ROLLING SHUTTER CAMERA TRACKING AND VIDEO RECTIFICATION USING VISUAL AND INERTIAL MEASUREMENTS

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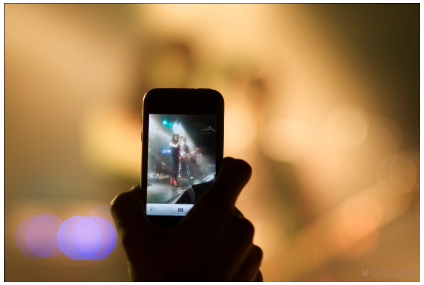
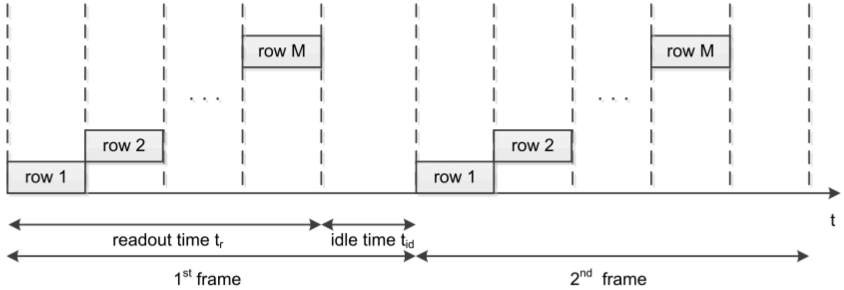
Overview

- Rolling shutter effects
- Previous work using IMUs
- Sensor fusion
  - Feature point correspondence in rolling shutter camera
  - EKF-based sensor fusion
  - Outlier detection using 1-point RANSAC
- Experiments and comparison

Rolling Shutter Effects



- Handheld cameras – fast motion
- CMOS image sensors:
  - Rows in sensor array are exposed sequentially from top to bottom



$$t(\mathbf{u}, i) = t_i + t_r \times \frac{u_y}{h}$$

- Rolling shutter effects:

Rectify Rolling Shutter Effects

- Pose estimation for each row needed
- Pure rotational model
  - Main cause of pose difference between rows
  - Fast rectification

$$\mathbf{u} \sim \mathbf{K}\mathbf{R}(t(\mathbf{u}, j))\mathbf{x} \qquad \mathbf{u}' \sim \mathbf{K}\mathbf{R}((t_j)\mathbf{R}^T(t(\mathbf{u}, j))\mathbf{K}^{-1}\mathbf{u}$$

- Previous work on pose estimation
  - [Karpenko 2011]
  - Integrate gyro readings (100Hz on Nexus S)
  - Use SLERP for exposure time between samples
  - Unknown bias and noise; Fast changing motion

  - [Hanning 2011]
  - EKF-based estimation with accelerometer readings as measurements
  - acceleration = f (pose, gravity)
  - Good loop closing property
  - Gravity is not the only source of acceleration

