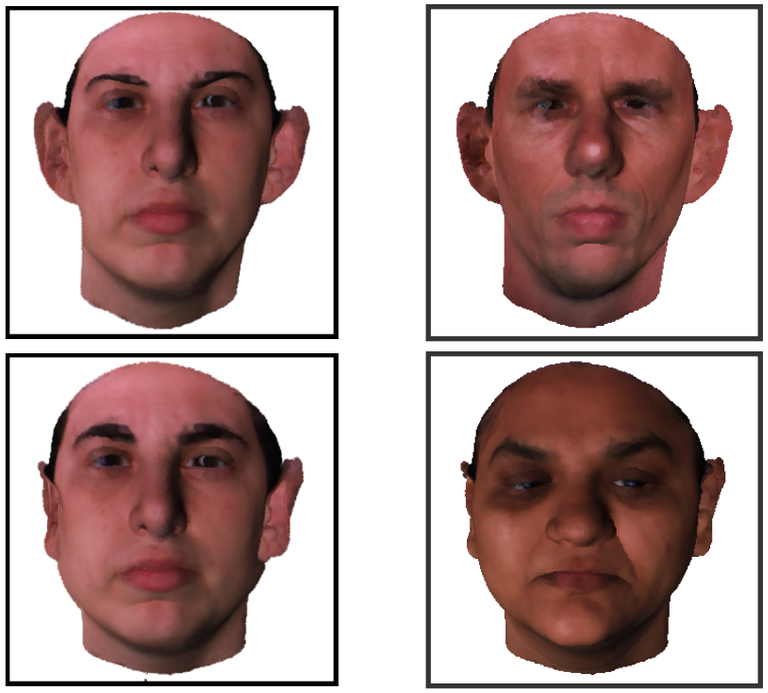

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- Selection from database, using semantic similarity.

Results

Results

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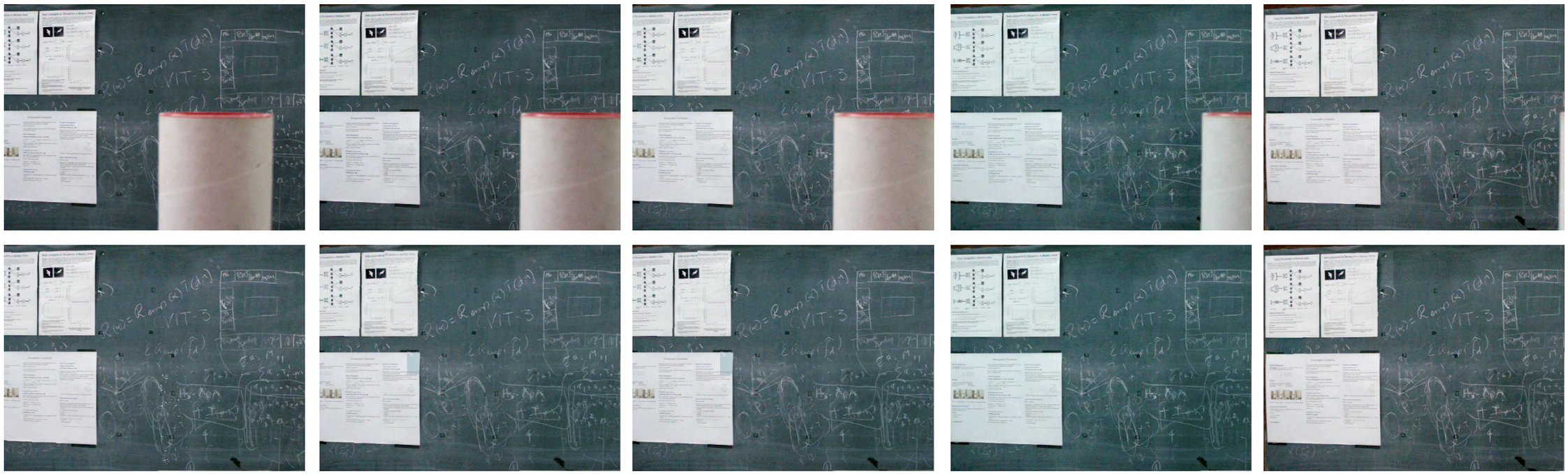

Results

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Summary

- Inpainting and IBR.
- Complimentary.
- Voting scheme for Inpainting.
- Large texture change.
- IBR based on semantic similarity.
- Impossible views. Many variations.

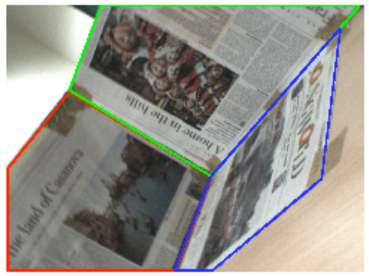
Conclusion

- MVG is very mature.
- Applications to Robotics and Video Manipulation.
- Traditional problems in these areas overcome.
- Rich MVG literature makes future interesting.

Thank You.

Questions ?

KLT Tracker for Illumination and Occlusion



(a)

(b) Illumination change

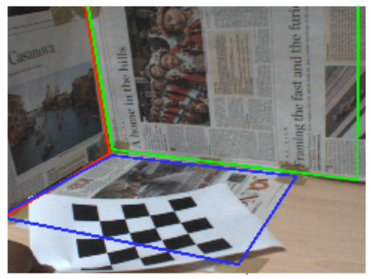
(c)

(d)

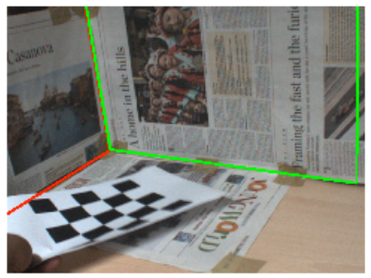
(e)

(f)

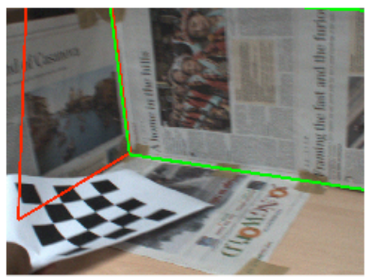
(g)

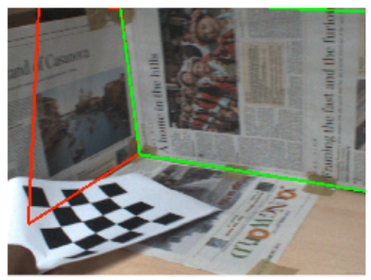


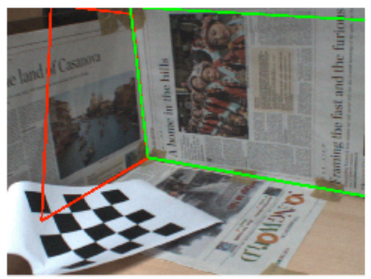
(h)



(i)







Robotic Manipulation

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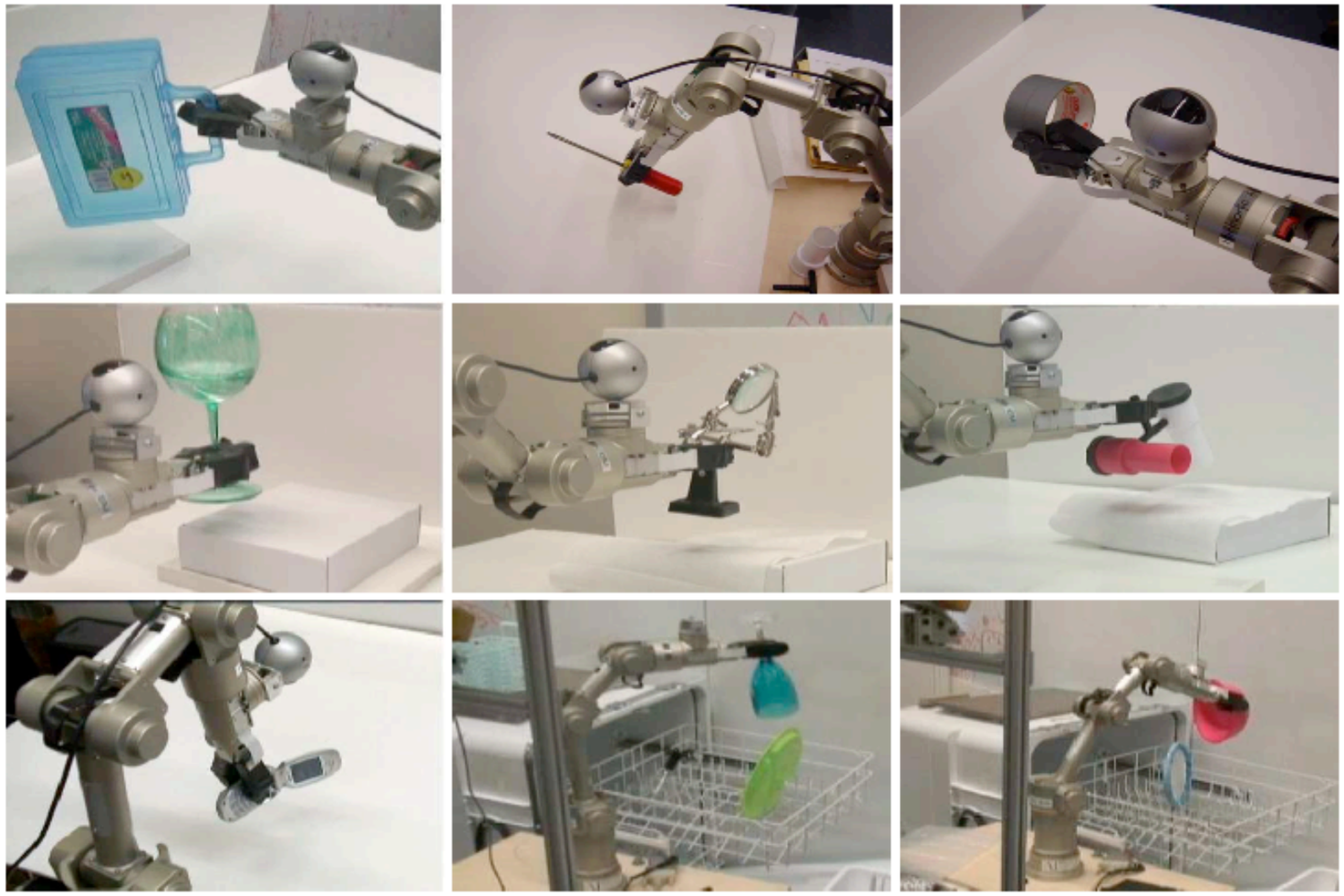
- Traditional sense.



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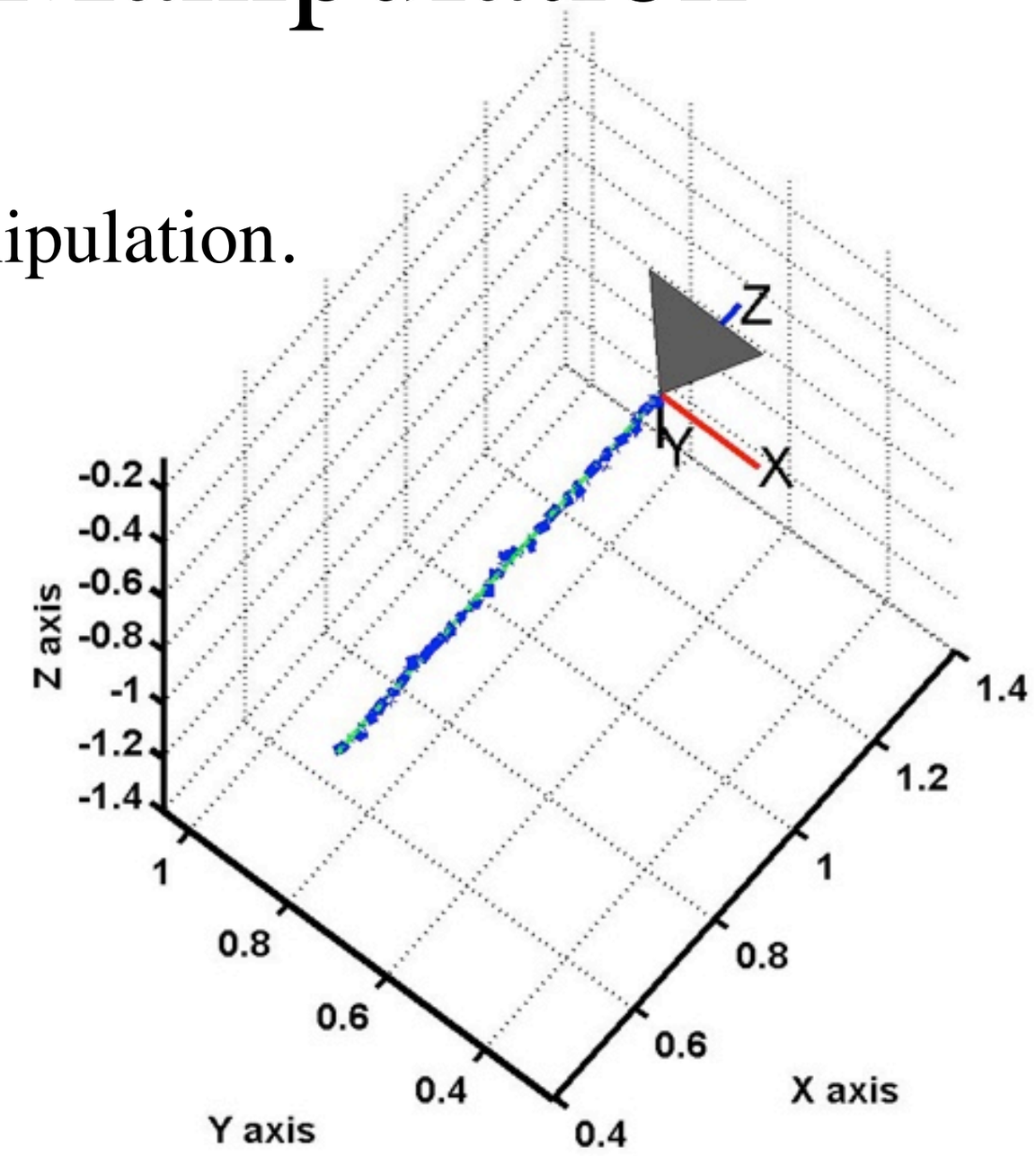

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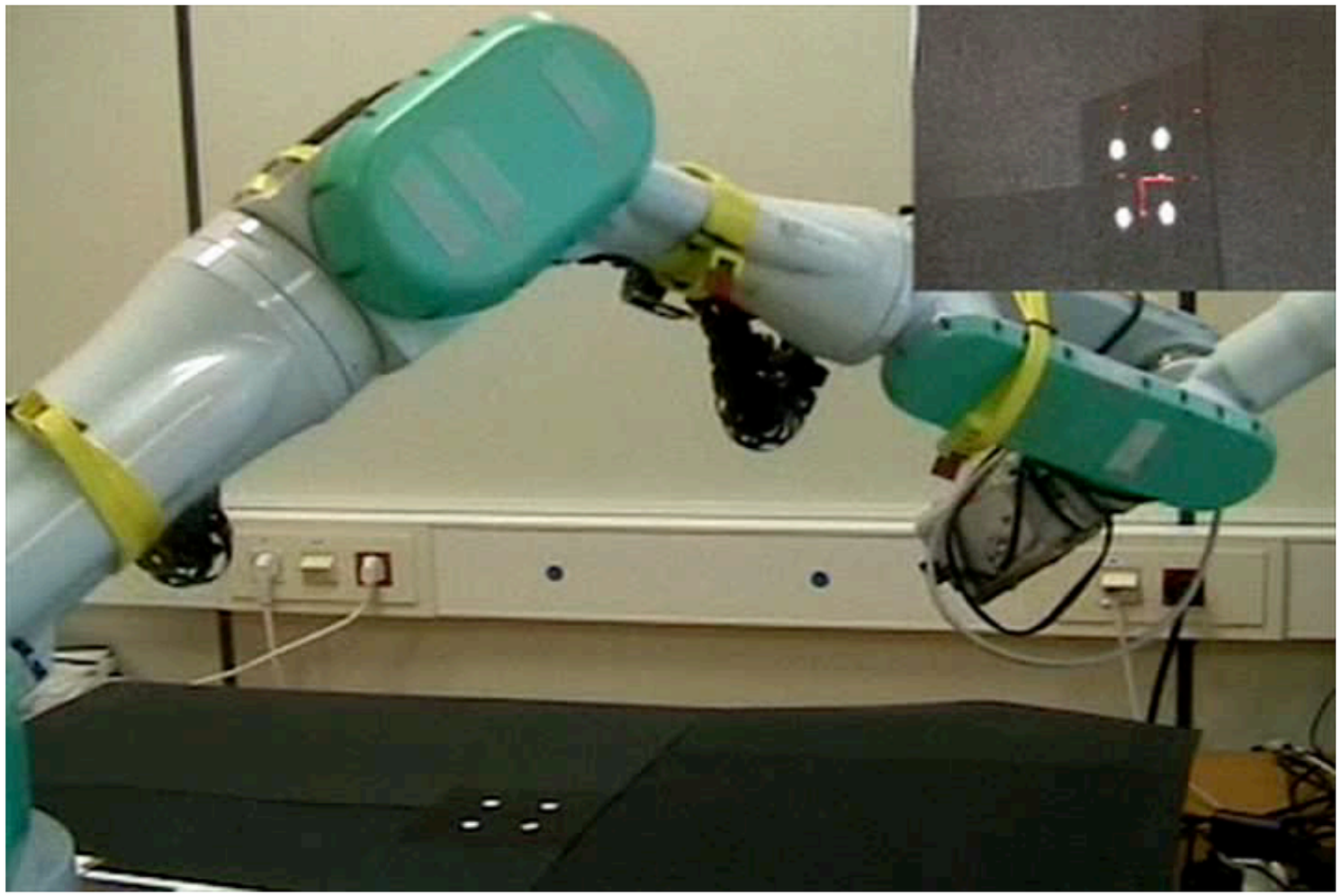

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Tracking Challenges

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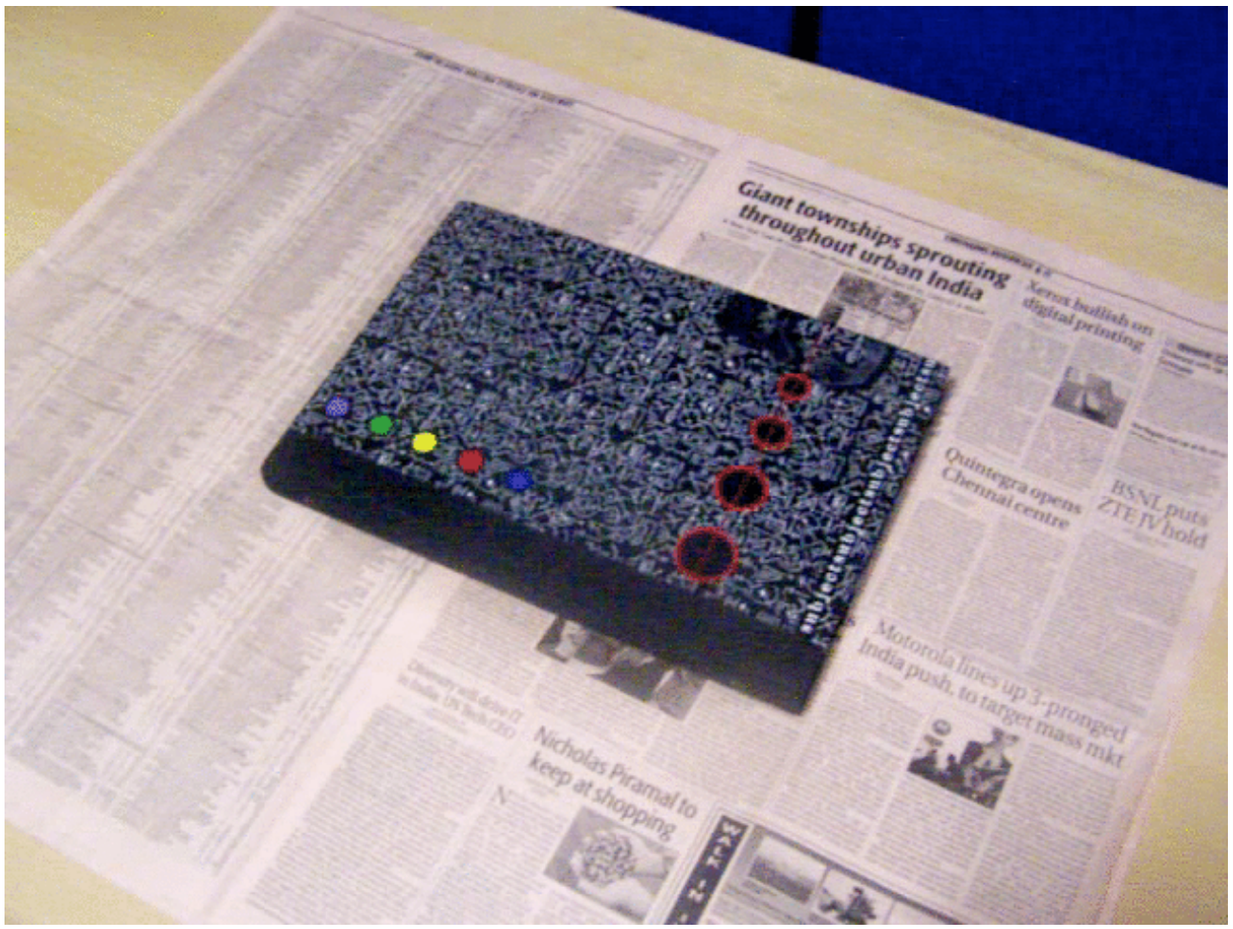
- Motion



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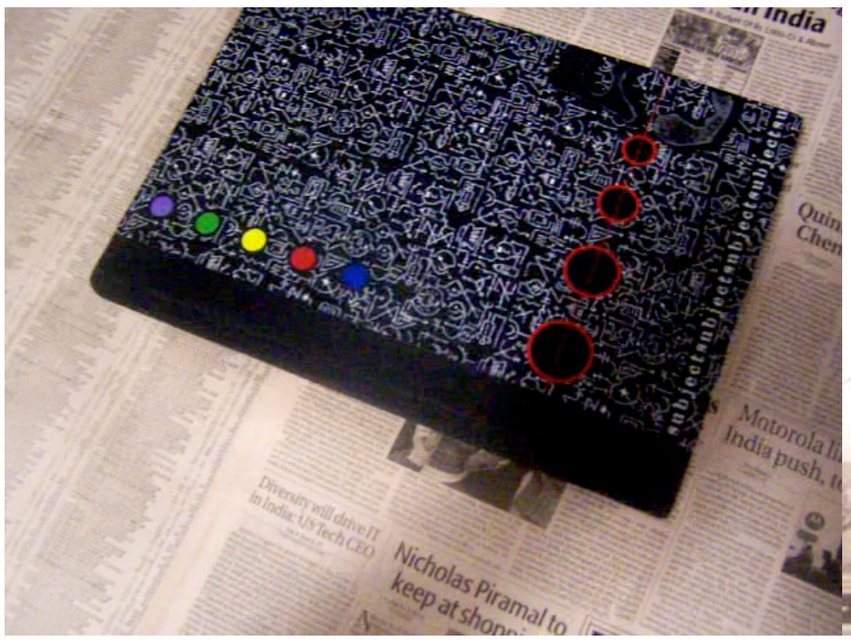

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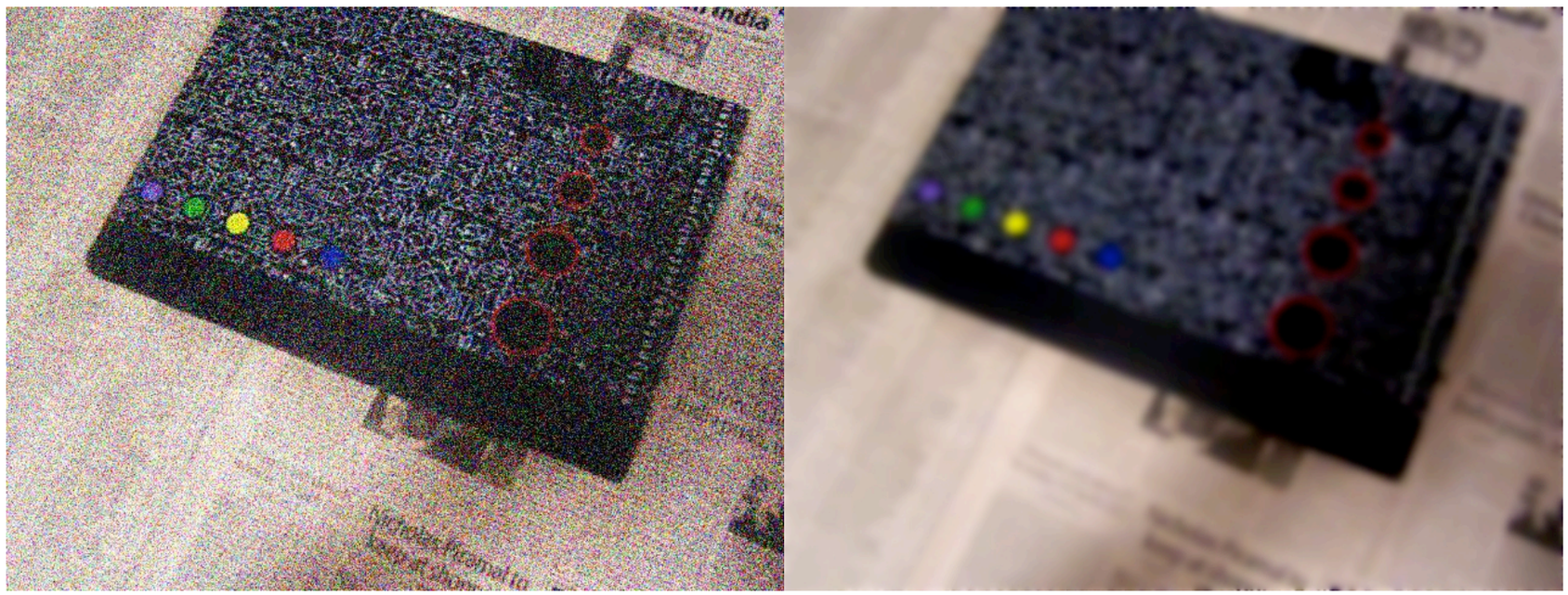

Tracking Challenges

- Motion
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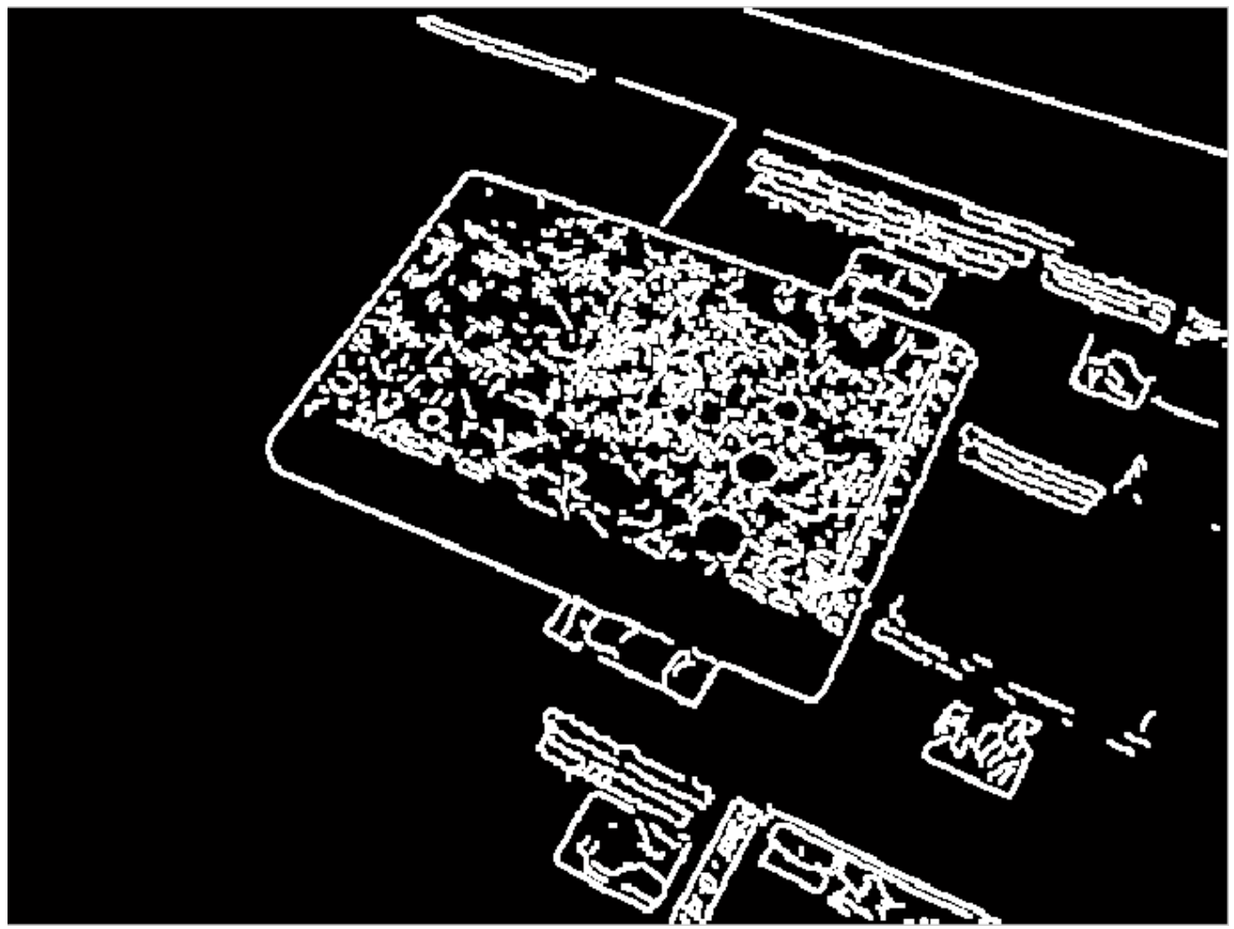
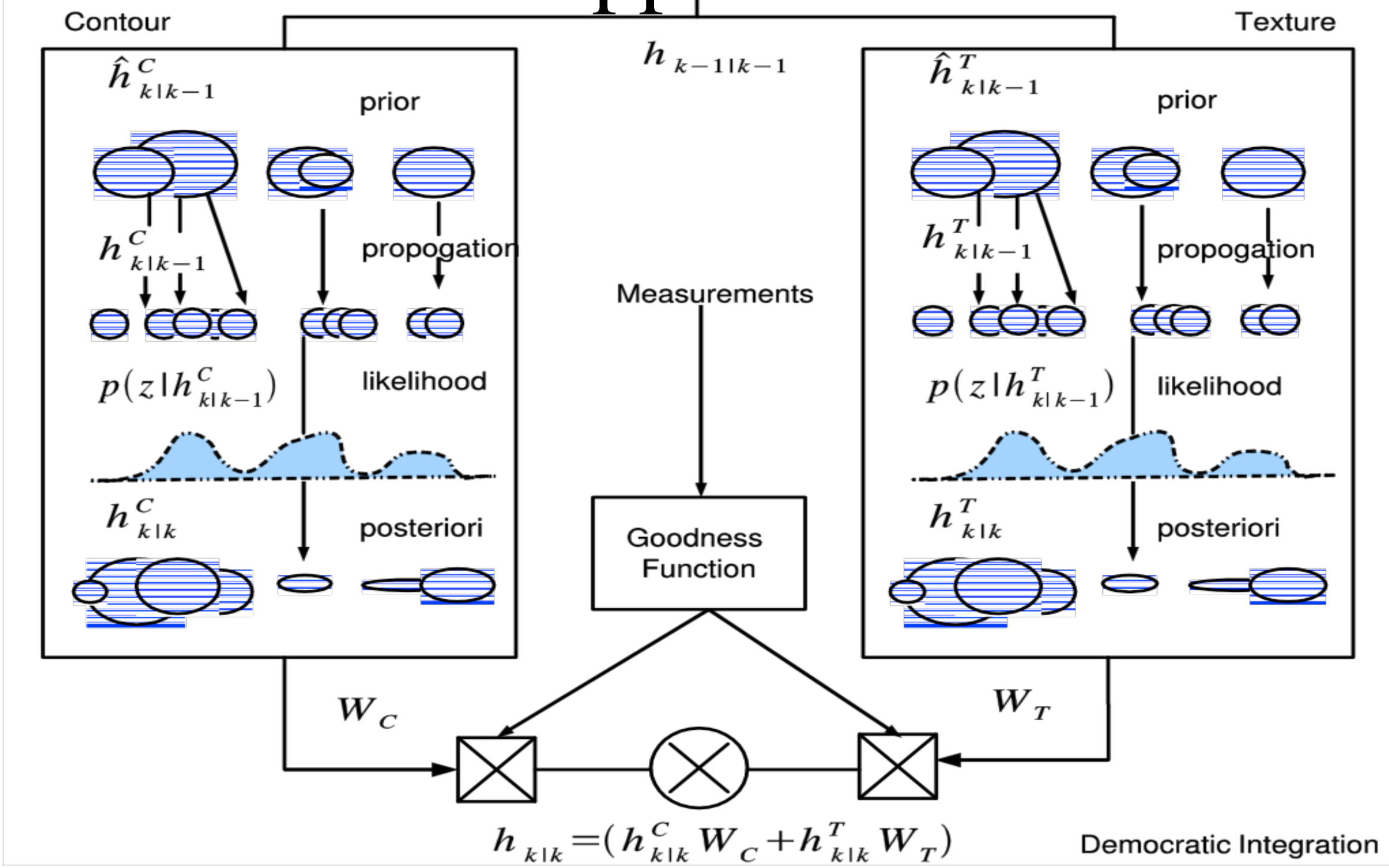
- Noise and Blur
- Clutter



Approach


Contour
Texture
$h_{k-1|k-1}$
$\hat{h}^{C}_{k|k-1}$
prior
$h^{C}_{k|k-1}$
propogation
Measurements
$p(z|h^{C}_{k|k-1})$
likelihood
$h^{C}_{k|k}$
posteriori
Goodness Function
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W_C
W_T
$h_{k|k}=(h^{C}_{k|k}W_C+h^{T}_{k|k}W_T)$
Democratic Integration

Texture information

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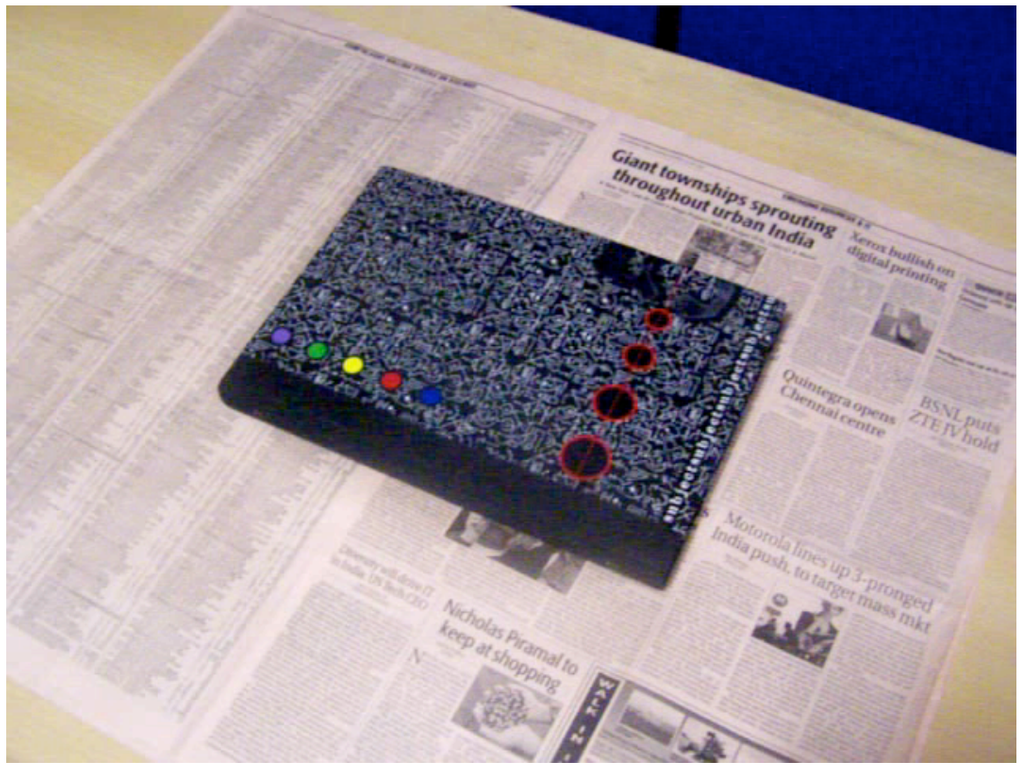

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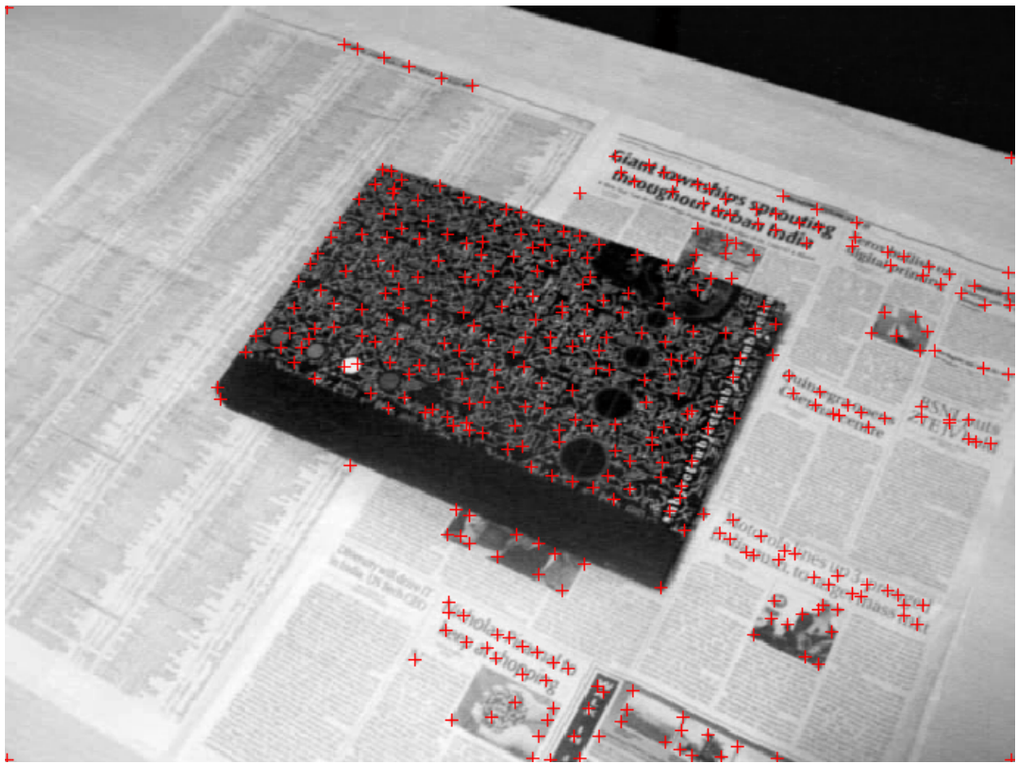

Texture information

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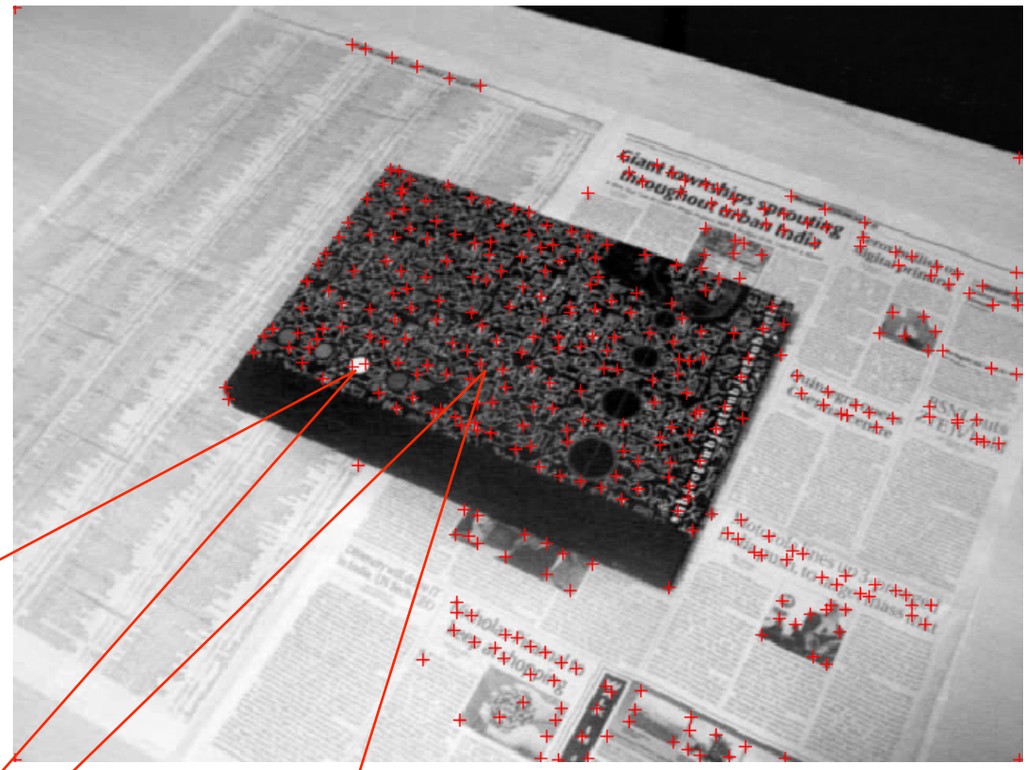

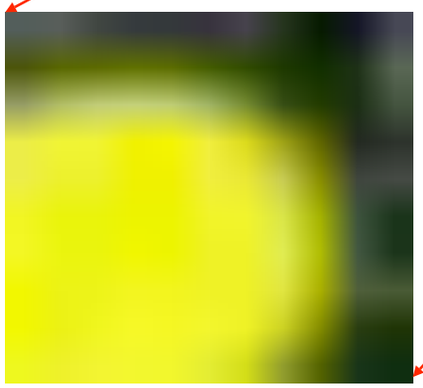

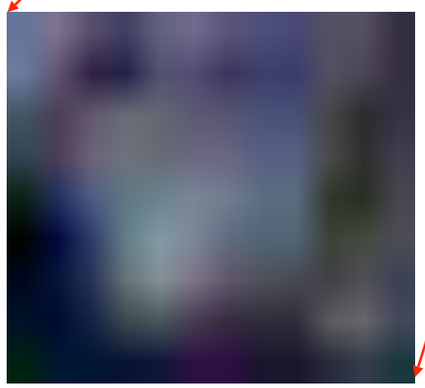

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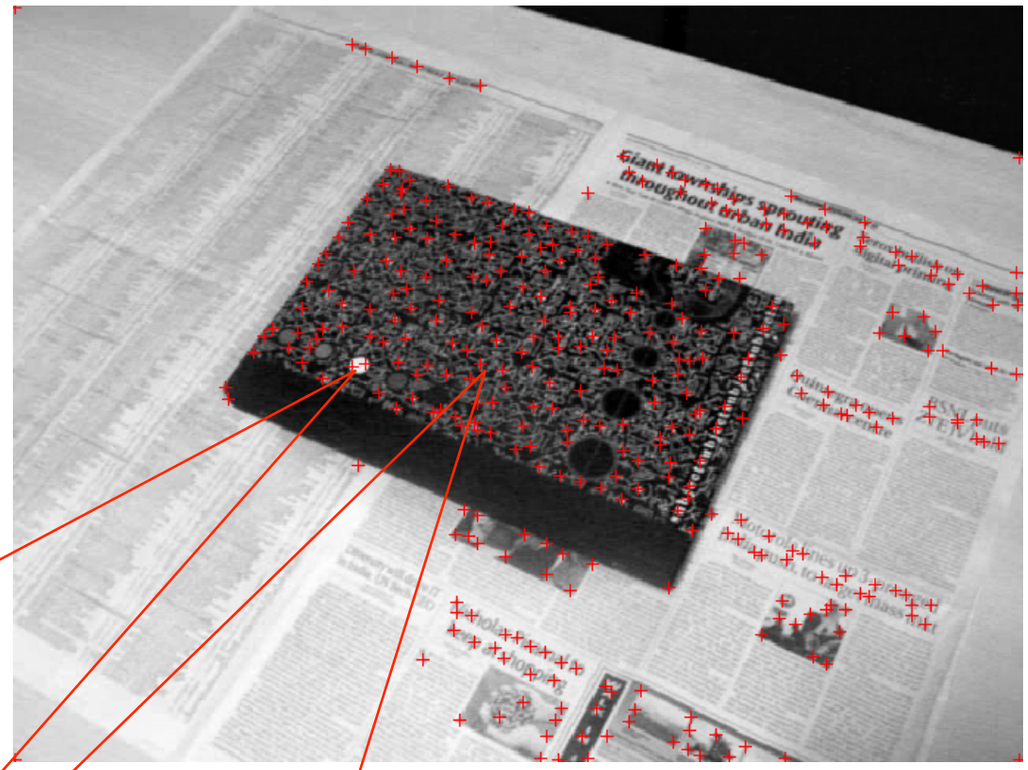

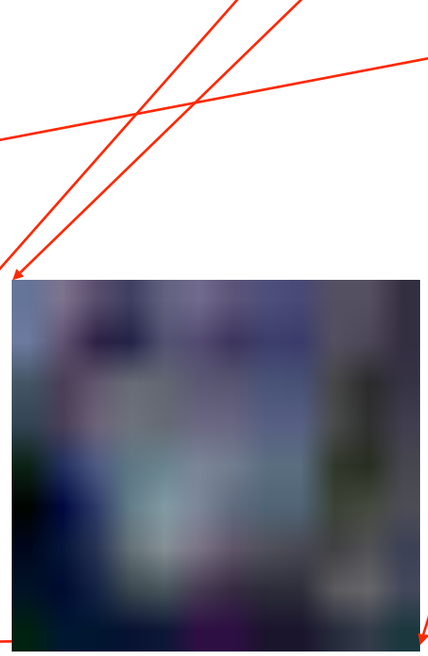

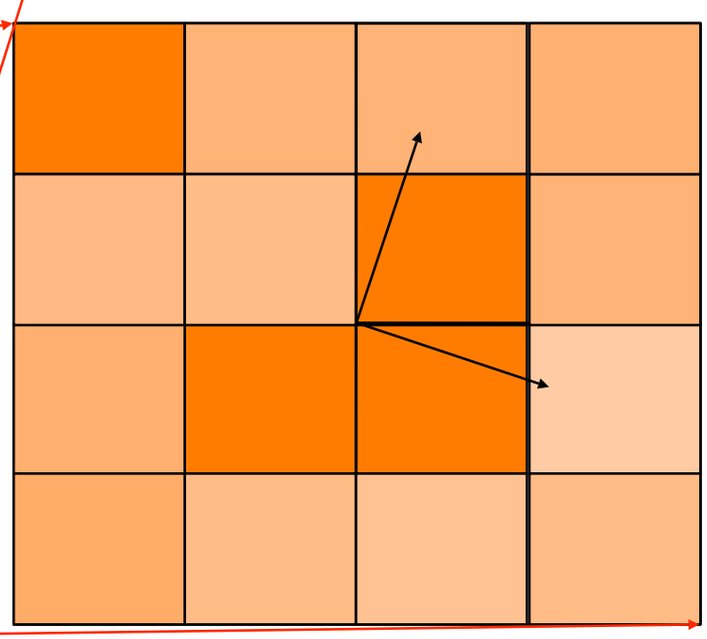

Texture information

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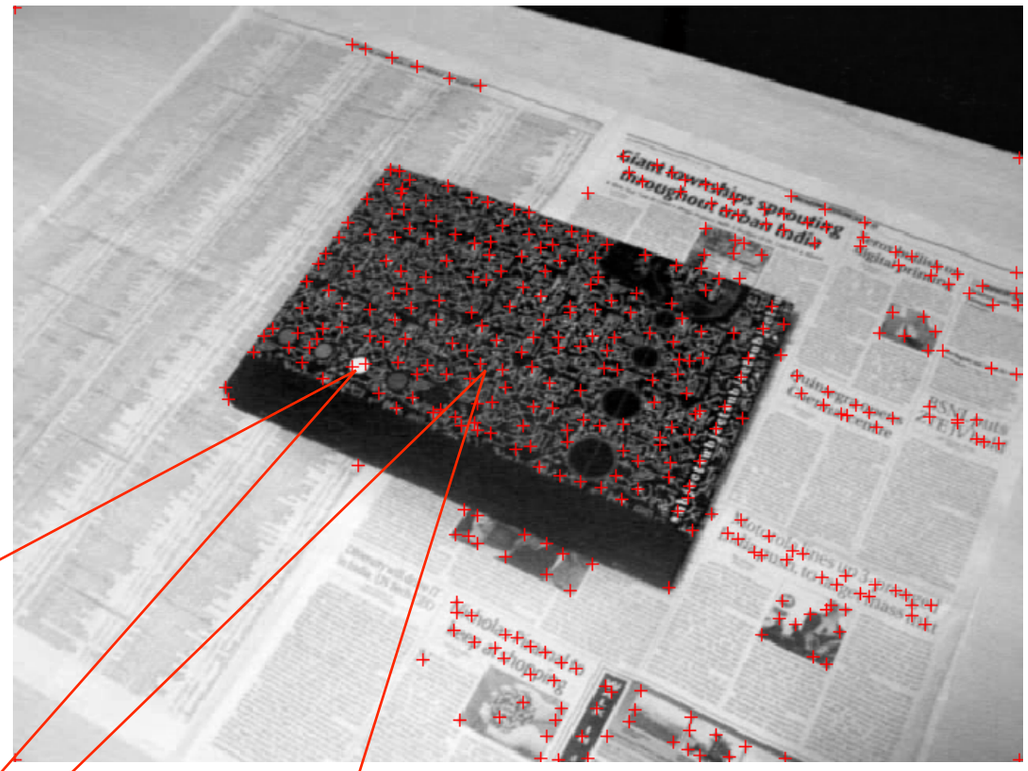
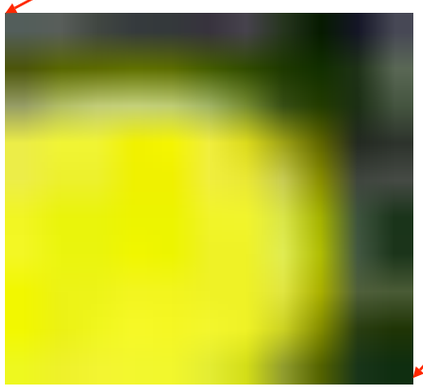
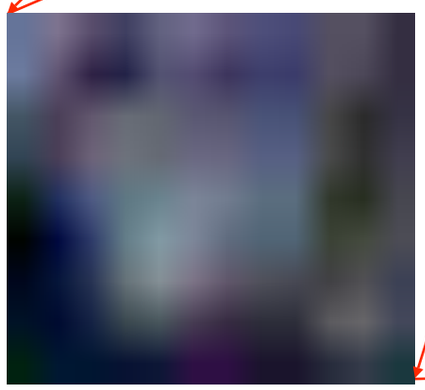
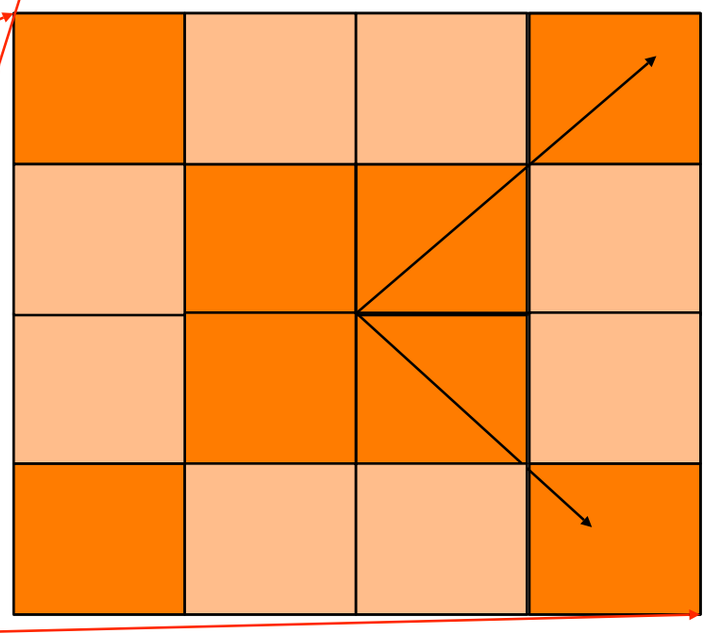
- Condition for good texture.