Proposed Method

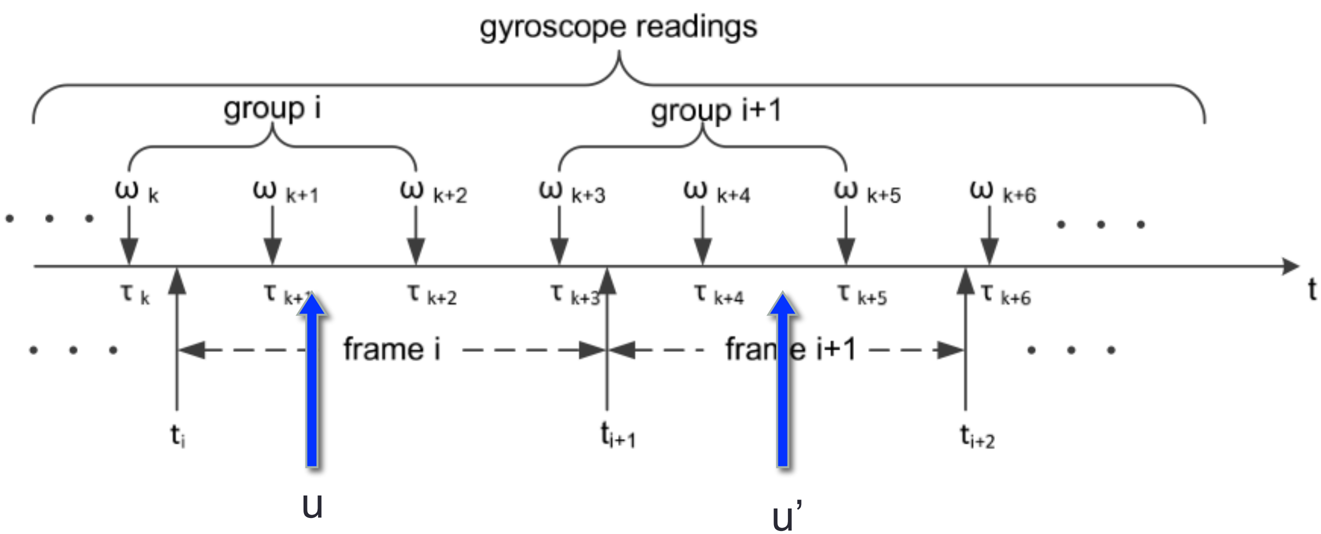
- Gyro readings integrated with visual measurements

- Feature point correspondences provide accurate geometric clue
  - Structure from Motion; Simultaneous Localization and Mapping (SLAM)
  - How to relate matched features with high-frequency camera poses in rolling shutter model
  - How to effectively detect outliers

- Research platform
  - Android smartphones (Google Nexus S)
  - Use app “data logger” to record video and gyro readings (with timestamp) at the same time
    - How to synchronize sensor measurements

Gyro and Feature Point Correspondence

- Gyro returns measurements with higher sampling rate



- Compute the relative rotation between two exposure time

$$\mathbf{R}(t(\mathbf{u}', i+1))\mathbf{R}^T(t(\mathbf{u}, i)) = \prod_{n=k+1}^{k+4} \Delta\mathbf{R}(\omega_n \Delta t_n)$$

$$\Delta\mathbf{R}(\omega_n \Delta t_n) = \exp(\text{skew}(\omega_n)\Delta t_n)$$

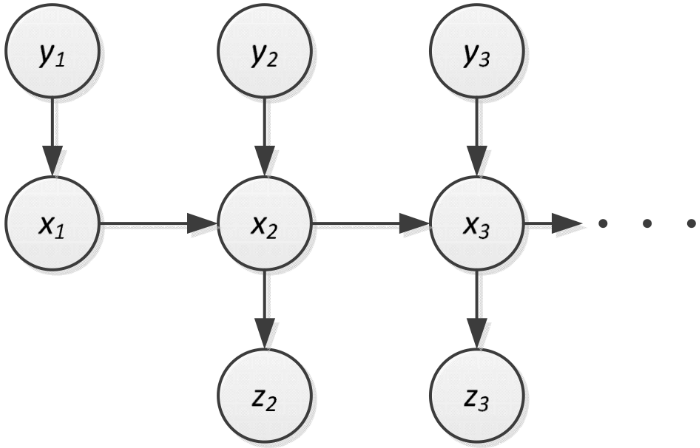
EKF-based Estimation

- State vector: two groups of angular velocities

$$\mathbf{x}_i = [\omega(i-1,1),\ldots,\omega(i-1,N_{i-1}),\omega(i,1),\ldots,\omega(i,N_i)]^T$$