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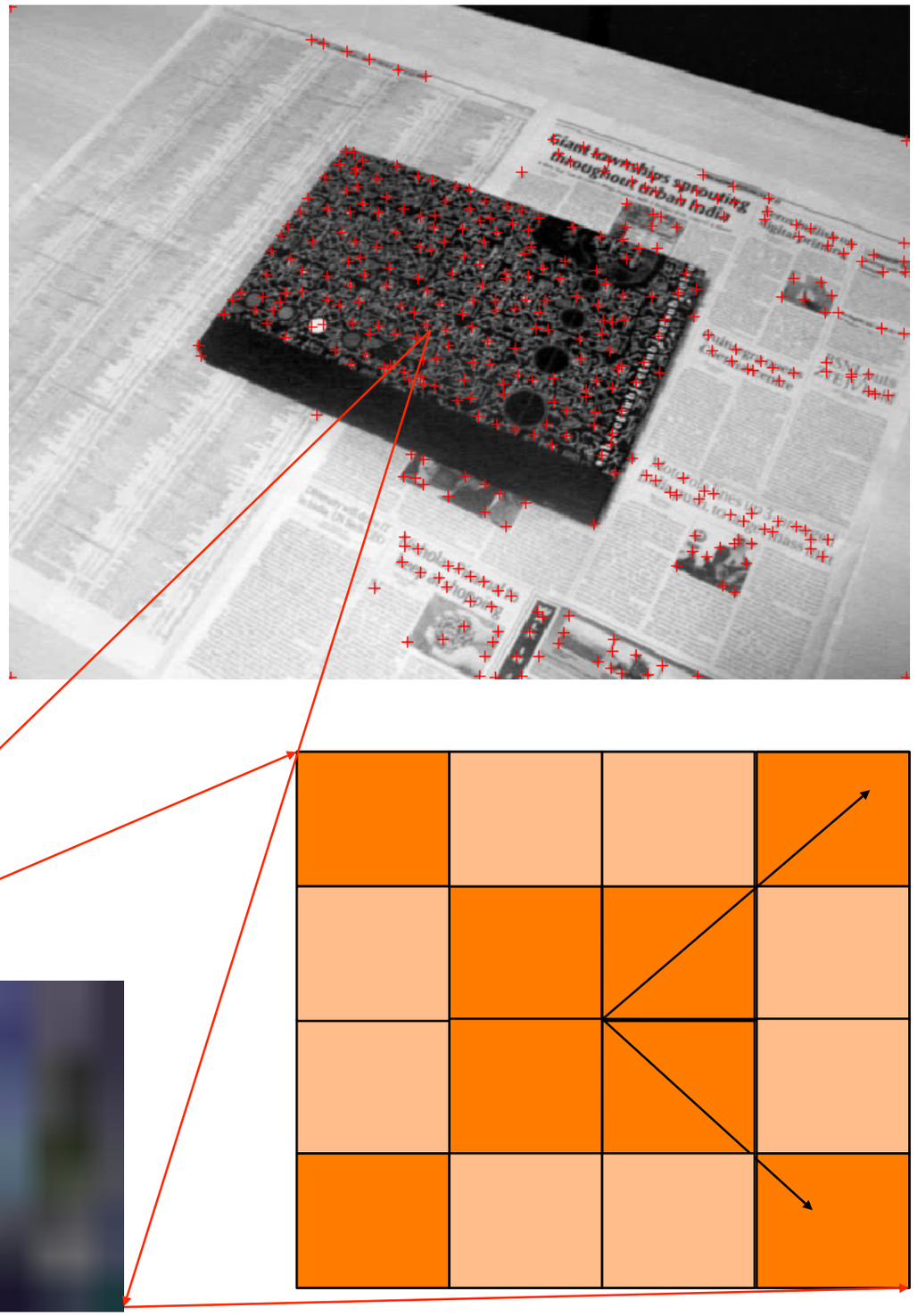

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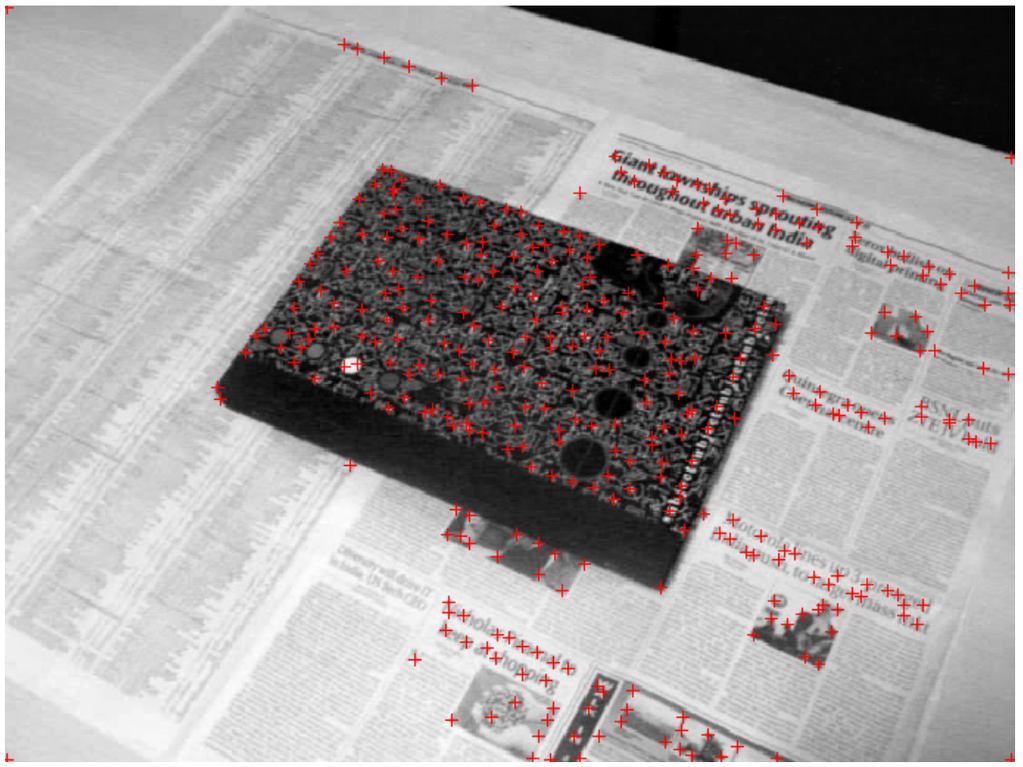

$$\min(\lambda_1, \lambda_2) > t$$

Texture - Drawbacks

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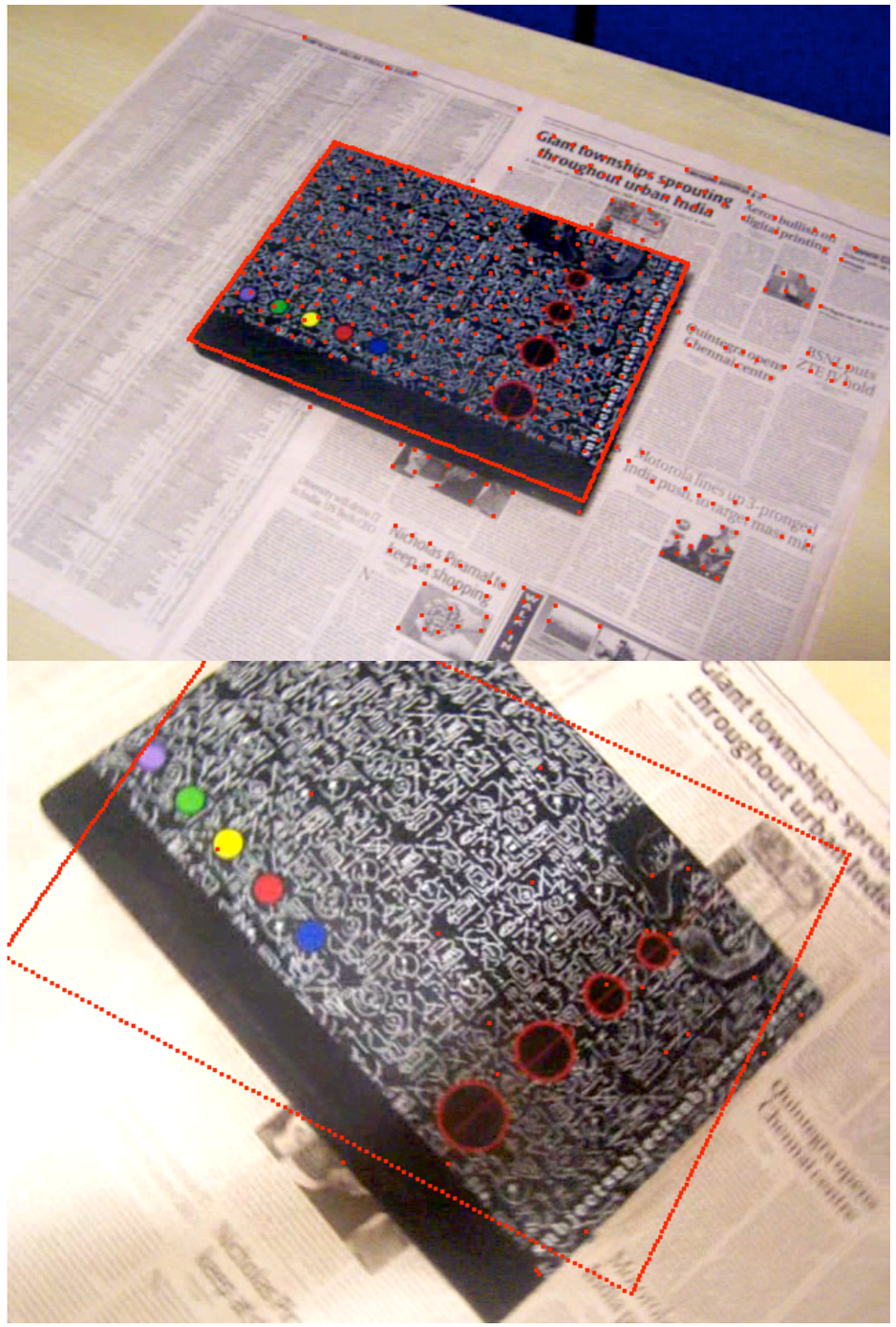
Loss/Inaccuracy in tracking may result because of :-



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Texture - Drawbacks

Loss/Inaccuracy in tracking may result because of :-

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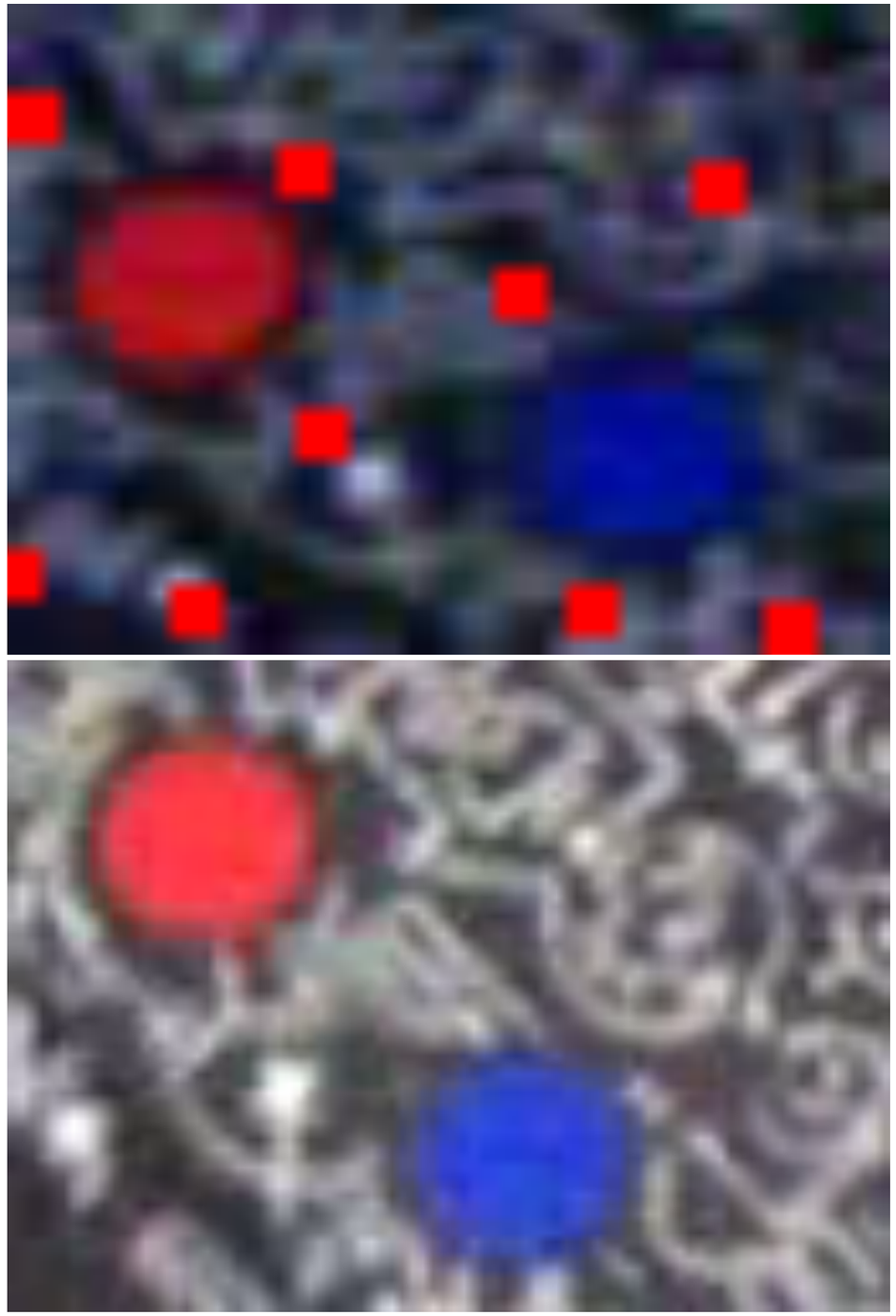
- Large illumination change.



Texture - Drawbacks

Loss/Inaccuracy in tracking may result because of :-

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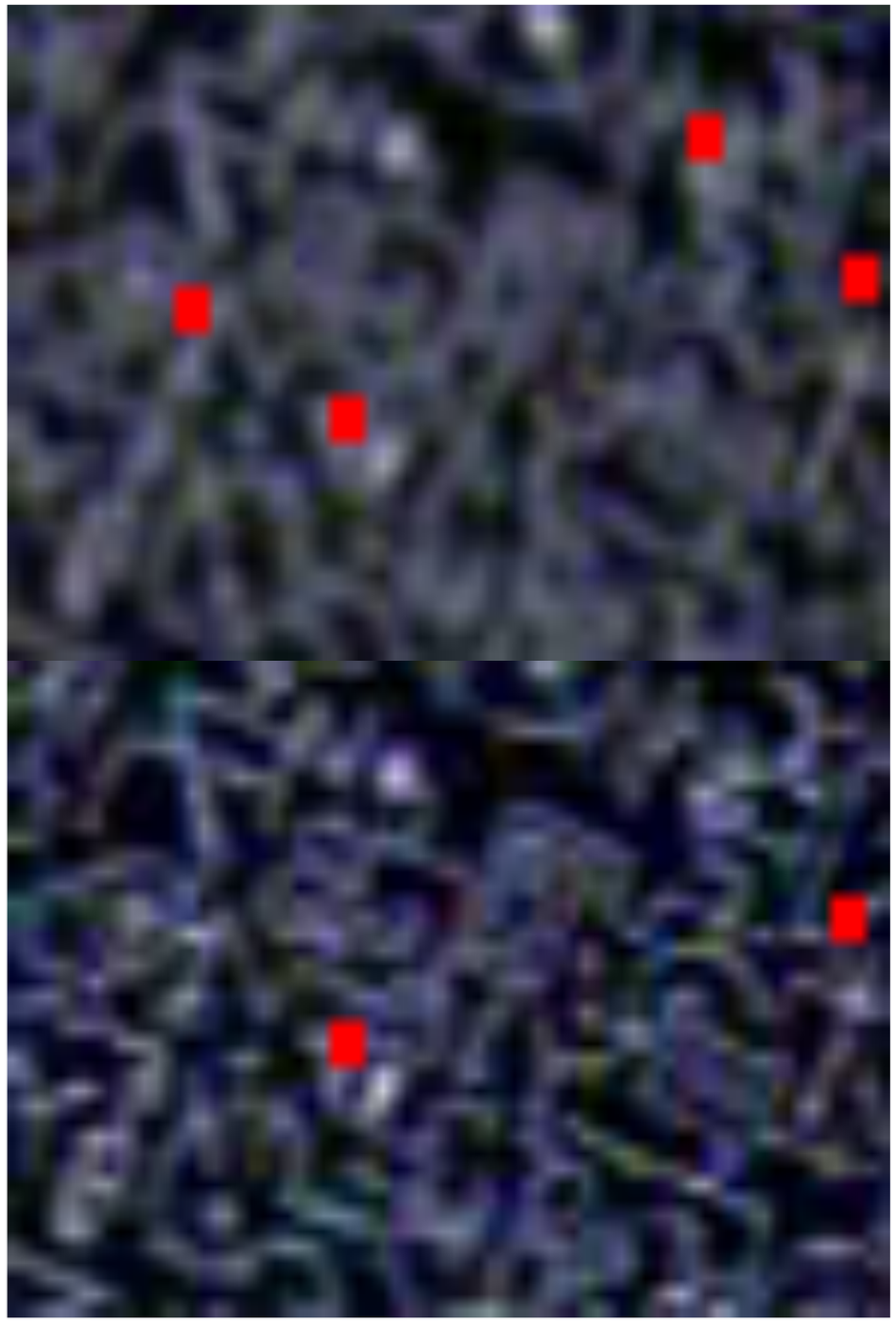
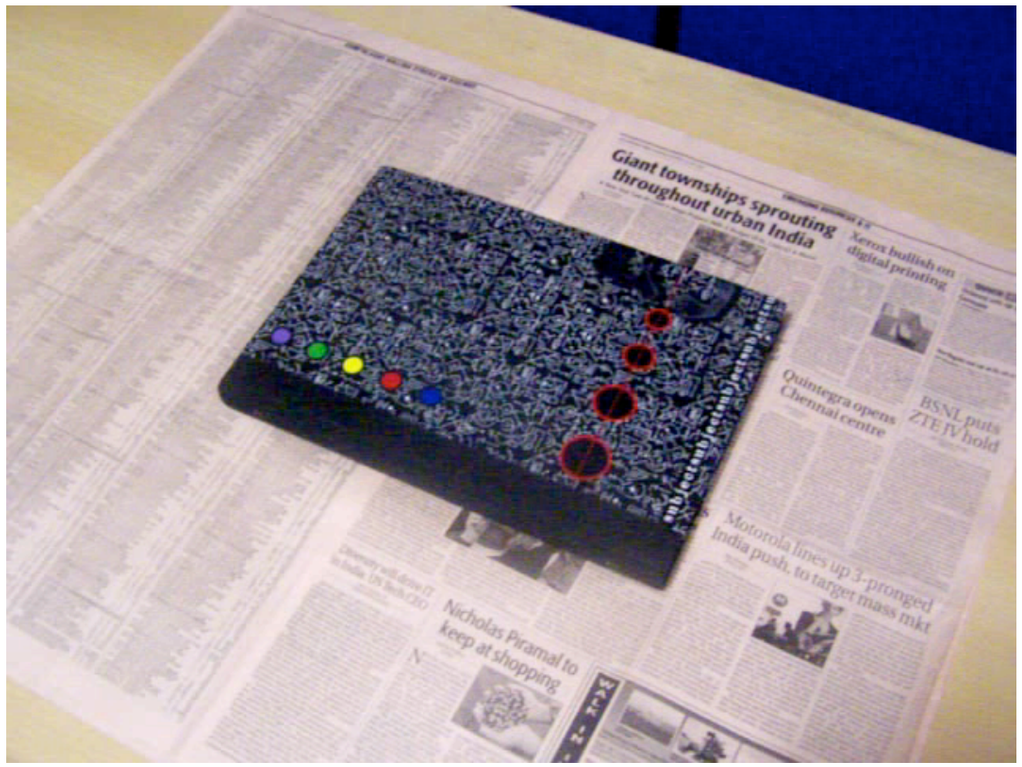
- Large illumination change.
- Noise / Blur.



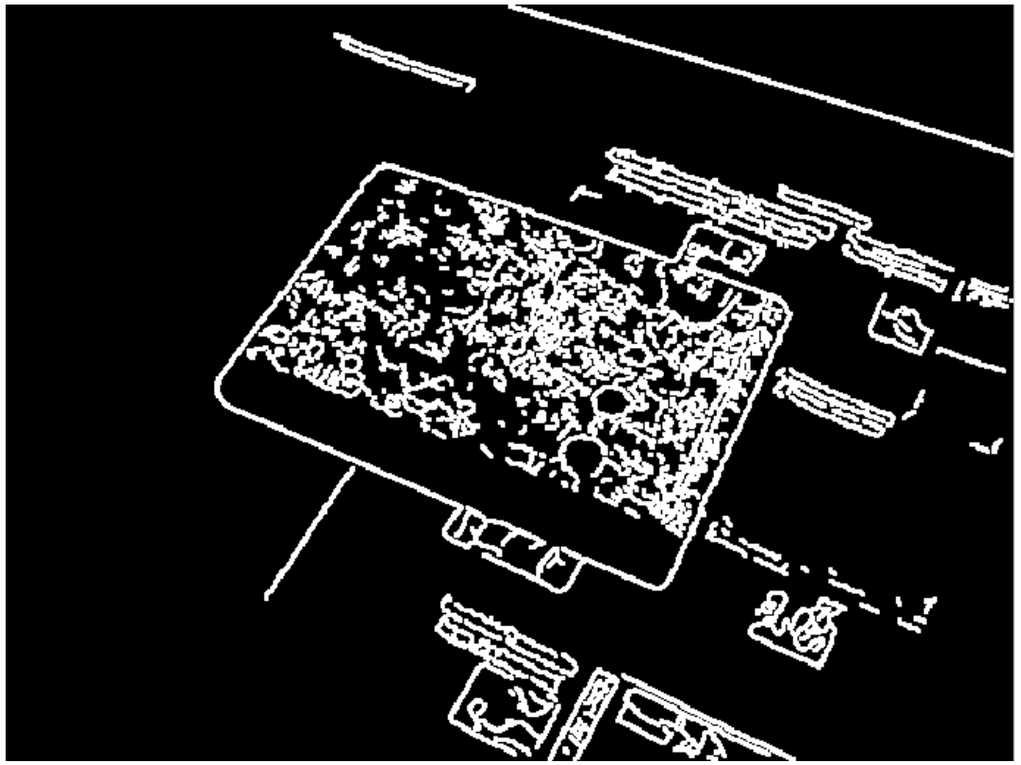
Contour Information

Contour Information



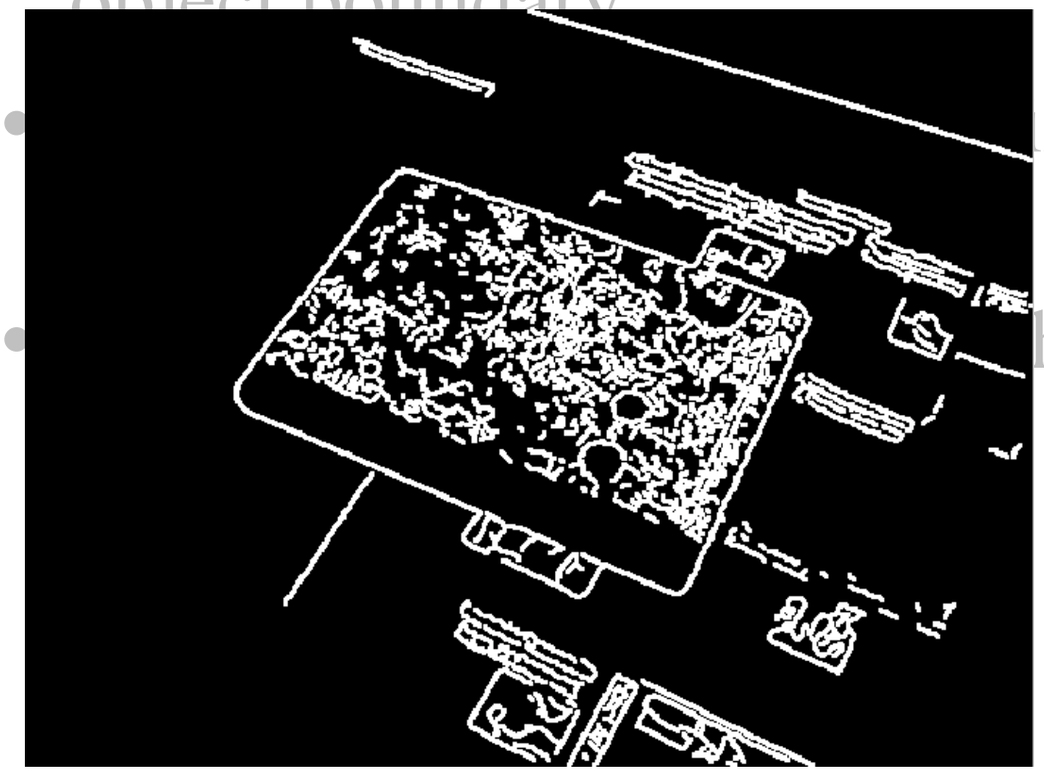
Contour Information

- Represent edge information of object boundary.