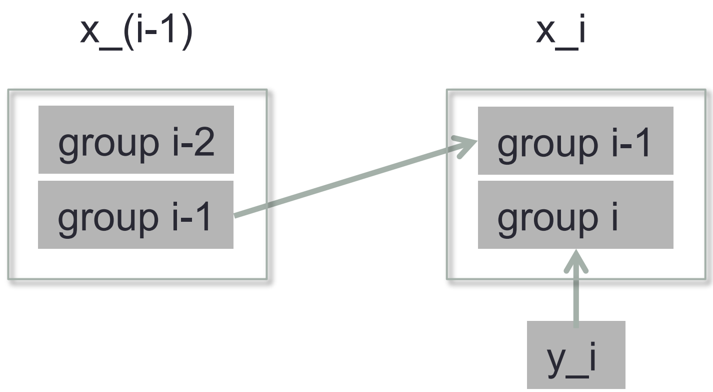
  - Why two groups?
    - The visual measurements depend on both the group of the current frame and the group of the previous frame
  - Why angular velocity instead of rotation representation (unit quaternion)
    - Equivalent for relative rotation estimation
    - No SLERP needed (simple Jacobian in EKF)

- Probabilistic Graphical Model



Dynamic Motion Model (State Prediction)

- Group cloning in prediction



$$\mathbf{x}_i = \begin{bmatrix} \mathbf{x}_{i,1} \\ \mathbf{x}_{i,2} \end{bmatrix} = \begin{bmatrix} \mathbf{x}_{i-1,2} \\ \mathbf{y}_i \end{bmatrix} + \begin{bmatrix} \mathbf{0} \\ \mathbf{w}_i \end{bmatrix}$$

- Linear model

$$A_i = \left.\frac{\partial f}{\partial \mathbf{x}}\right|_{\mathbf{x}_{i-1}} = \begin{bmatrix} \mathbf{0} & I \\ \mathbf{0} & \mathbf{0} \end{bmatrix}, W_i = \left.\frac{\partial f}{\partial \mathbf{w}}\right|_{\mathbf{w}_i} = \begin{bmatrix} \mathbf{0} \\ I \end{bmatrix}$$

Measurement Model (State Update)

- Use only feature points in current frame as the measurements; their matching points in previous frame are used as parameters

$$\mathbf{u}_{i,j} = g\left(K\Delta R K^{-1}\begin{bmatrix}\mathbf{u}_{i-1,j} - \mathbf{v}_{i-1,j} \\ 1\end{bmatrix}\right) + \mathbf{v}_{i,j}$$

state vector determines the relative rotation

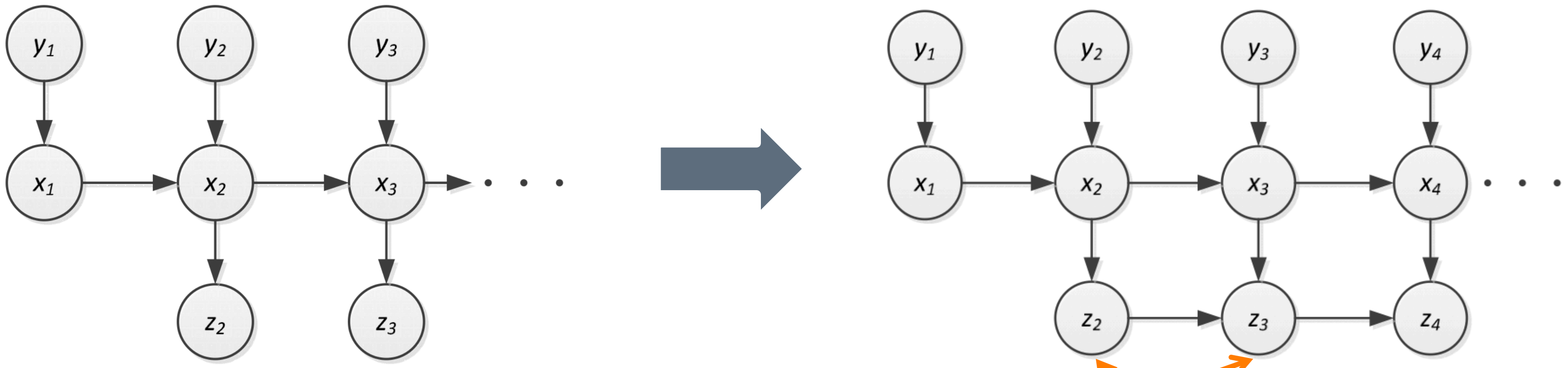
$$\prod_{k=1}^{N_{i-1}} \Delta R(\omega(i-1,k)\Delta t_{i-1,j,k}) \prod_{k=1}^{N_i} \Delta R(\omega(i,k)\Delta t_{i,j,k})$$