Contour Information

- Represent edge information of object boundary
- rst
- h



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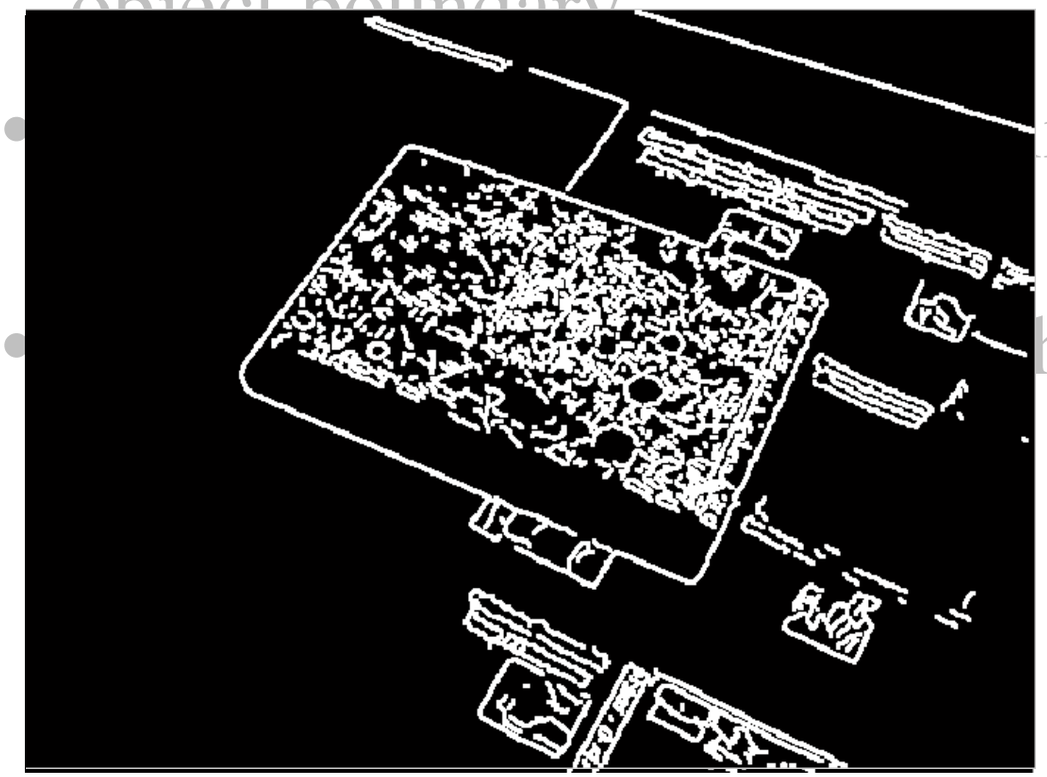

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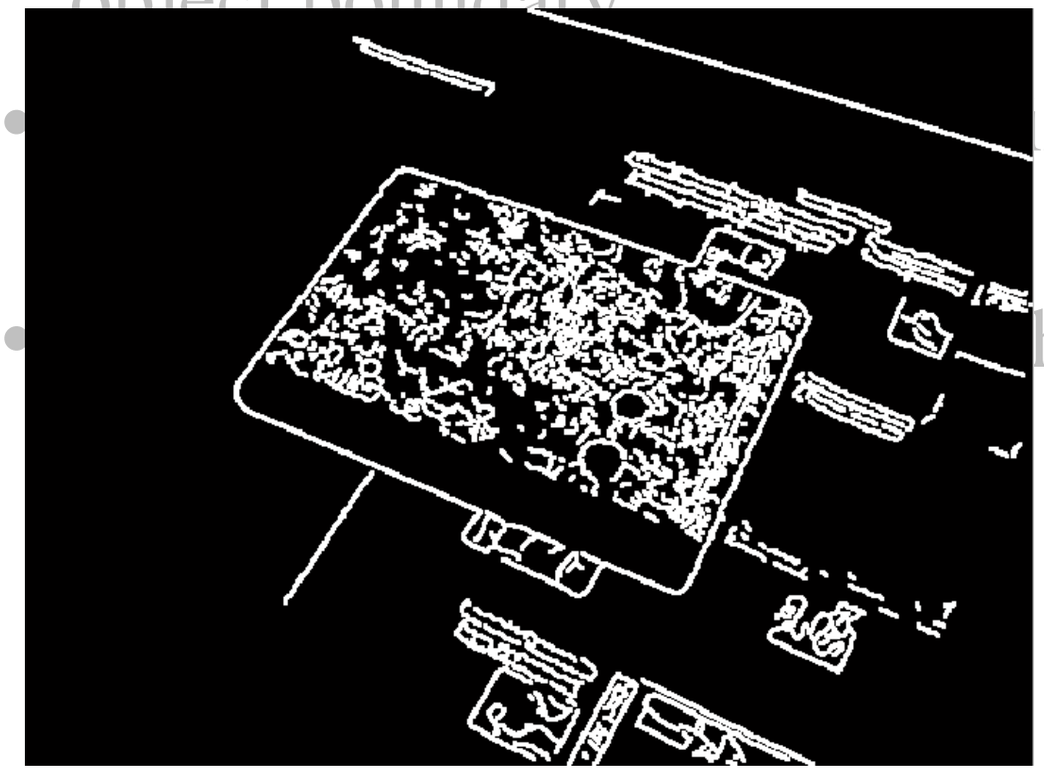

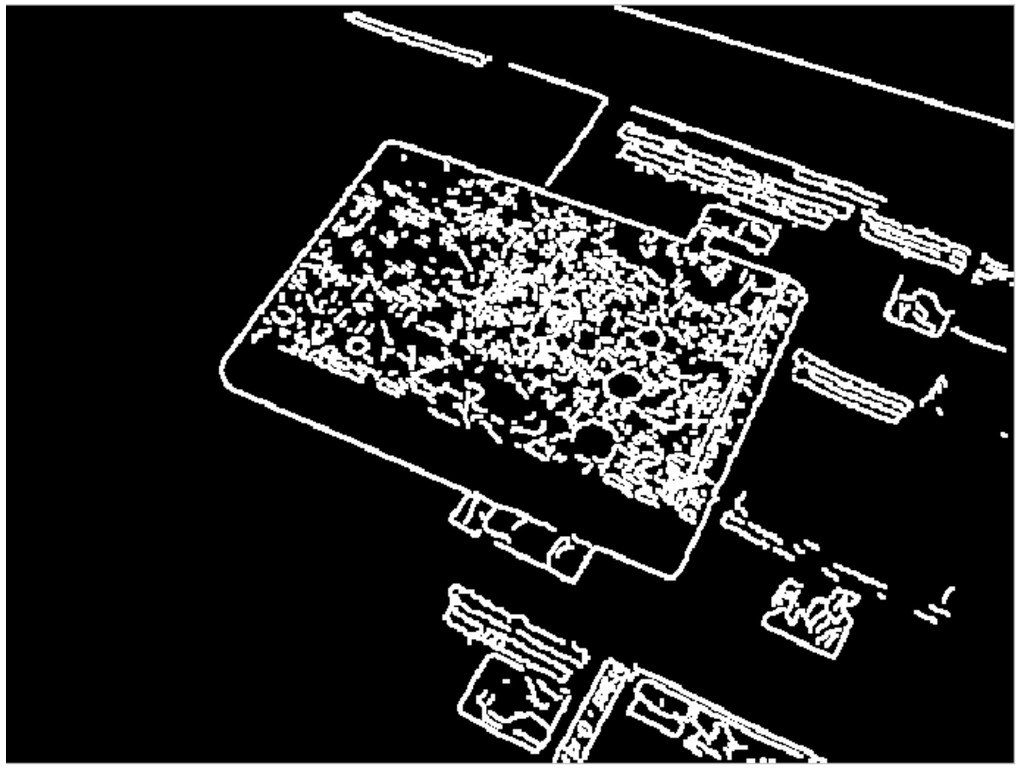

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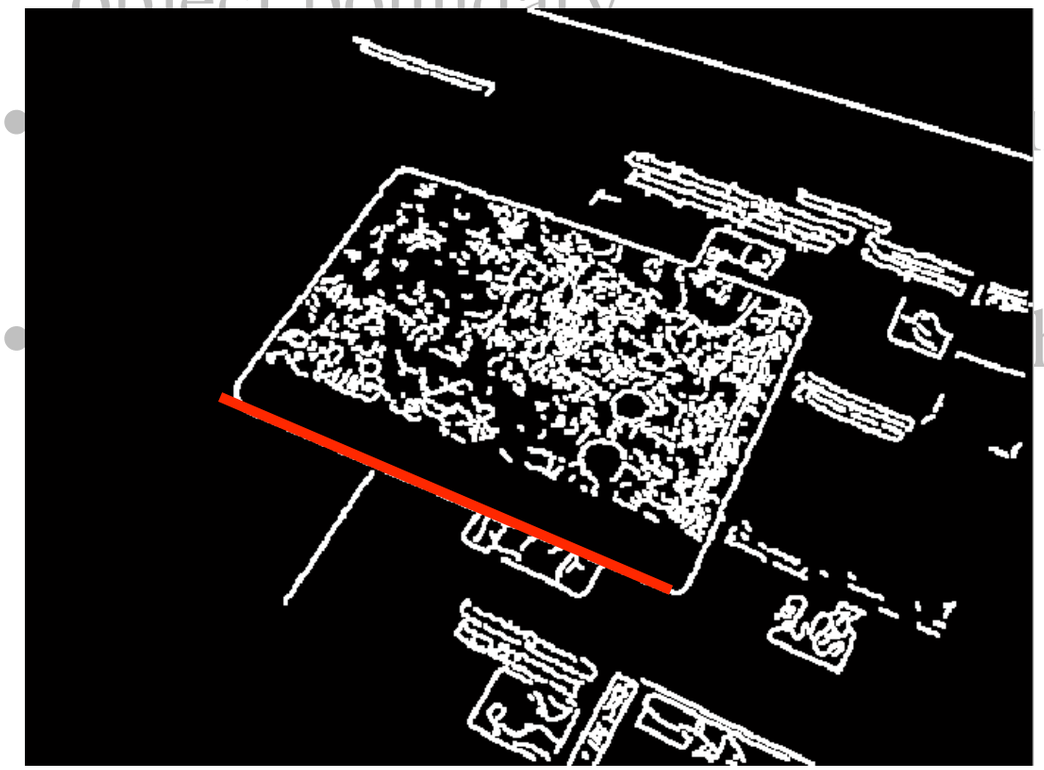
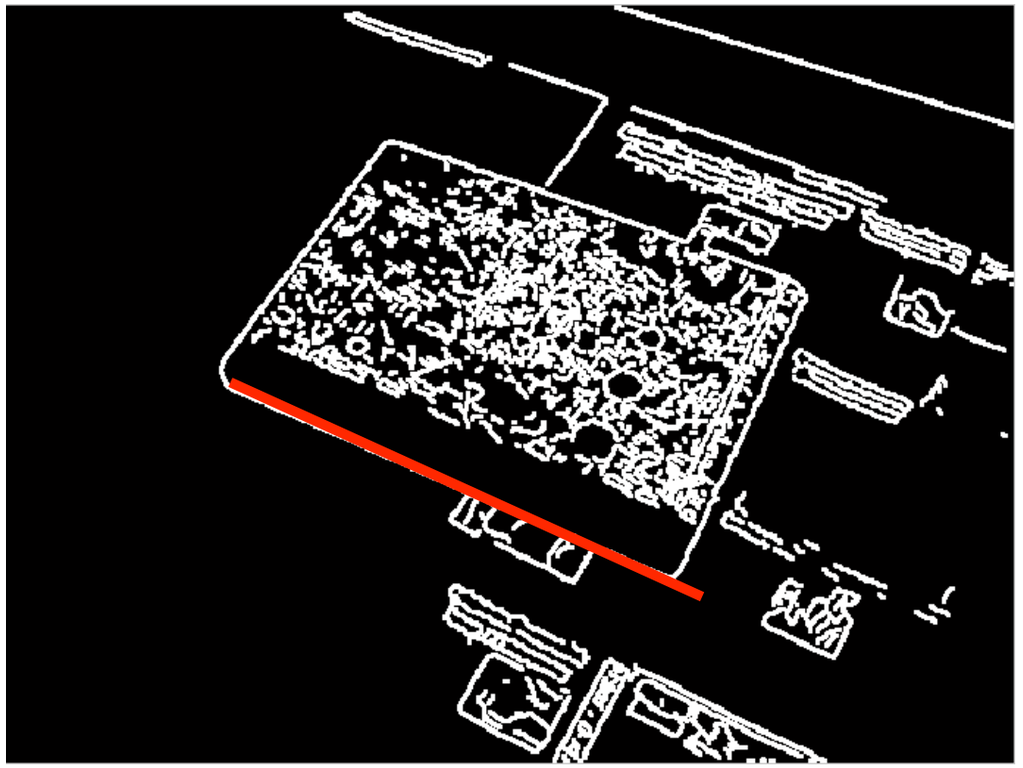
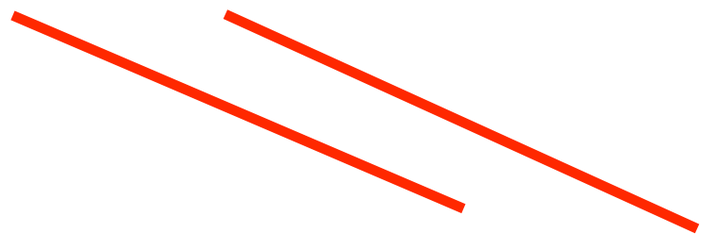
- rst
- h





Contour Information

- Represent edge information of object boundary.
- Select certain points along first contour.



Contour Information

- Represent edge information of object boundary.
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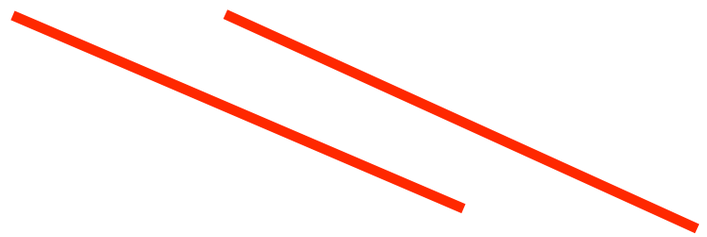
- Find correspondence through search along normal



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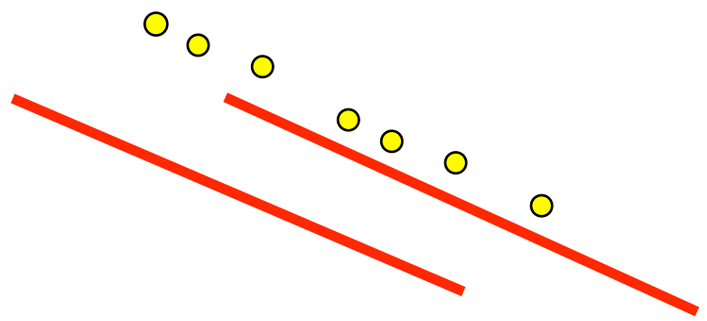

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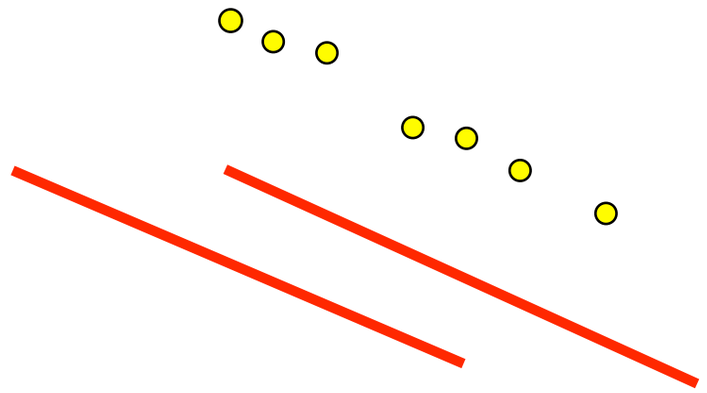

Contour - Drawbacks

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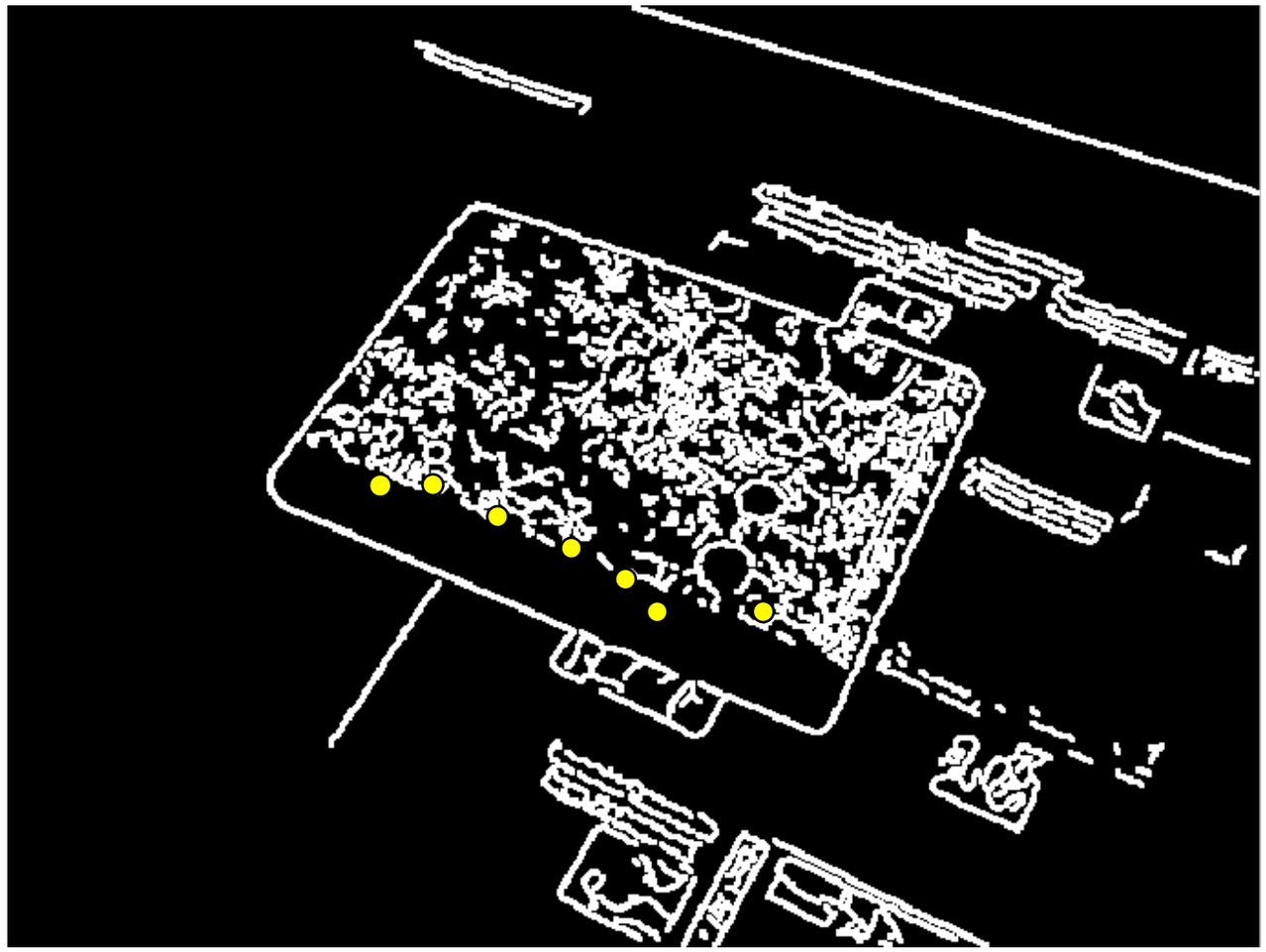
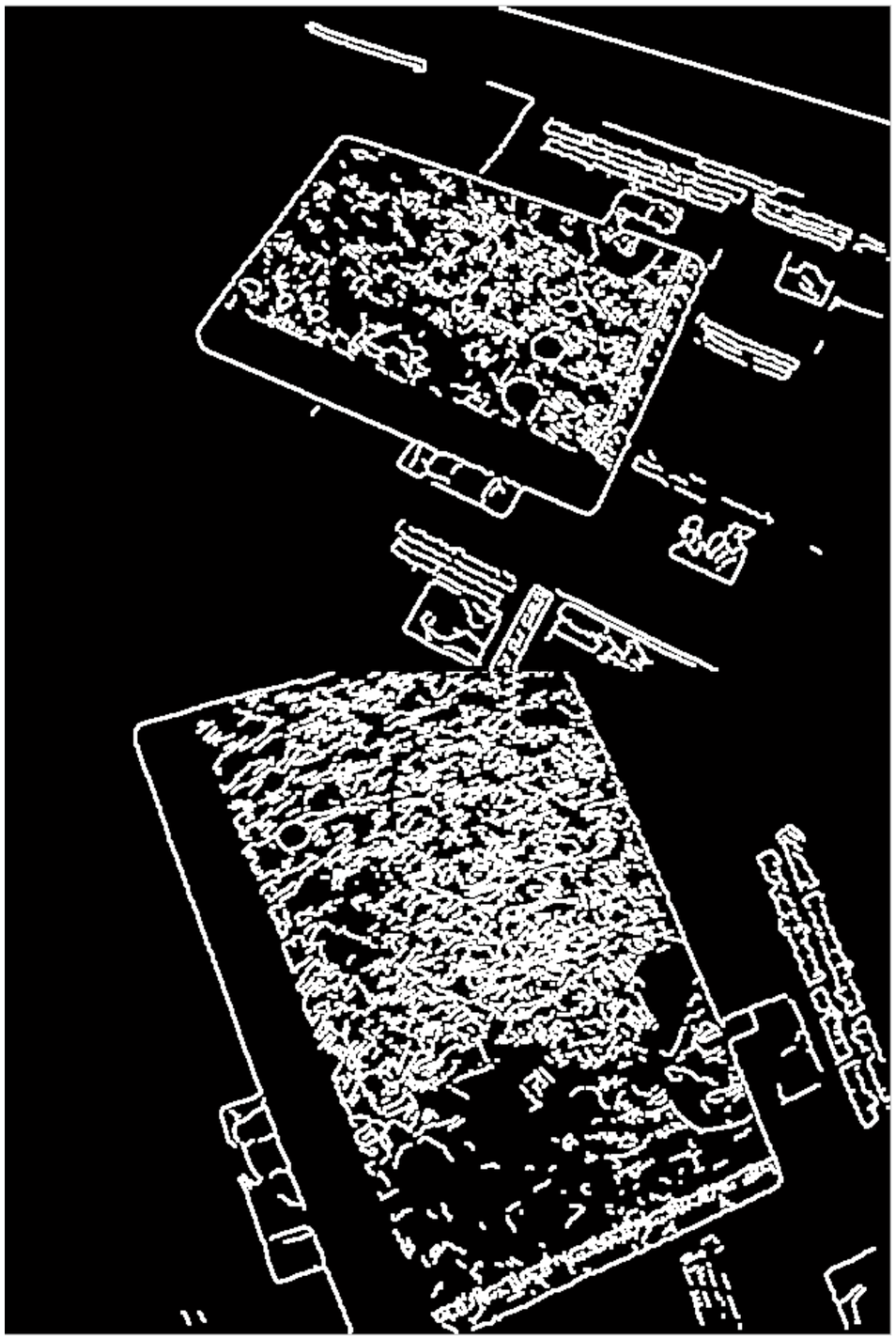


Contour - Drawbacks

Loss/Inaccuracy in tracking may result because of :-

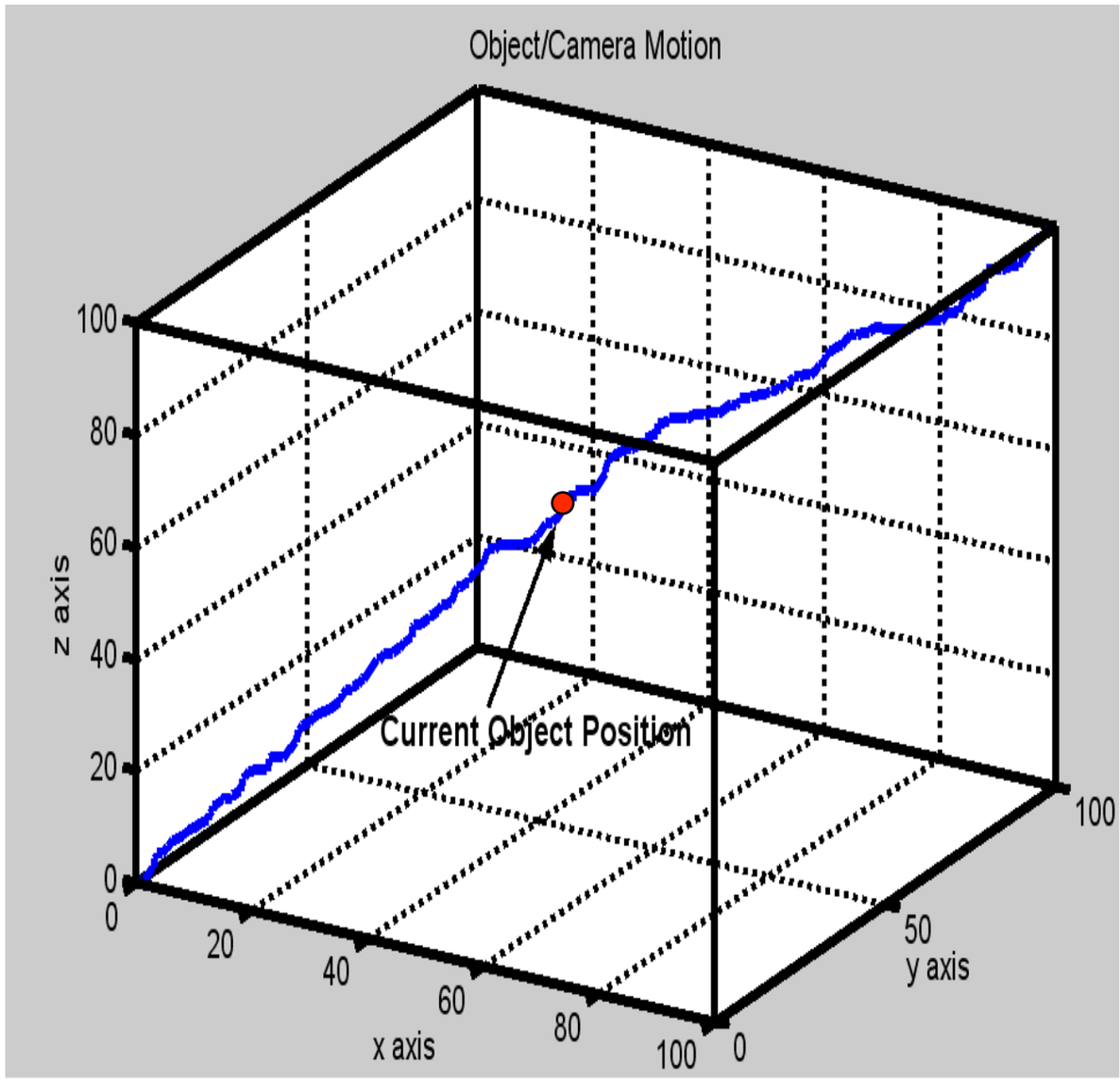
- Background clutter.
- Shadow/illumination – edge might be lost.



Condensation

Condensation

- Homography pose relationship.



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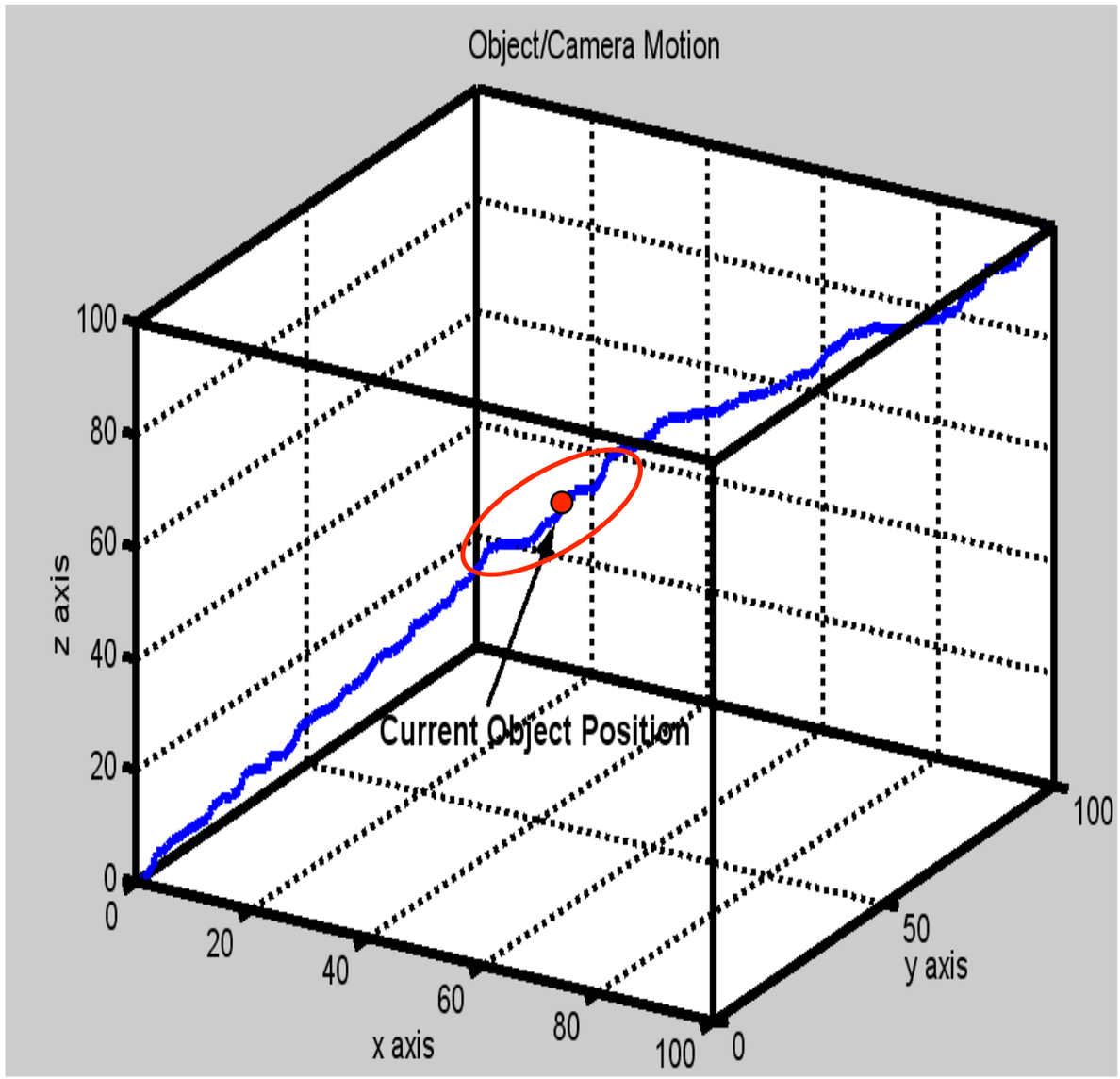

Condensation

- Homography pose relationship.
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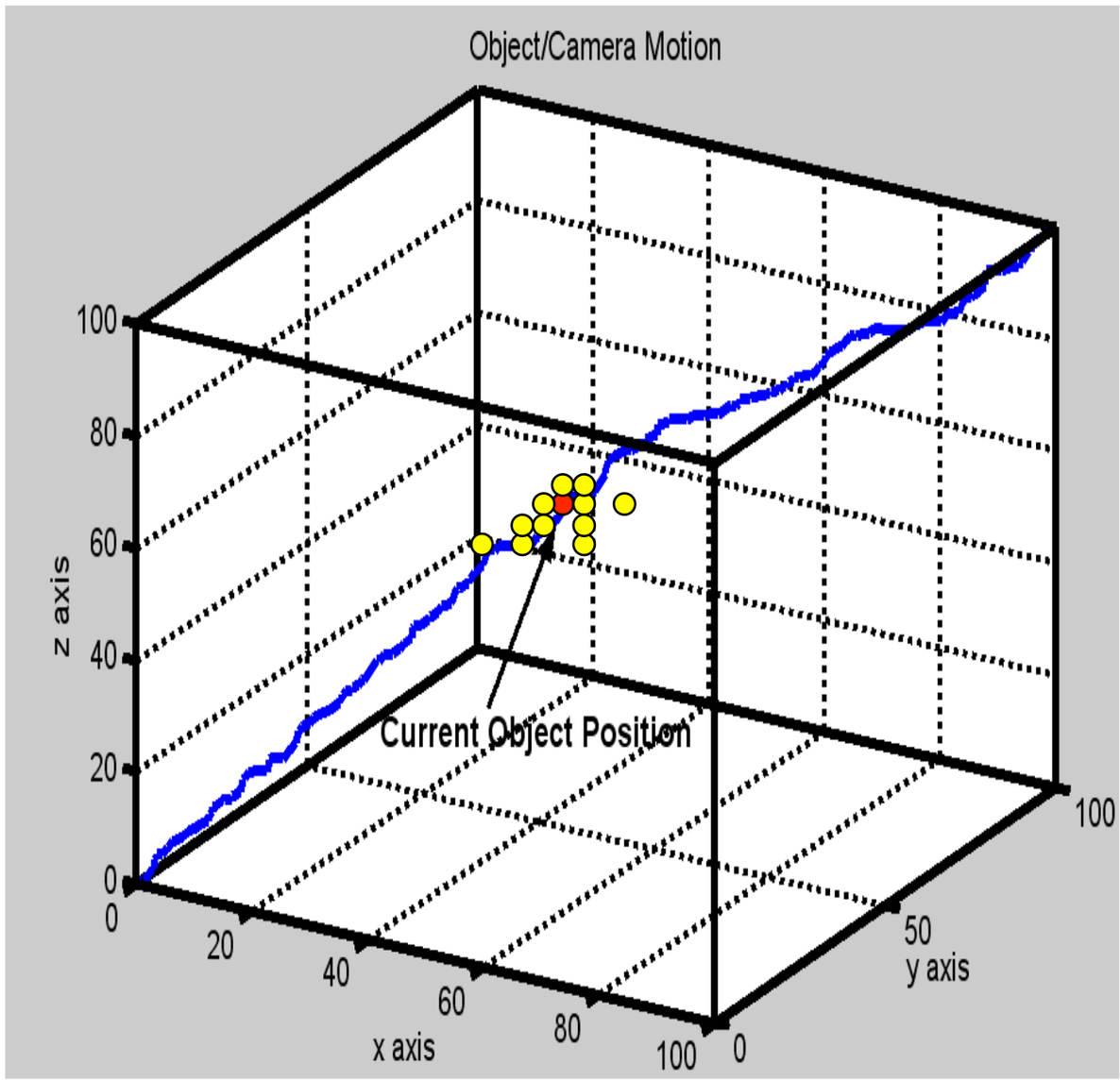
- Particles are drawn, and transform to homographies.



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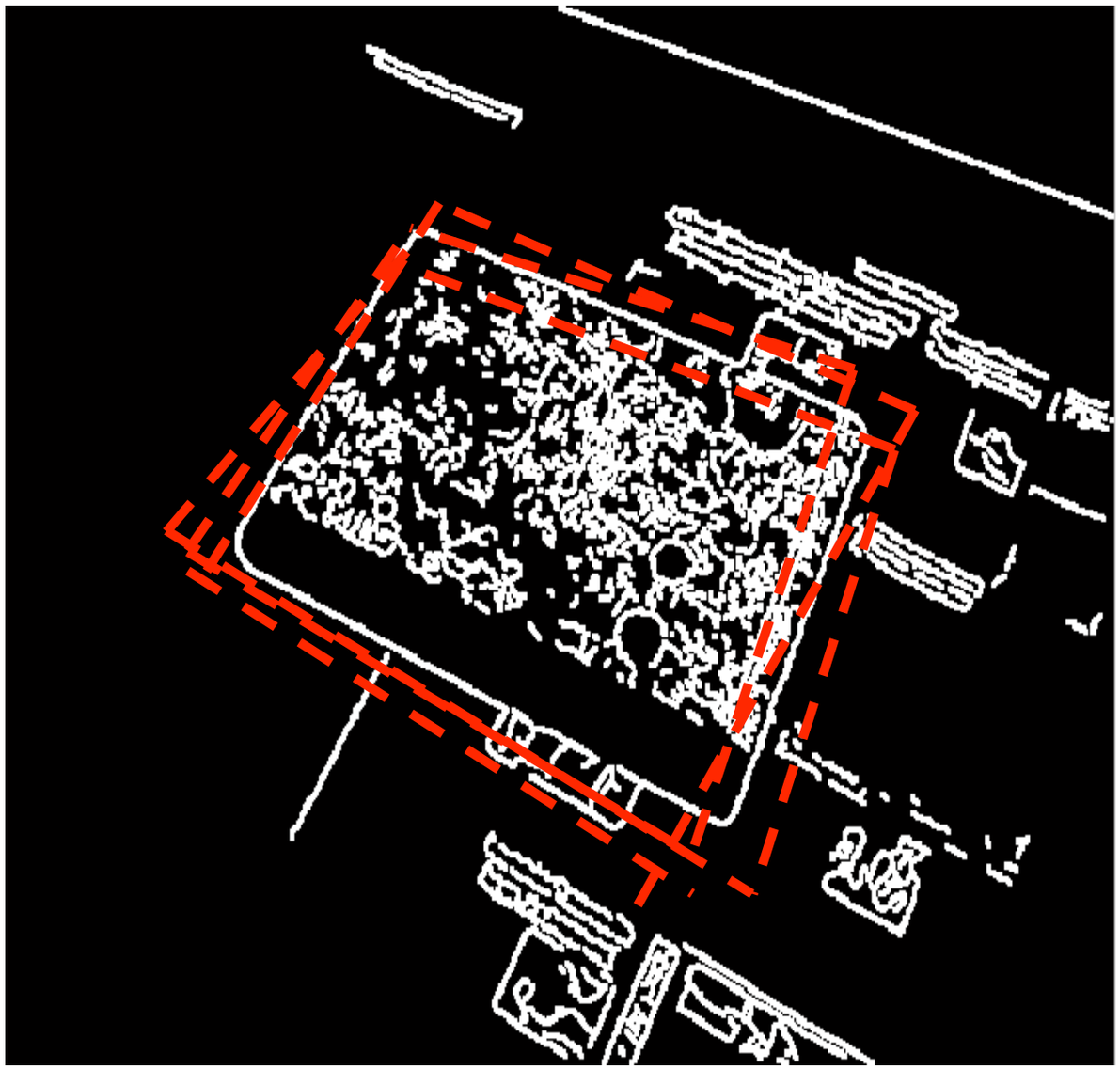

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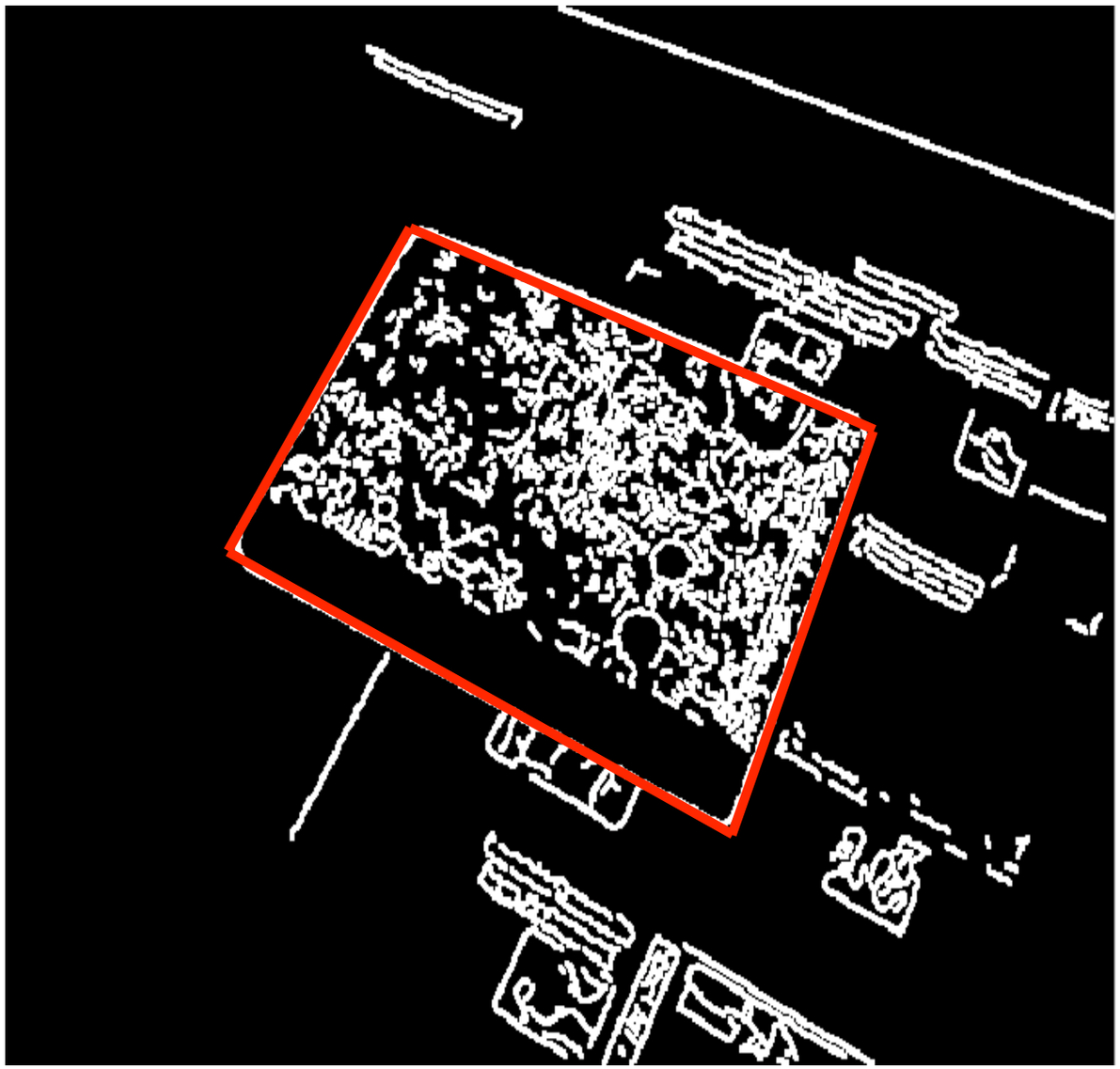

Why Particle Filters

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- Any tracking algorithm must consider non-linearity of the process dynamics and non-Gaussian nature of noise.

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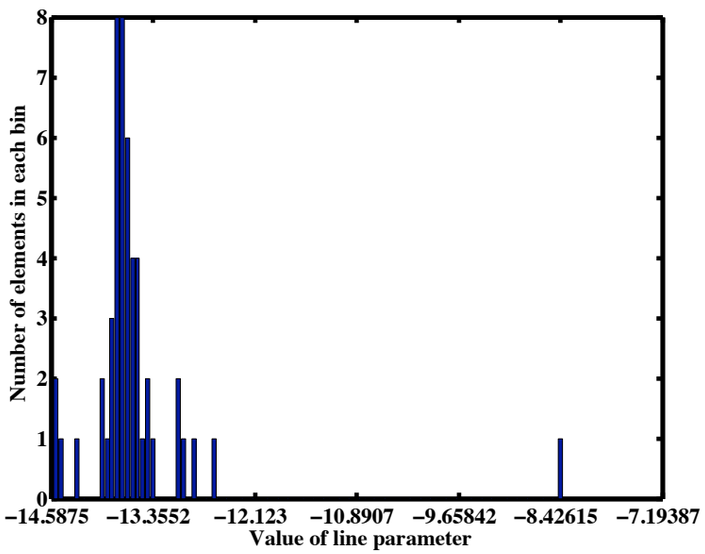

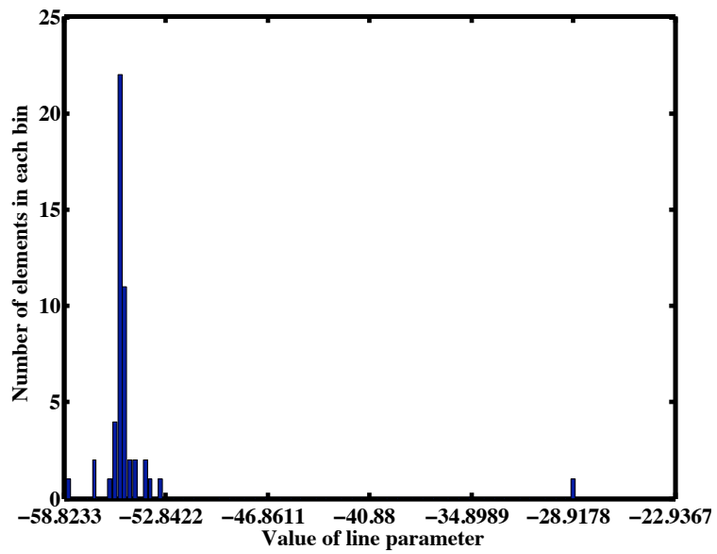

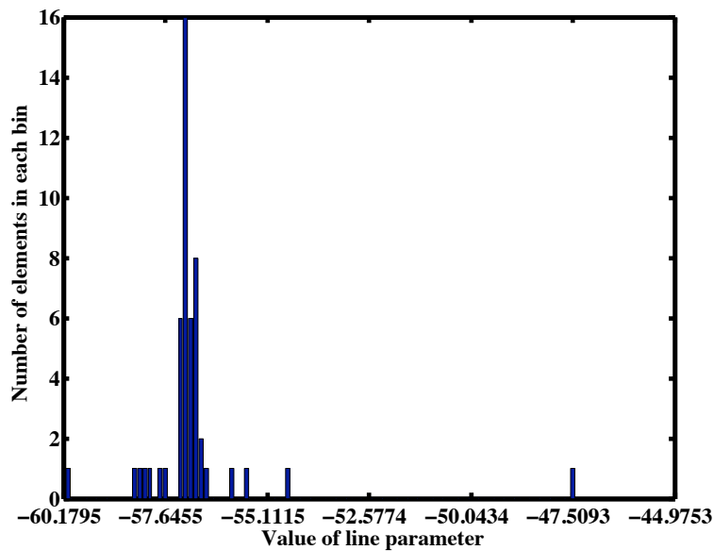

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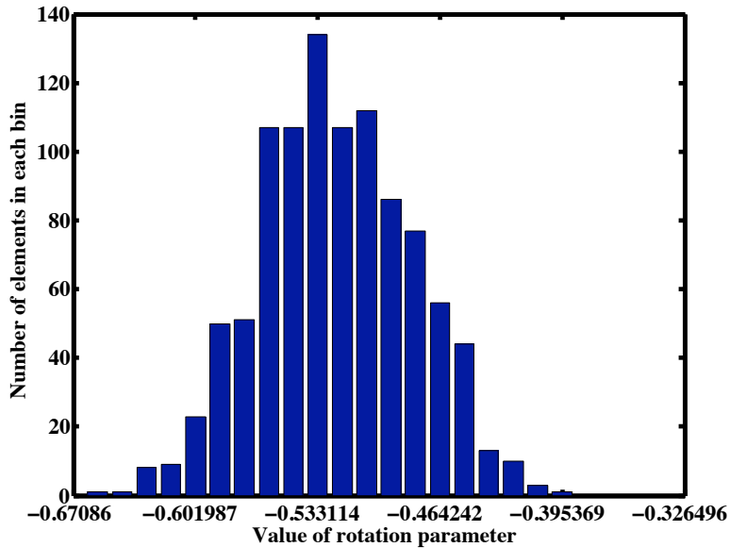
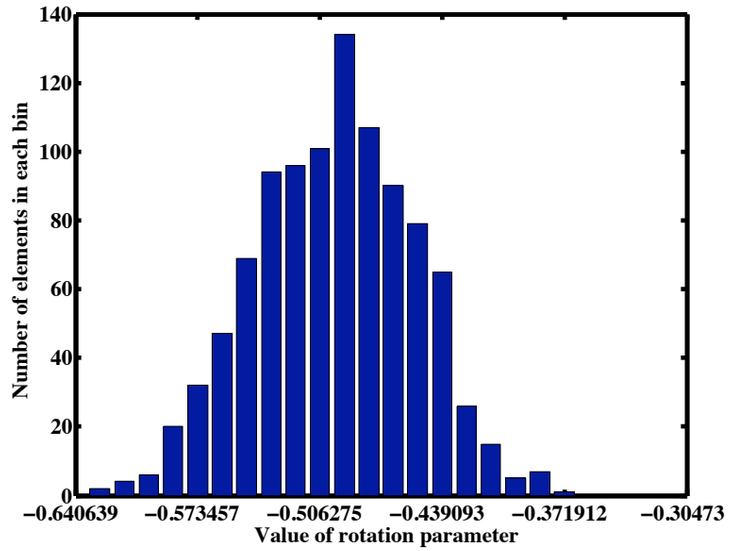
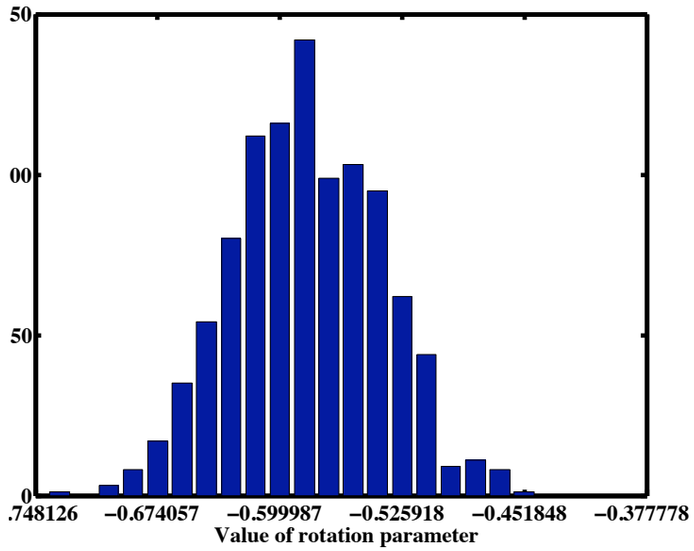
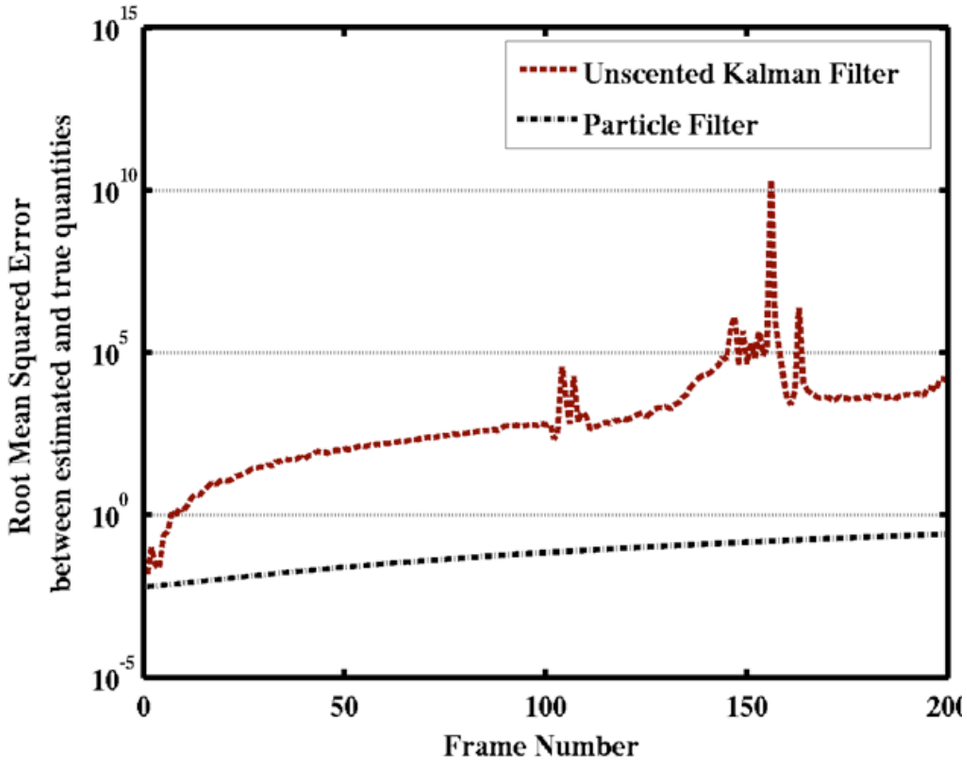


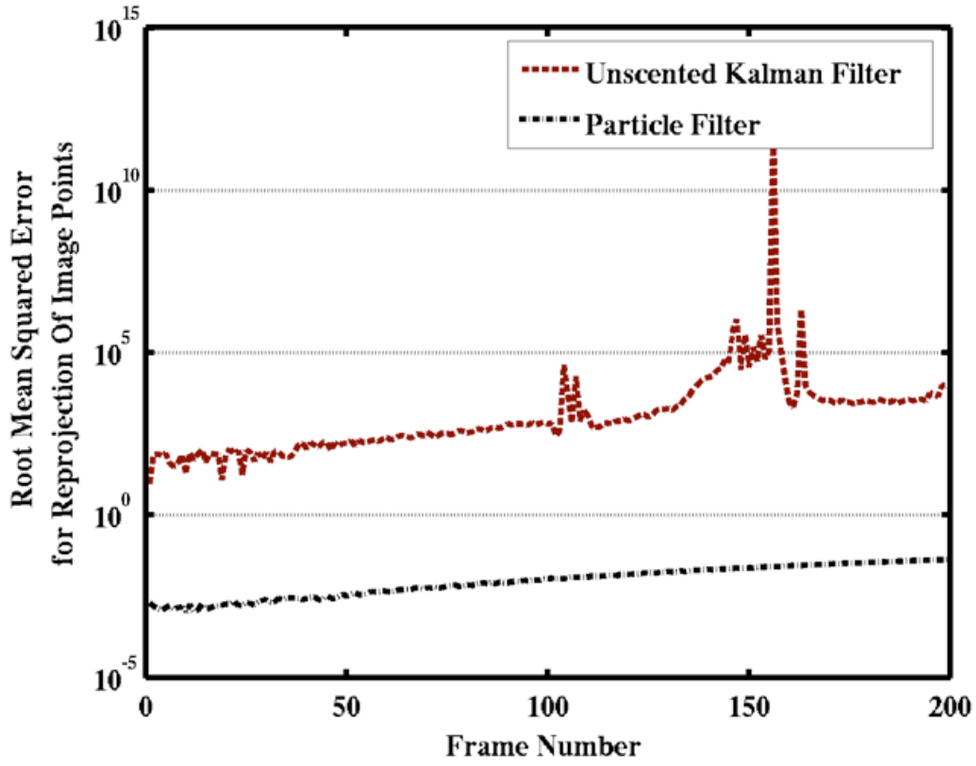




Why Particle Filters

- Comparison of particle vs unscented kalman filter.
- Case evaluated for estimating homography, while considering contour/line measurements.