measurement noise

- Final measurement equation for state update
  - Closed form Jacobian matrix using chain rule

$$\mathbf{z}_i = \begin{bmatrix}\mathbf{u}_{i,1} \\ \mathbf{u}_{i,2} \\ \vdots \\ \mathbf{u}_{i,M}\end{bmatrix} = \begin{bmatrix} h_1(\mathbf{x}_i, \mathbf{u}_{i-1,1} - \mathbf{v}_{i-1,1}) + \mathbf{v}_{i,1} \\ h_2(\mathbf{x}_i, \mathbf{u}_{i-1,2} - \mathbf{v}_{i-1,2}) + \mathbf{v}_{i,2} \\ \vdots \\ h_M(\mathbf{x}_i, \mathbf{u}_{i-1,M} - \mathbf{v}_{i-1,M}) + \mathbf{v}_{i,M}\end{bmatrix}$$

Measurement Model (State Update)



$$\mathbf{u}_{i,j} = g\left(K \Delta R K^{-1} \begin{bmatrix} \mathbf{u}_{i-1,j} - \mathbf{v}_{i-1,j} \\ 1 \end{bmatrix}\right) + \mathbf{v}_{i,j}$$

- State prediction of current stage is **correlated** with the noise of the observation (measurements) in previous stage
- Solution: augment the state vector with the measurement noise

Outliers Removal

- For global shutter model
  - Epipolar constraint / Homography fitting

- 1-point RANSAC in EKF
  - In standard RANSAC, each hypothesis need the minimum number of points necessary to estimate the parameters
  - For EKF, we have got a prior distribution of the parameters (state vector) by prediction
  - The minimum number of points to estimate the parameters can be reduced to one (in the rolling shutter case we choose three)

Outlier Removal

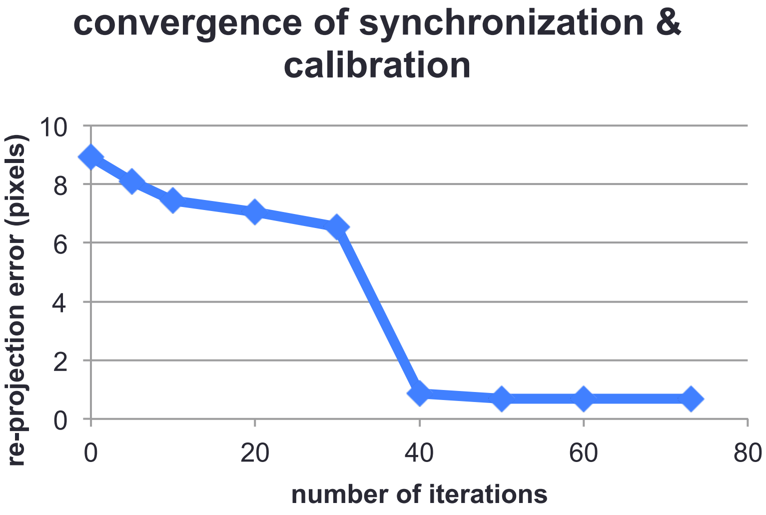
- Track features using the state prediction result, refine by KLT
- inliers = [ ]
- for i = 1 to N_hyp
  - randomly choose 3 matches
  - update the states through EKF filtering
  - computer the re-projection error (innovation) and choose current_inliers
  - if num_current_inliers > max_num
    - inliers = current_inliers
    - max_num = num_current_inliers
  - end
- Use inliers to compute the EKF update