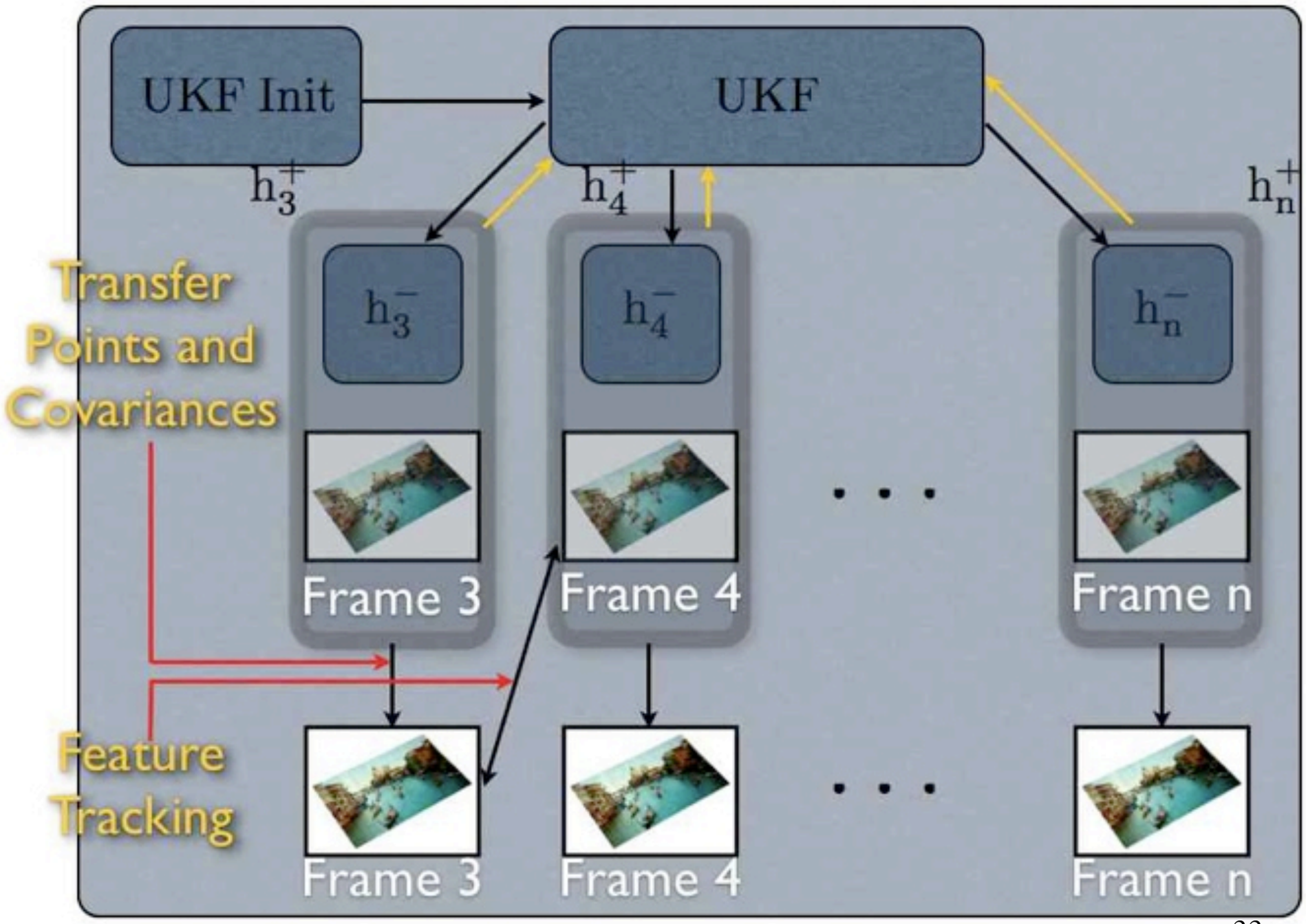




Conclusions

- Particle Filter Framework for integrating edge and texture cues for planar tracking.
- The tracker is robust to large change of perspective and illumination.
- Analysis and Justification for choosing particle filter for tracking purposes.
- Comparison with Unscented Kalman Filter with edge cues for homography computation.

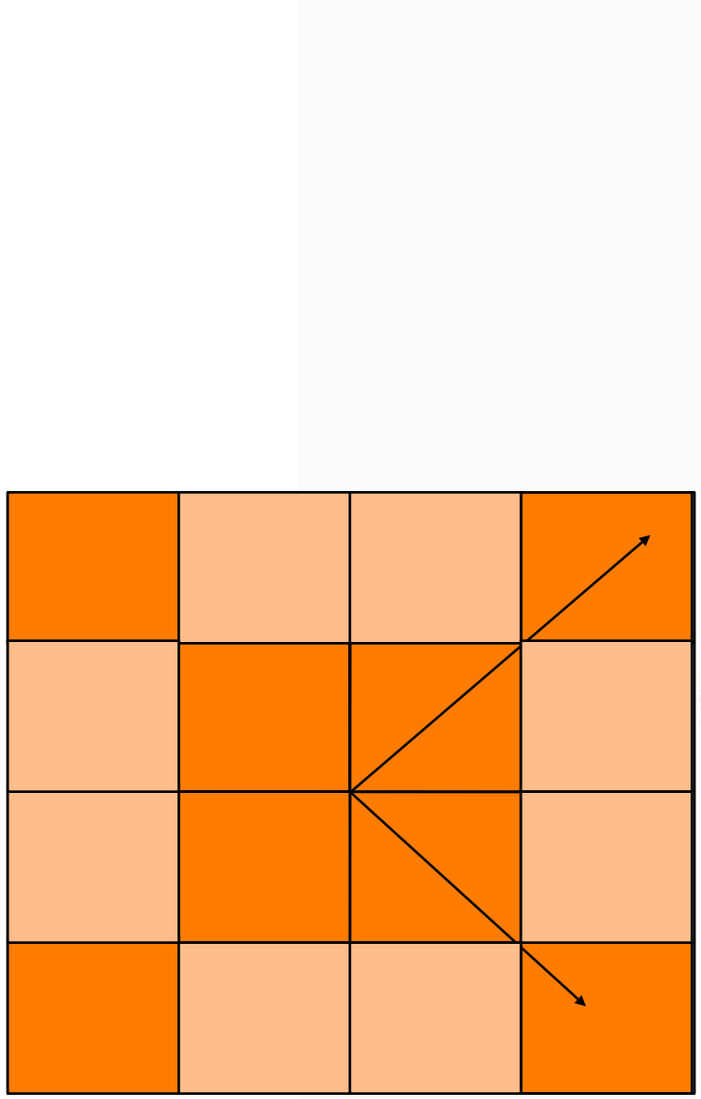
Approach

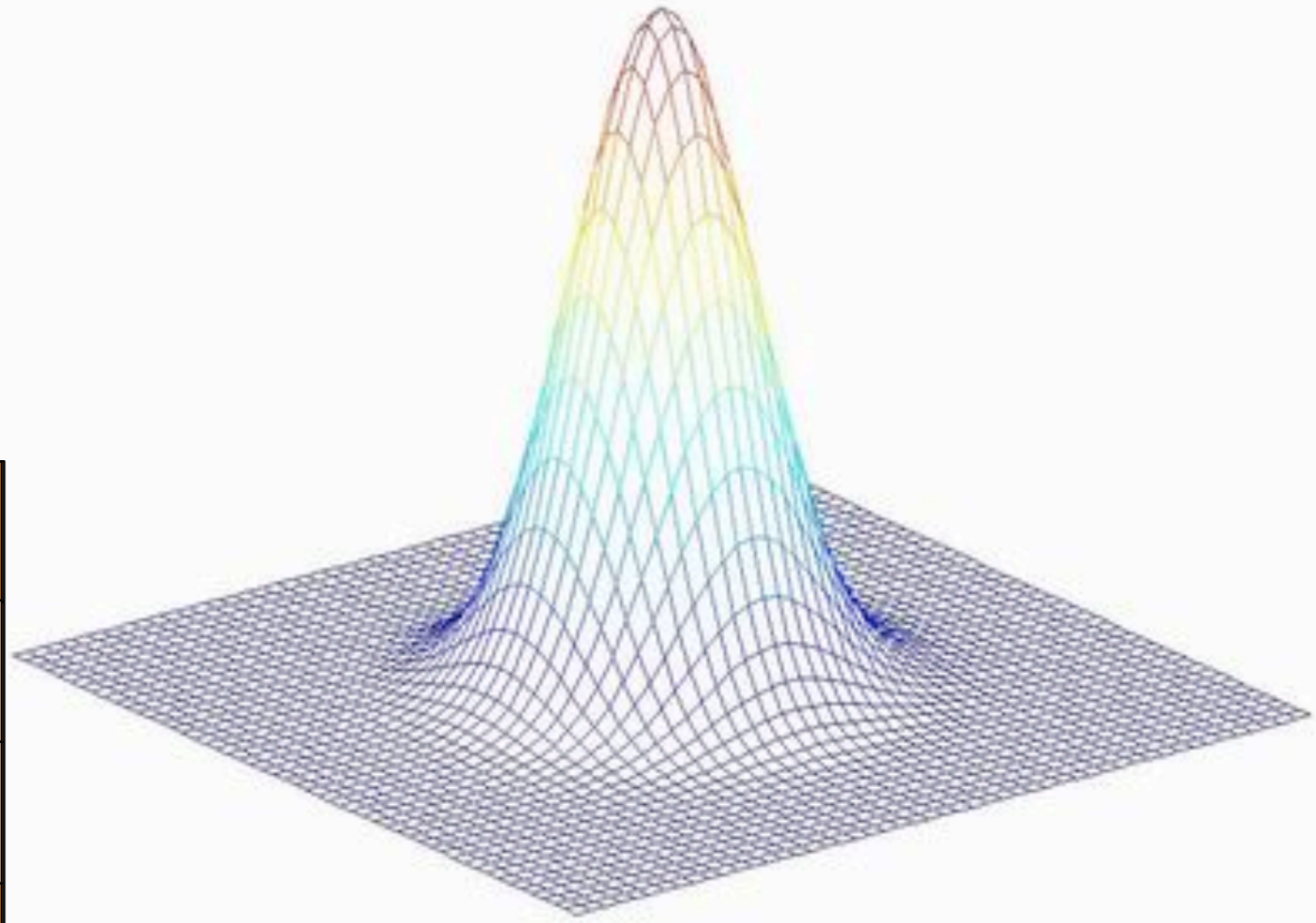

UKF Init
UKF
h_3^+
h_4^+
h_n^+
h_3^-
h_4^-
h_n^-
Transfer Points and Covariances
Feature Tracking
Frame 3
Frame 4
Frame n
Frame 3
Frame 4
Frame n

Modeling Uncertainty

Modeling Uncertainty

- Uncertainty Representation.





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Modeling Uncertainty

- Uncertainty Representation.
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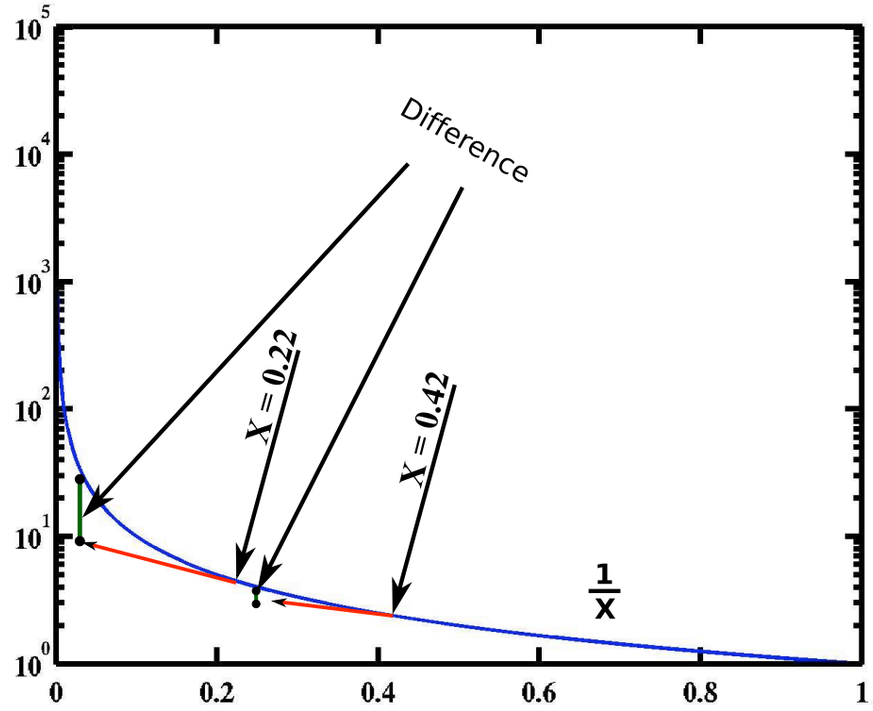
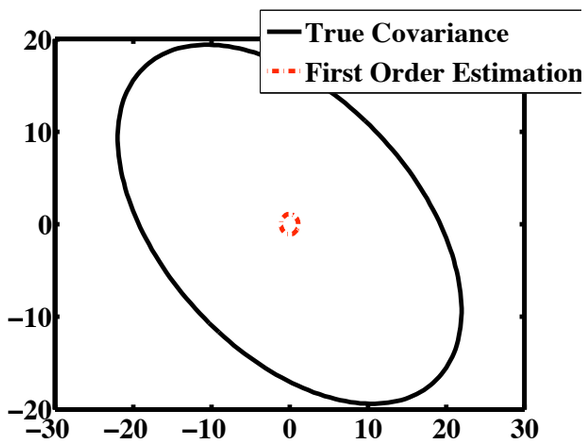
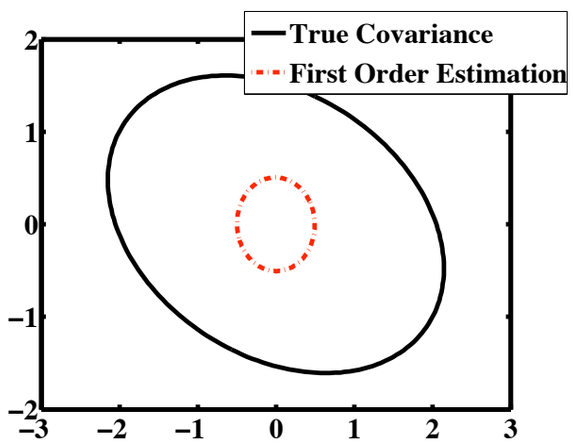
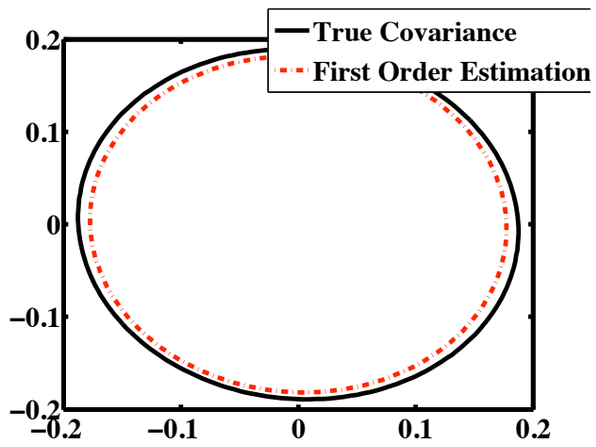
- Uncertainty Maintenance.









Modeling Uncertainty

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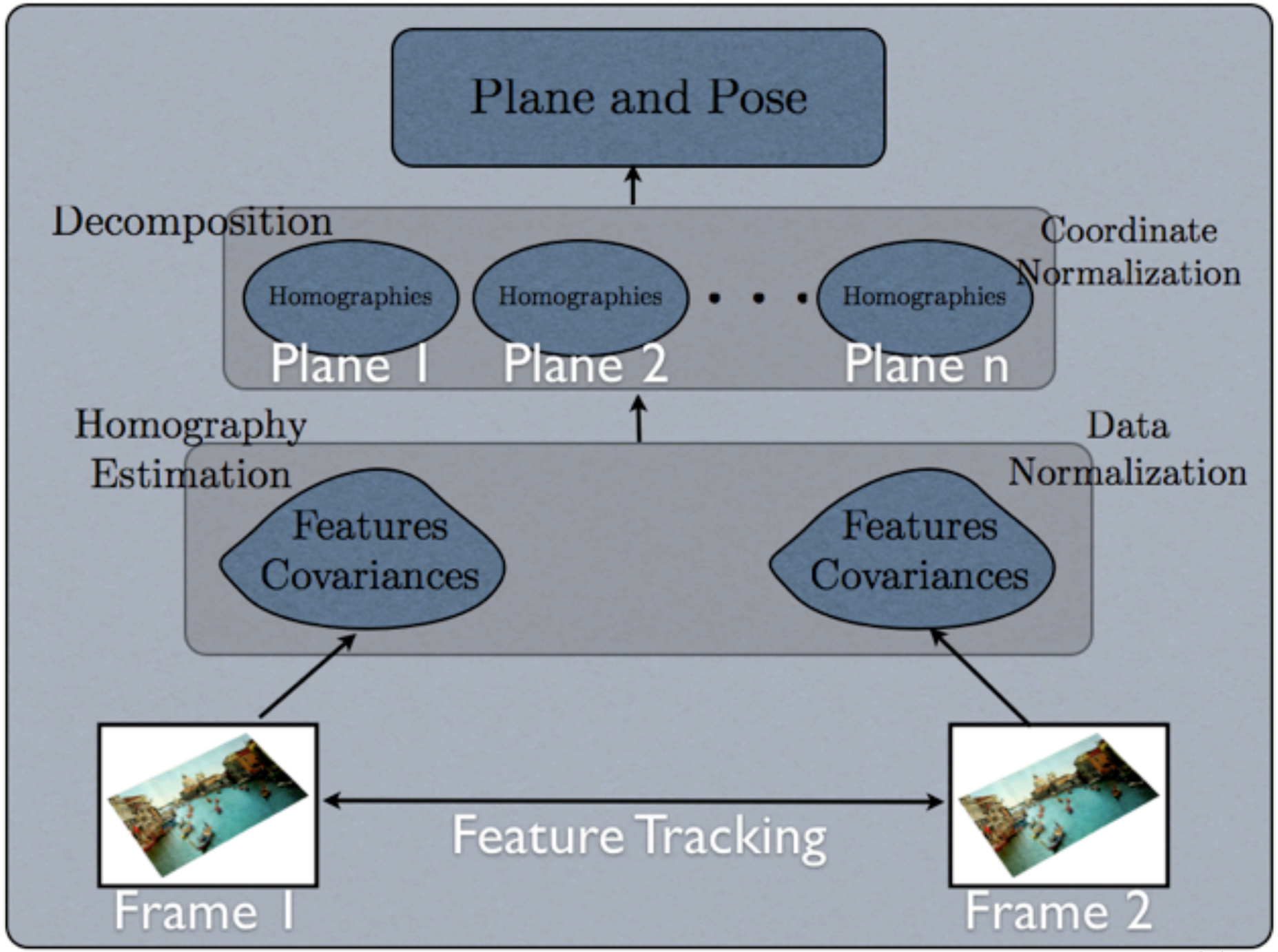
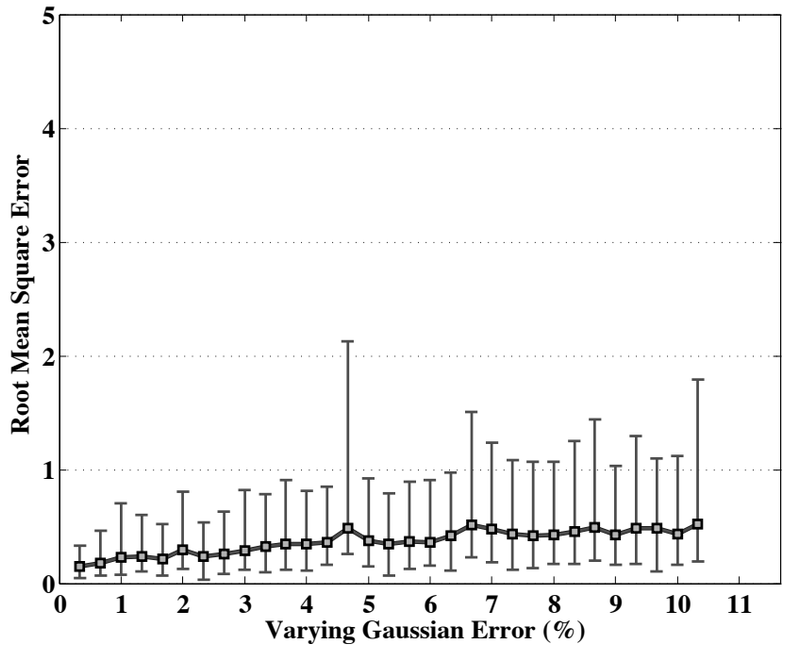
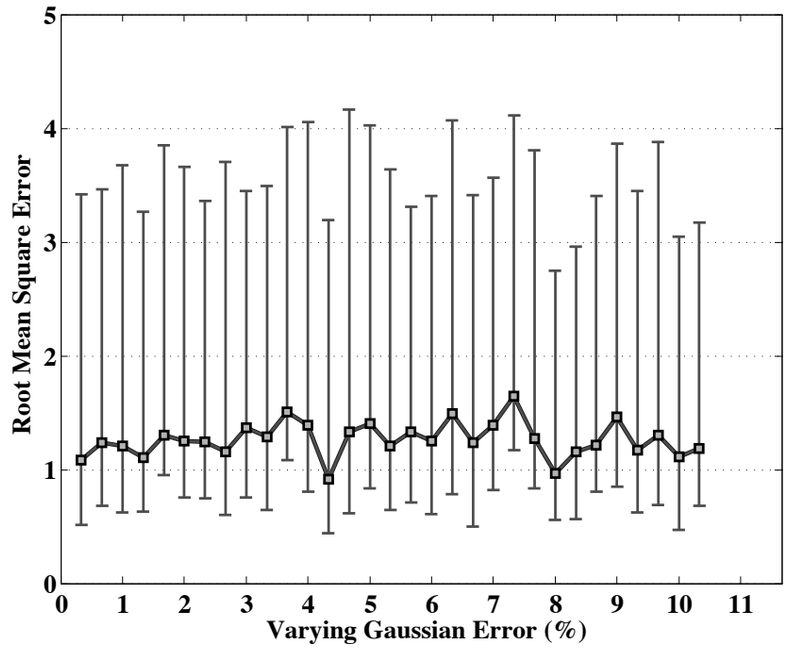
Initialization