75ms/frame in Matlab implementation on 2.3GHz Intel i5 processor
20 features tracked

Sensor Synchronization and Calibration

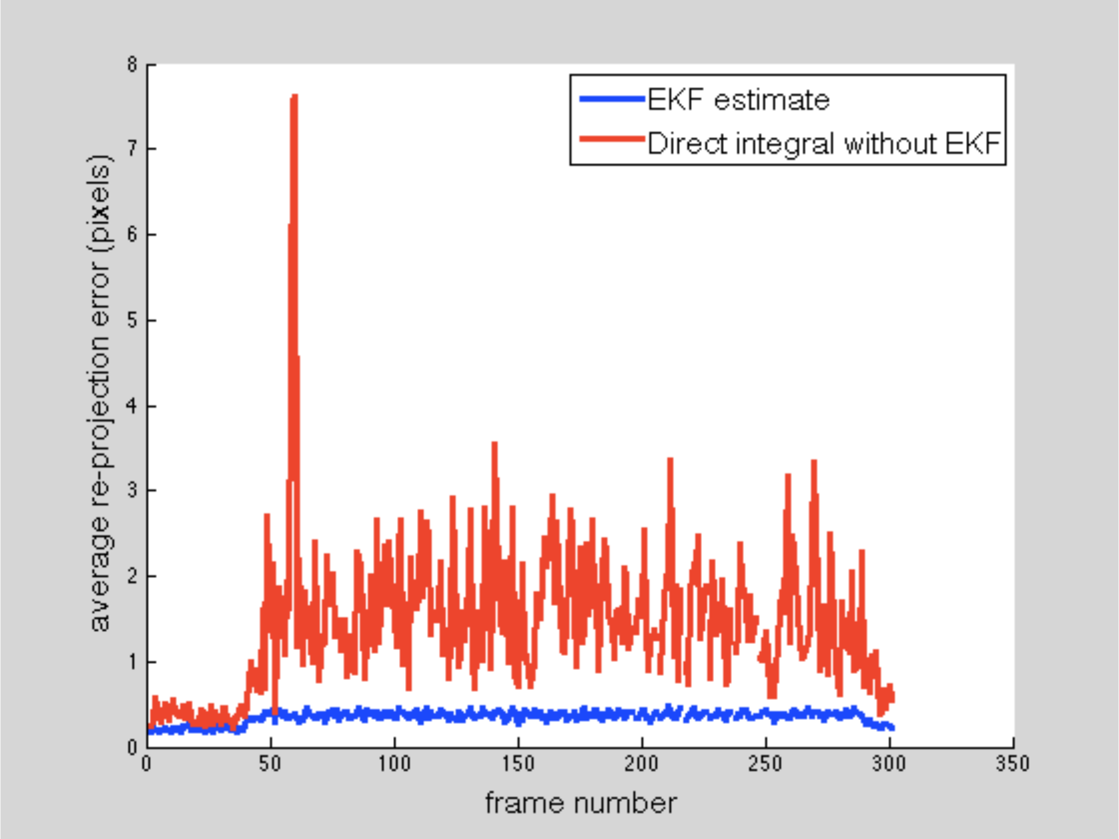
- Parameters
  - Rolling shutter speed (actual exposure time)
  - Intrinsic parameters of the camera
  - Delay between timestamps of IMUs and video
- Batch optimization [Karpenko 2011]
  - Camera intrinsic parameters initialized by Zhang's self-calibration
  - Get relative rotation from gyro readings
  - Optimize over all matching points, minimize the average re-projection error
  - Solve by Levenberg-Marquardt algorithm

$$J = \sum_i \sum_{\mathbf{u},\mathbf{v}} ||\mathbf{u} - \mathbf{K}\mathbf{R}(t(\mathbf{u}, i+1))\mathbf{R}^T(t(\mathbf{v}, i))\mathbf{K}^{-1}\mathbf{v}||^2$$