Results


Root Mean Square Error
Varying Gaussian Error (%)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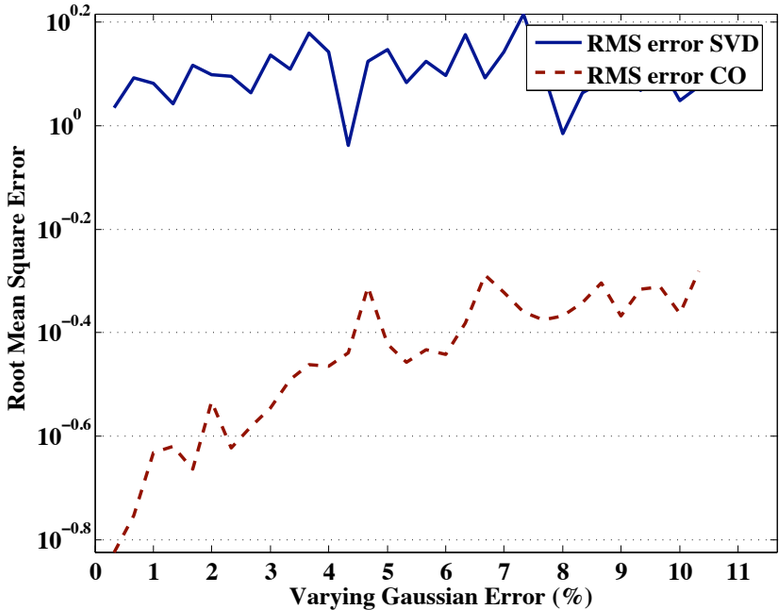
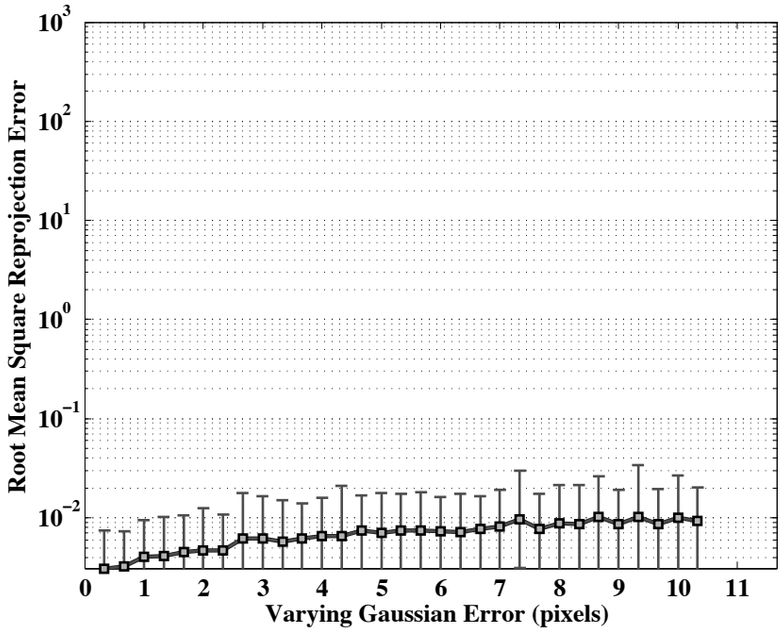
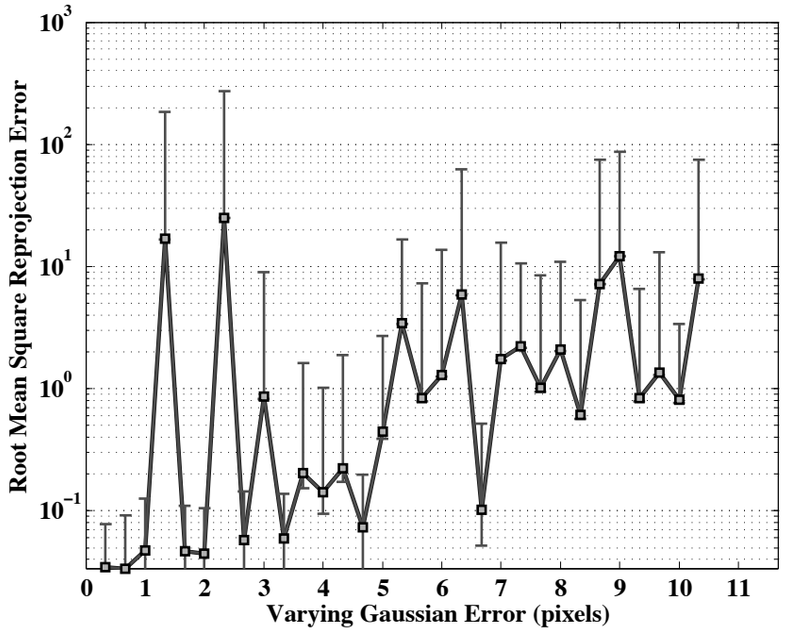
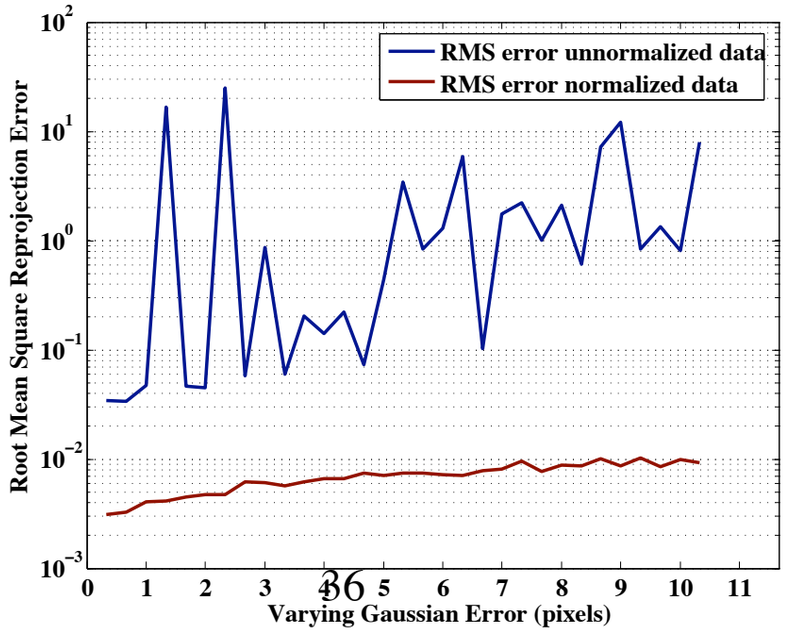

RMS error SVD
RMS error CO
Root Mean Square Error
Varying Gaussian Error (%)


Root Mean Square Reprojection Error
Varying Gaussian Error (pixels)

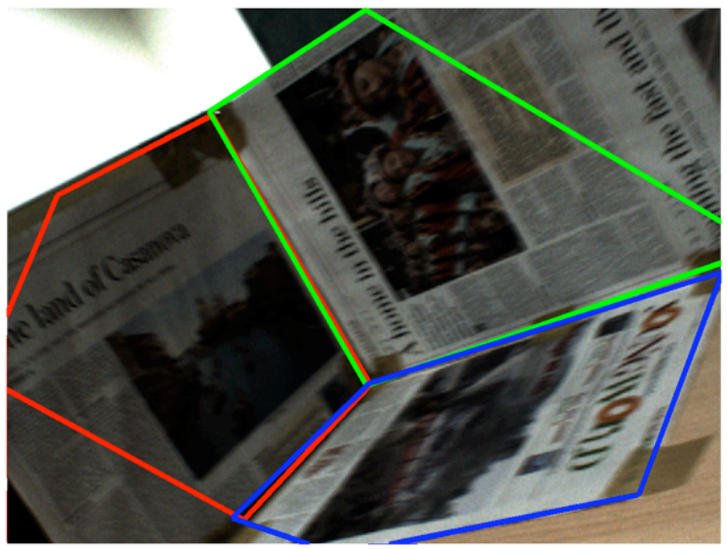
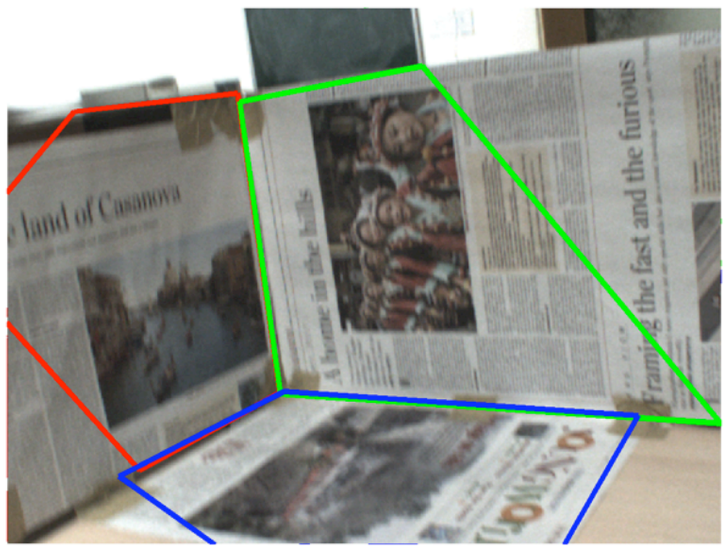

Root Mean Square Reprojection Error
Varying Gaussian Error (pixels)


RMS error unnormalized data
RMS error normalized data
Root Mean Square Reprojection Error
Varying Gaussian Error (pixels)

Results





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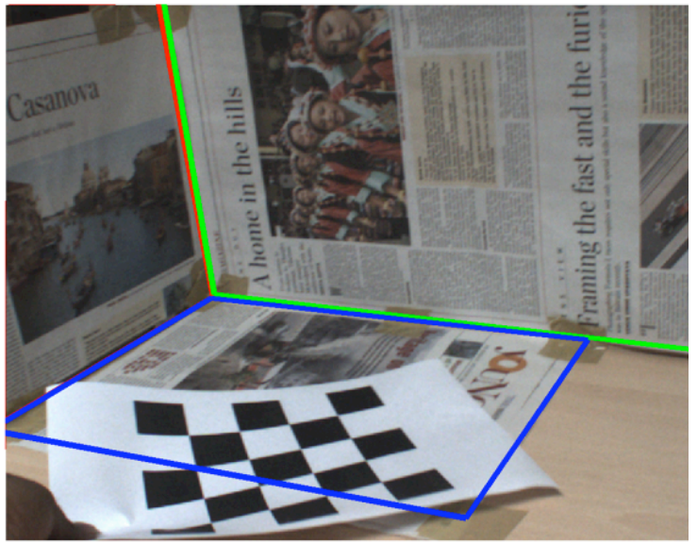
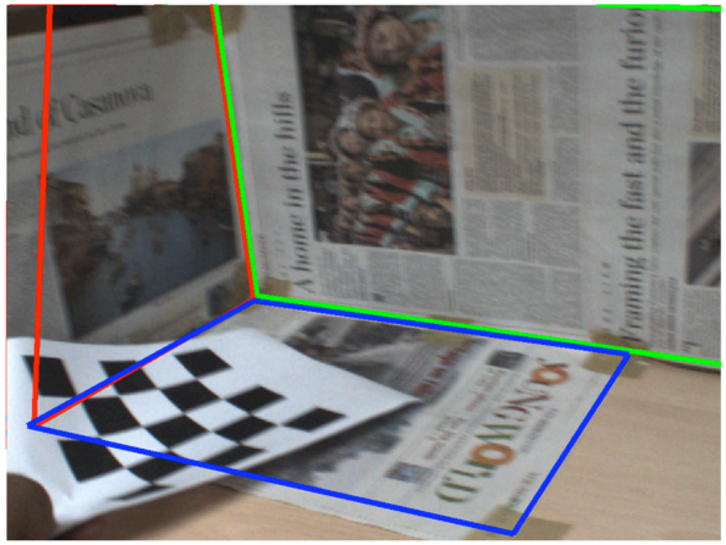

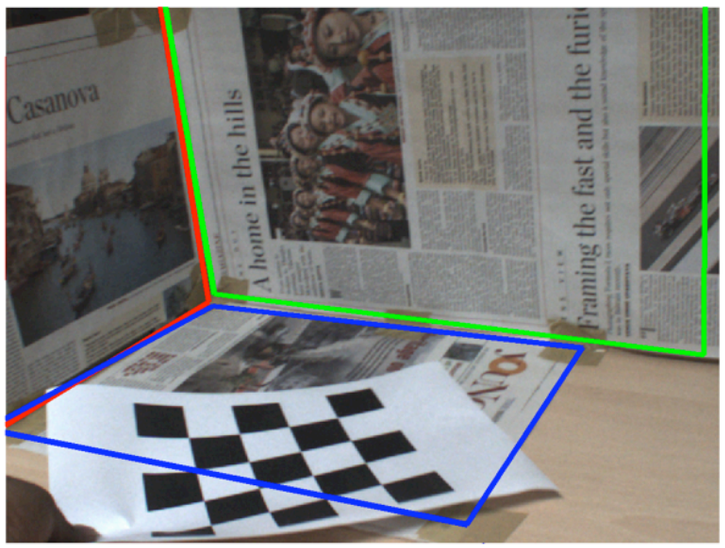
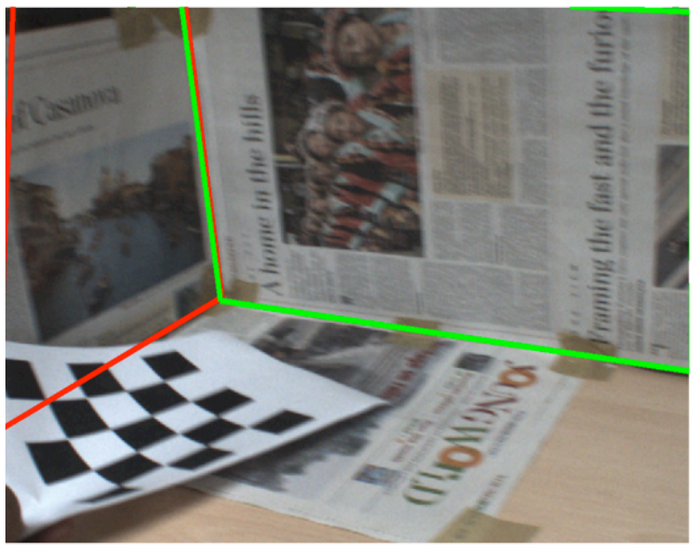

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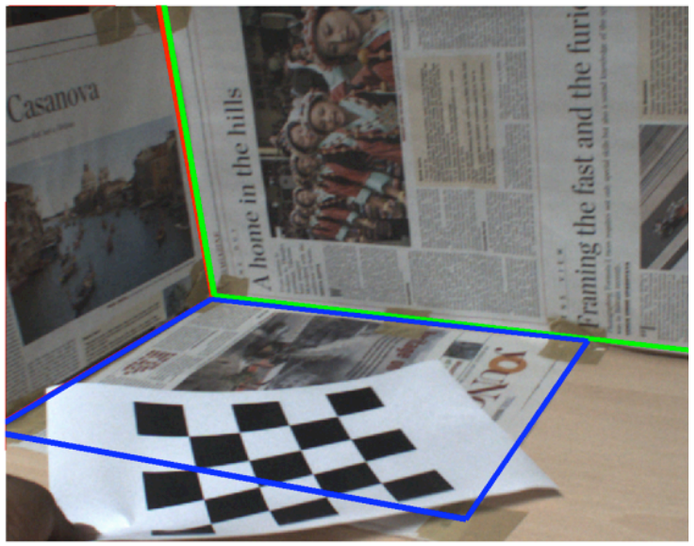
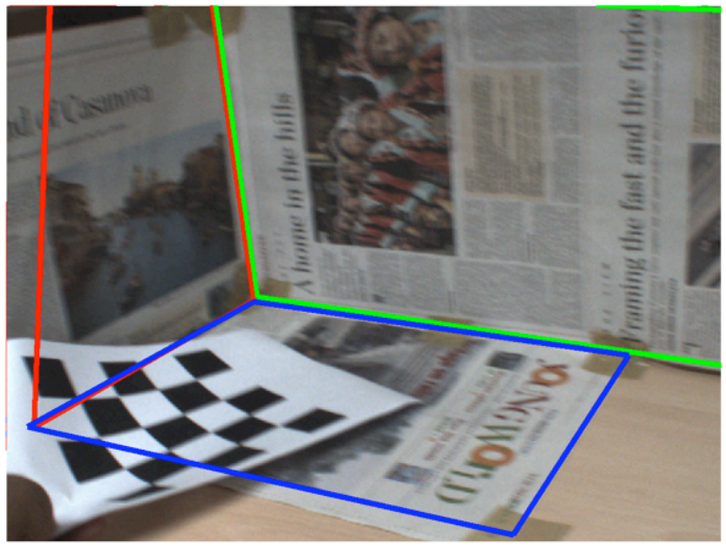
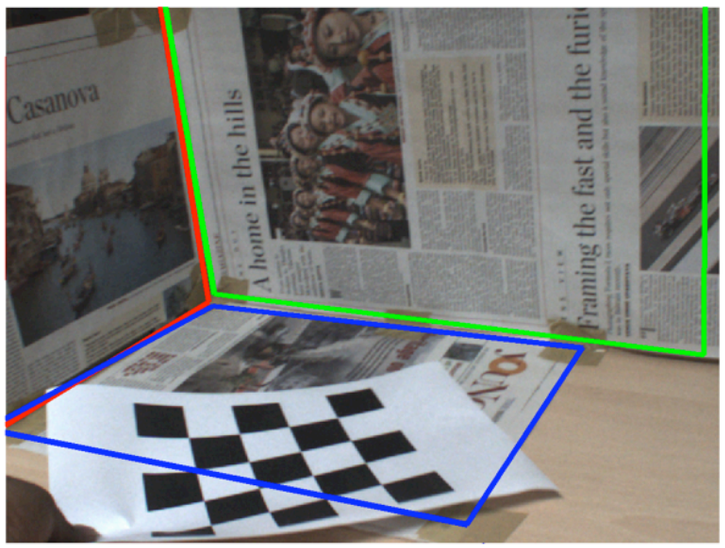
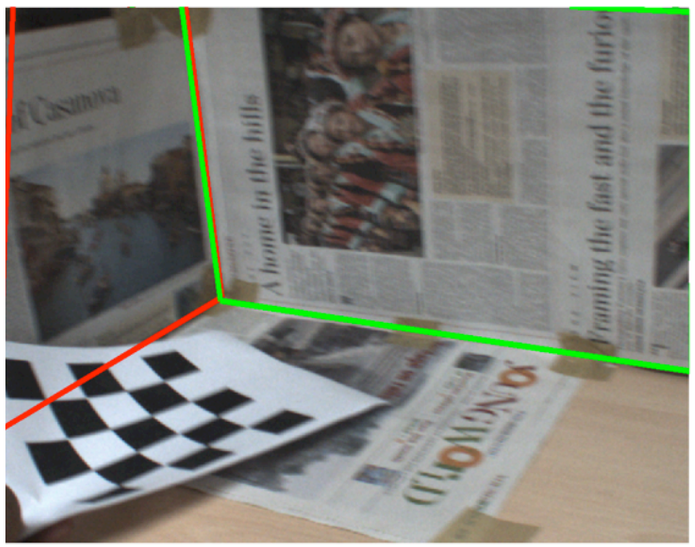



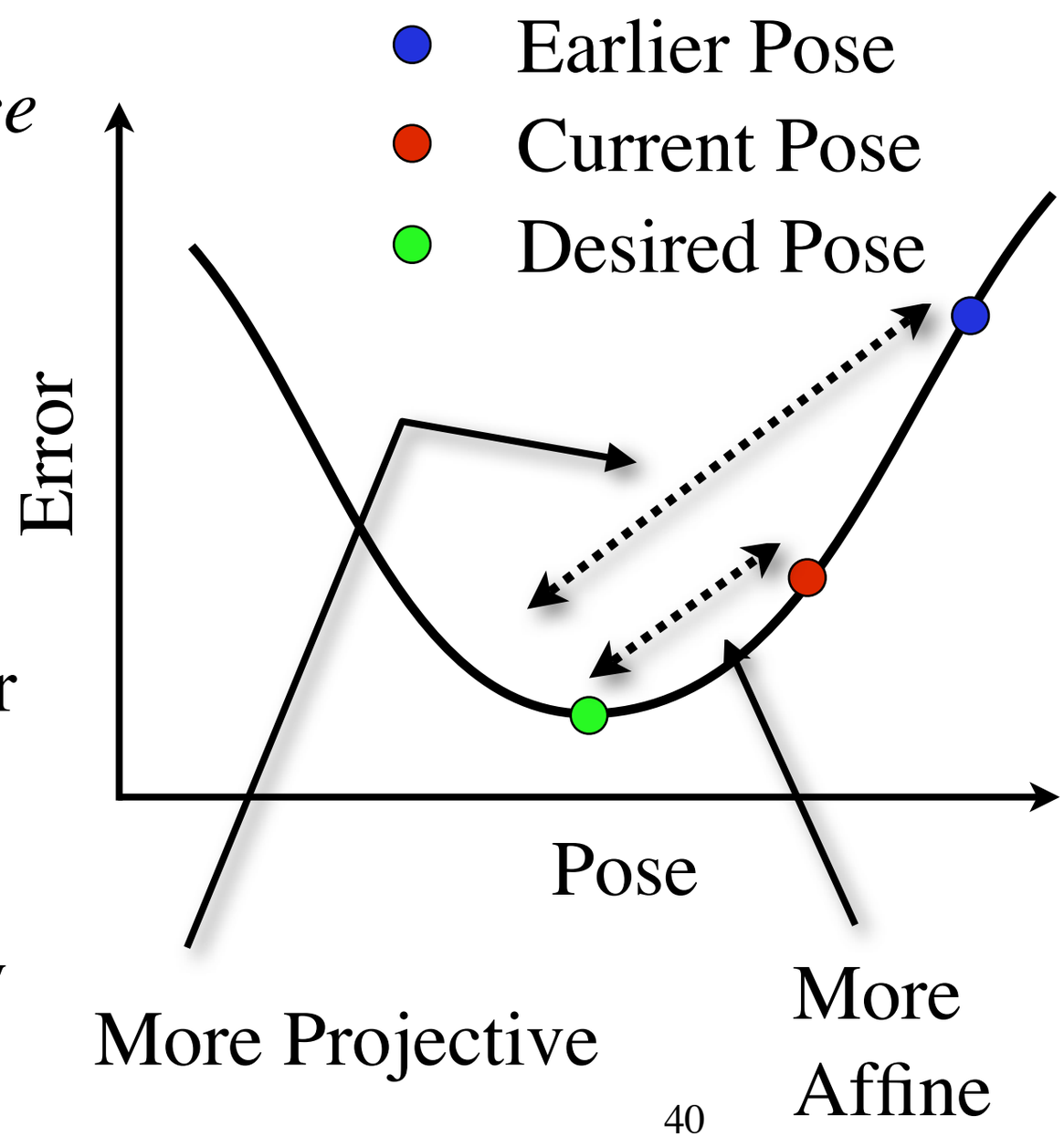
Visesh Chari, C. V. Jawahar. Multiple Plane Tracking using the Unscented Kalman Filter. IEEE International Conference on Robotics and Automation (ICRA'09) (Submitted).

Conclusions

- A multiple plane tracking algorithm that utilizes the “commonality of pose” for stabilization is proposed.
- The tracker is shown to be consistent across illumination change and occlusion.
- A globally optimal algorithm for initialization of the tracker is also proposed.
- Comparison with the standard KLT tracker is shown.

Correspondence-less Servoing

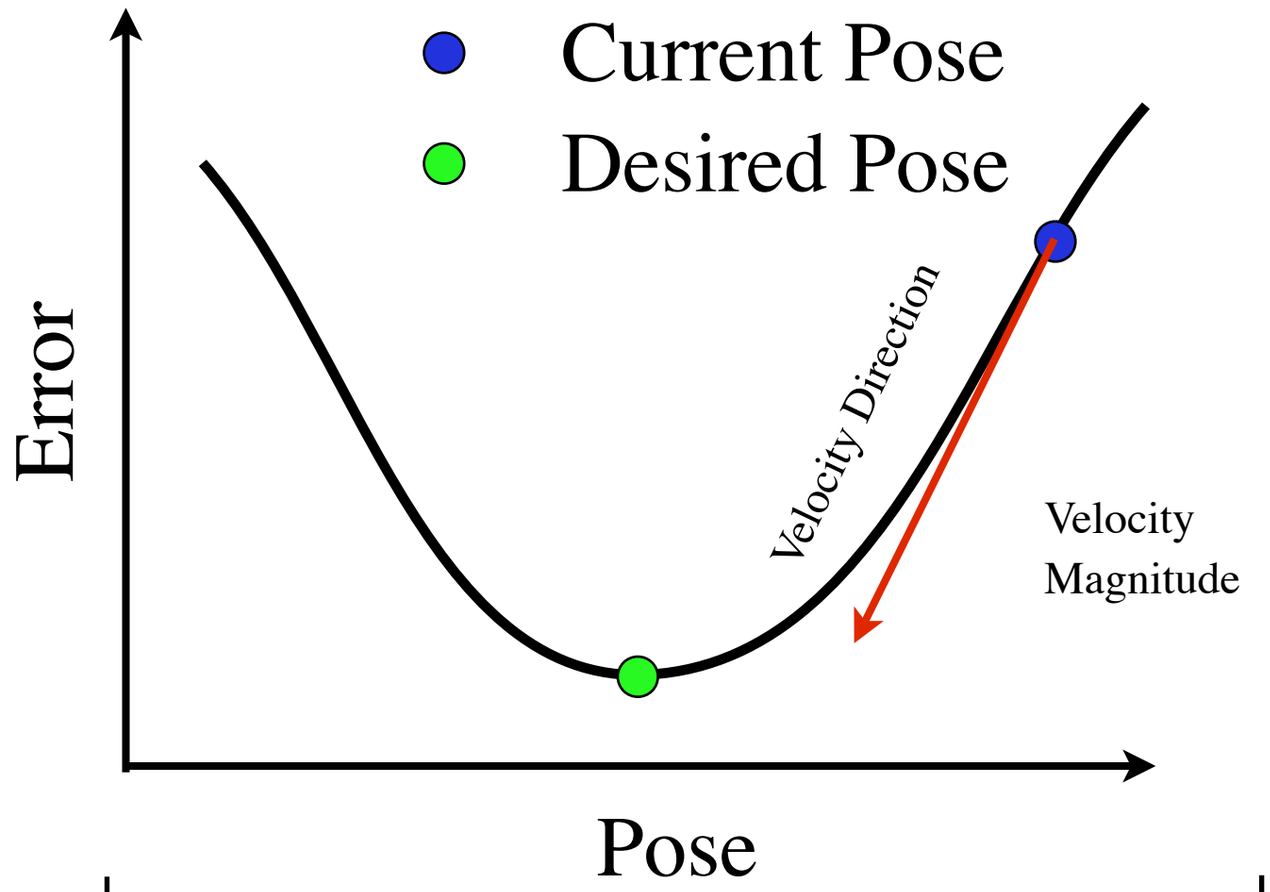
- Fourier based methods estimate homography in *absence* of correspondence for affine cases.
- Homography may then be used to obtain correspondence estimate.
- This estimate can be used for servoing.
- Affine estimates are initially inaccurate but get progressively better as current and desired views converge.



Straight Cartesian Path Servoing

Straight Cartesian Path Servoing

- Traditional IBVS.



IBVS Error = Difference in Image Coordinates.

Straight Cartesian Path Servoing

- Traditional IBVS.
- Cause of “non-straightness” - rotation along x, y axis.
- In contours, effect of rotation may be removed using Fourier applied to Taylor expansion.

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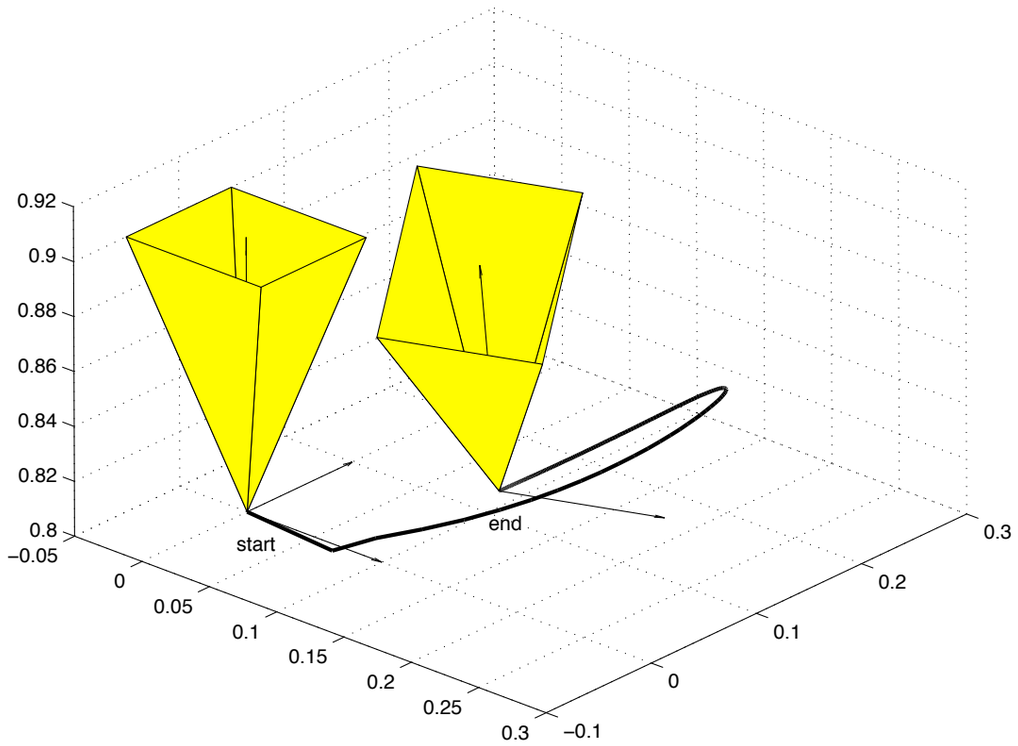

Straight Image Trajectory but non-straight Cartesian path.

Straight Cartesian Path Servoing

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Straight Cartesian Path Servoing

- Traditional IBVS.
- Cause of “non-straightness” - rotation along x, y axis.
- In contours, effect of rotation may be removed using Fourier applied to Taylor expansion.

Take Fourier of image points of current and desired pose.

In 5 DOF servoing, rotation may be linearized around identity matrix (first order approximation).

Coefficients of rx (or ry) can consequently computed using least squares method, by aggregating evidence from all image points.

Straight Cartesian Path Servoing

- Traditional IBVS.
- Cause of “non-straightness” - rotation along x, y axis.
- In contours, effect of rotation may be removed using Fourier applied to Taylor expansion.

Path Following

Path Following

- Camera trajectory in VS fixed.

Given initial and desired positions, the camera trajectory in visual servoing is determined by the minimization approach.

Path Following

- Camera trajectory in VS fixed.
- Disadvantage because of inability to plan path.

Thus avoiding obstacles, or in general the task of following a user specified trajectory is not possible.

Path Following

- Camera trajectory in VS fixed.
- Disadvantage because of inability to plan path.
- Fourier based approach captures global properties of contours.

Since each Fourier component captures details from the entire contour, each component represents a global quantity.

Path Following

- Camera trajectory in VS fixed.
- Disadvantage because of inability to plan path.
- Fourier based approach captures global properties of contours.
- Weighted Fourier error may be used for path following.

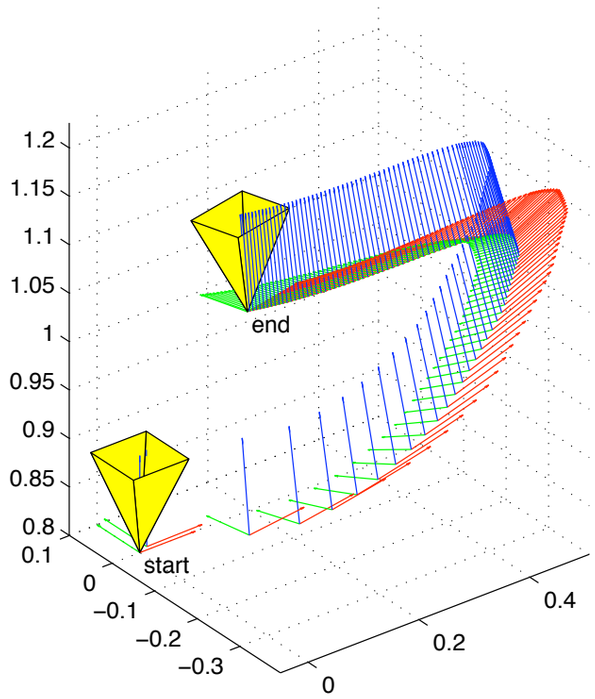
Thus weighting fourier components can change the global character of error space.

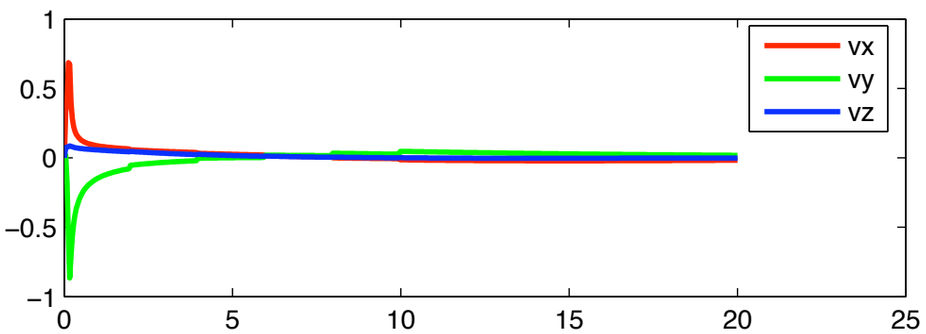
Here the path to be followed can be the output of a path planning algorithm.

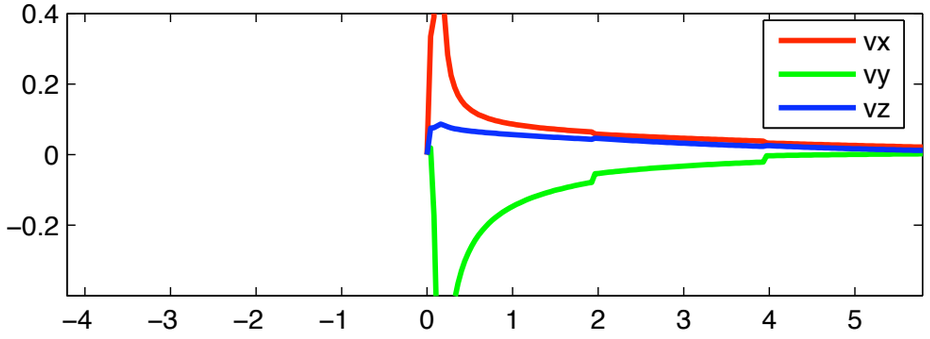
Results

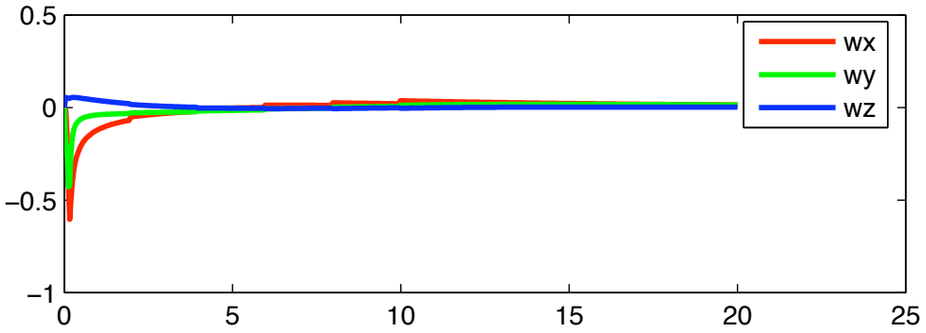
Results

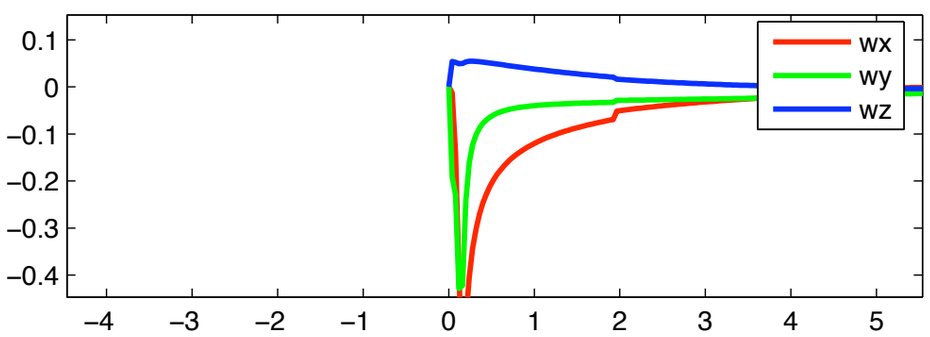
- Correspondence-less servoing.









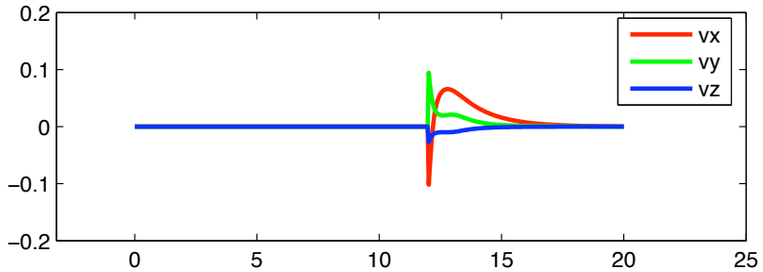


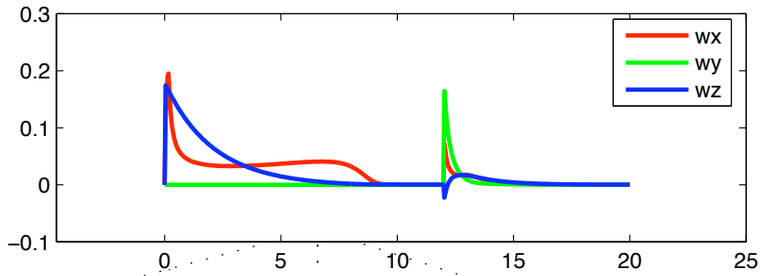
Results

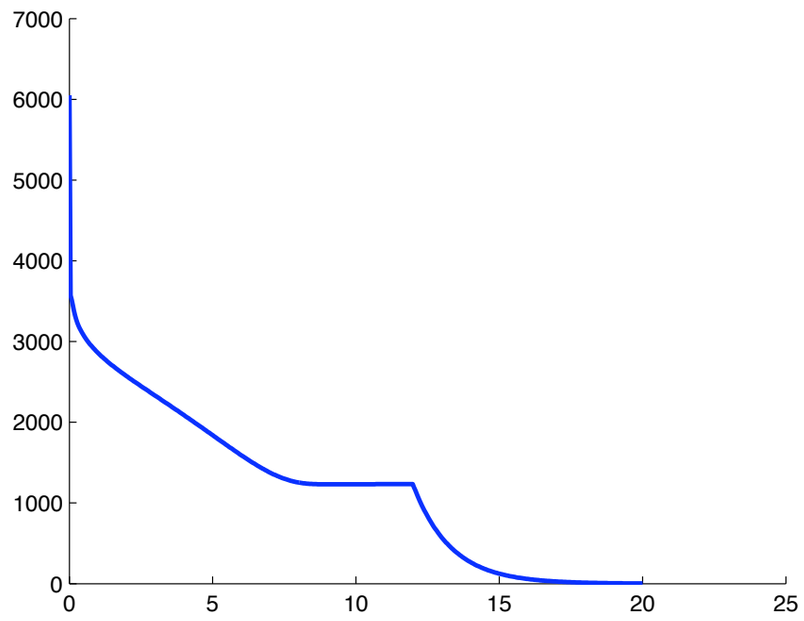
- Correspondence-less servoing.

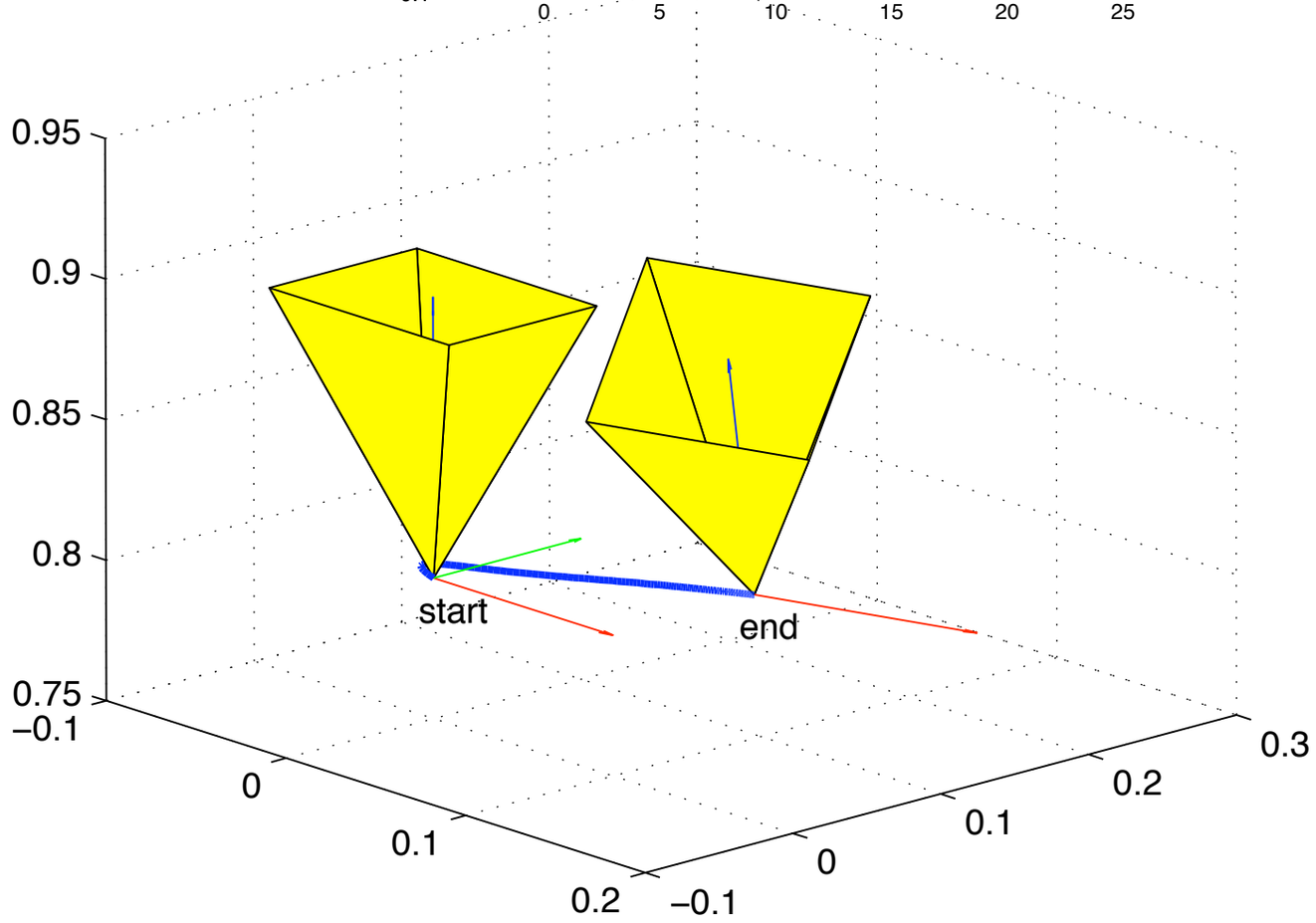
Results

- Correspondence-less servoing.
- Straight Cartesian path.







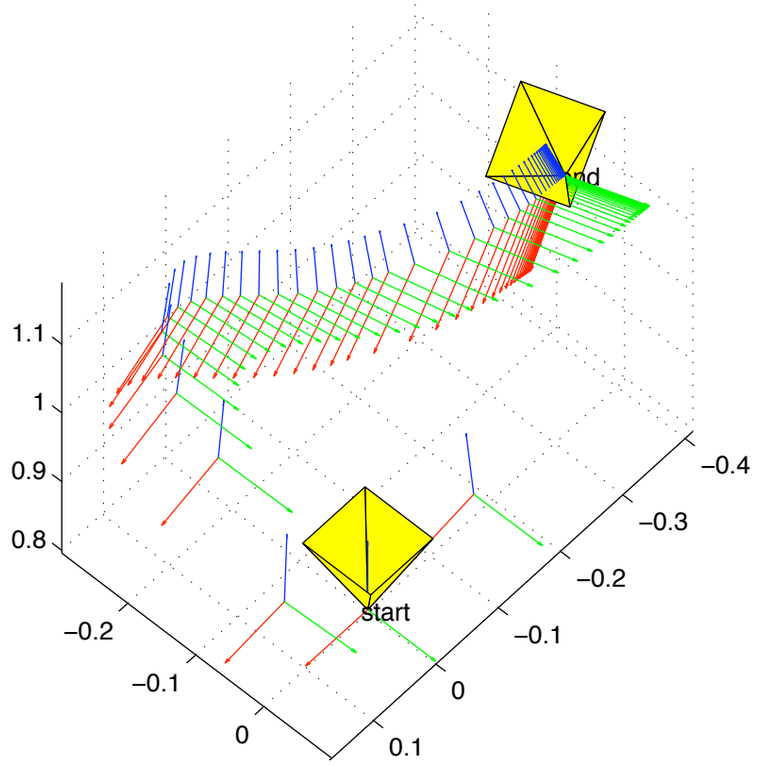


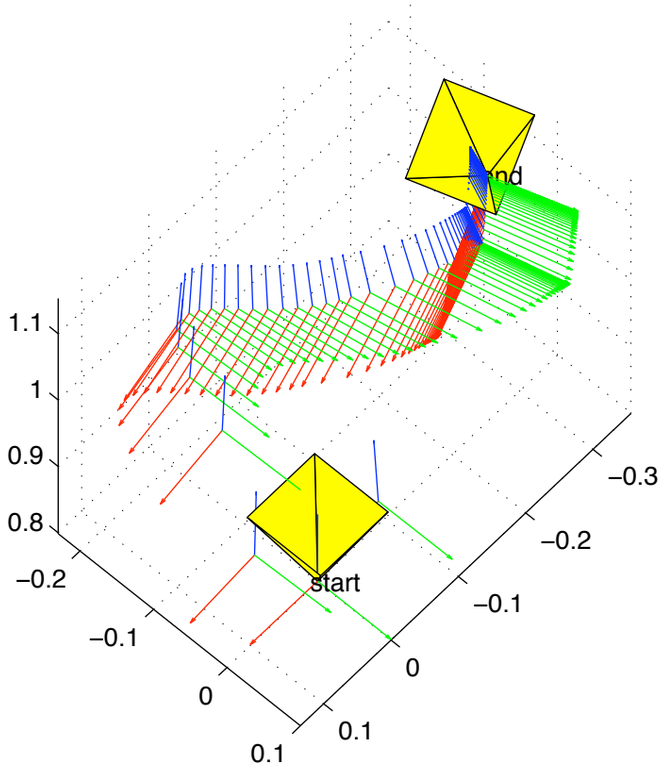
Results

- Correspondence-less servoing.
- Straight Cartesian path.

Results

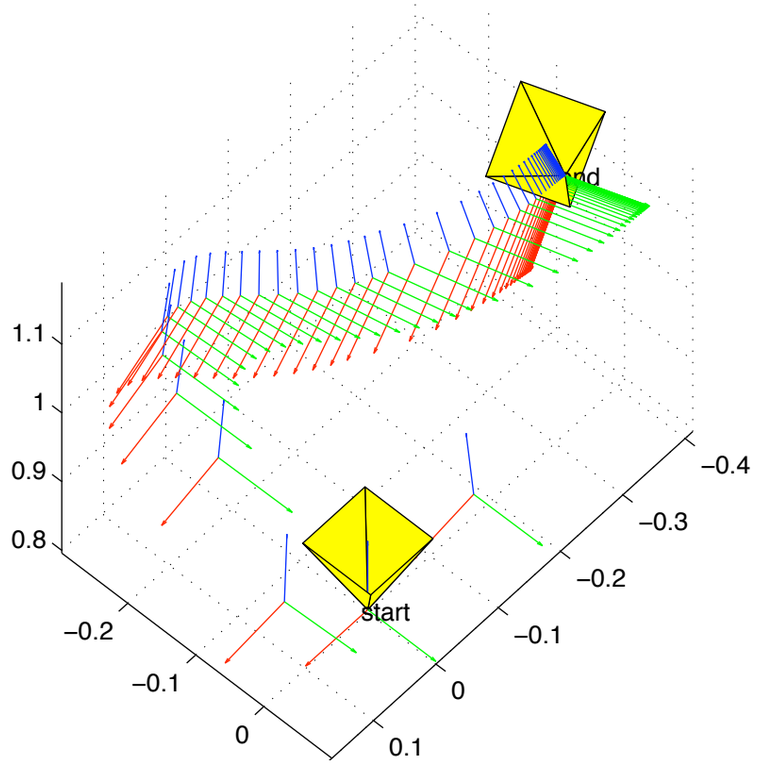
- Correspondence-less servoing.
- Straight Cartesian path.
- Path following.

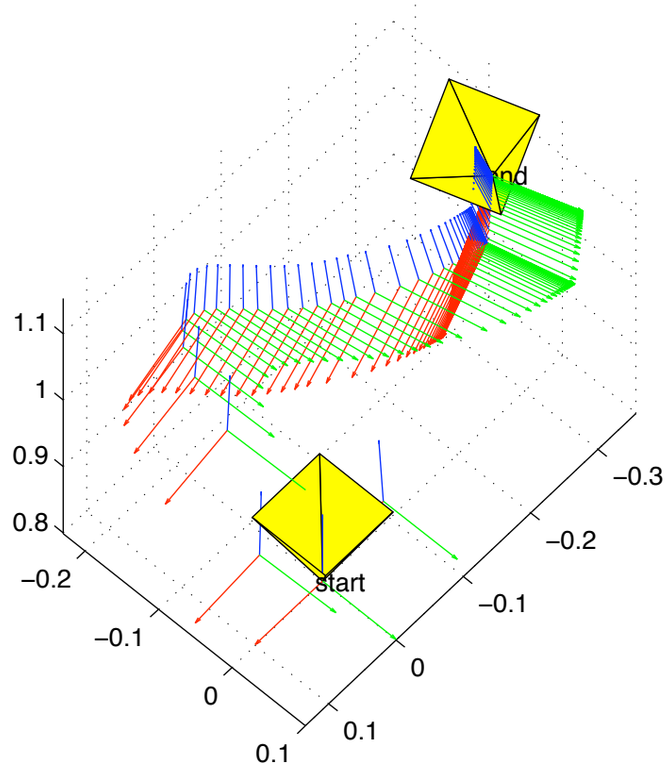




Results

- Correspondence-less servoing.
- Straight Cartesian path.
- Path following.





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Conclusions

- A visual servoing framework that uses Fourier based MVG is proposed.
- The proposed framework has several advantages, and 3 scenarios are presented to illustrate the same.
- Results for the 3 scenarios of correspondence-less servoing, Cartesian straight path servoing, and path following are shown.

Symmetry results

Symmetry results

Symmetry results

Symmetry Transfer