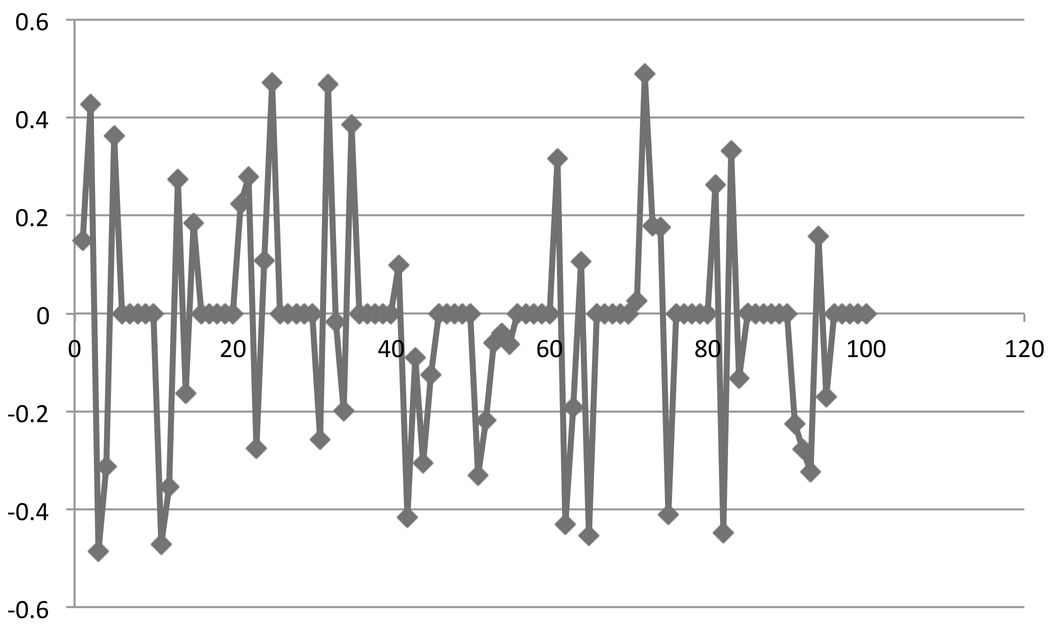
Average Re-projection Error per Point

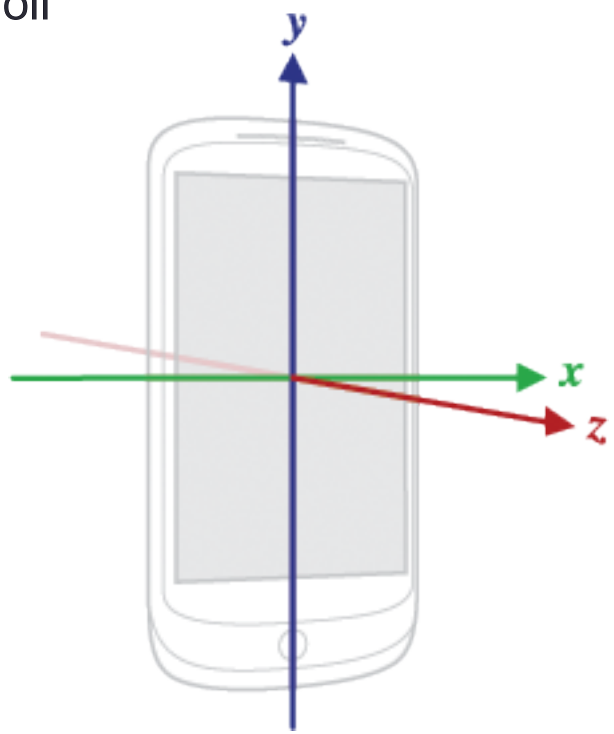
- RANSAC EKF vs. Integrating gyro readings



Rotation Estimation Accuracy

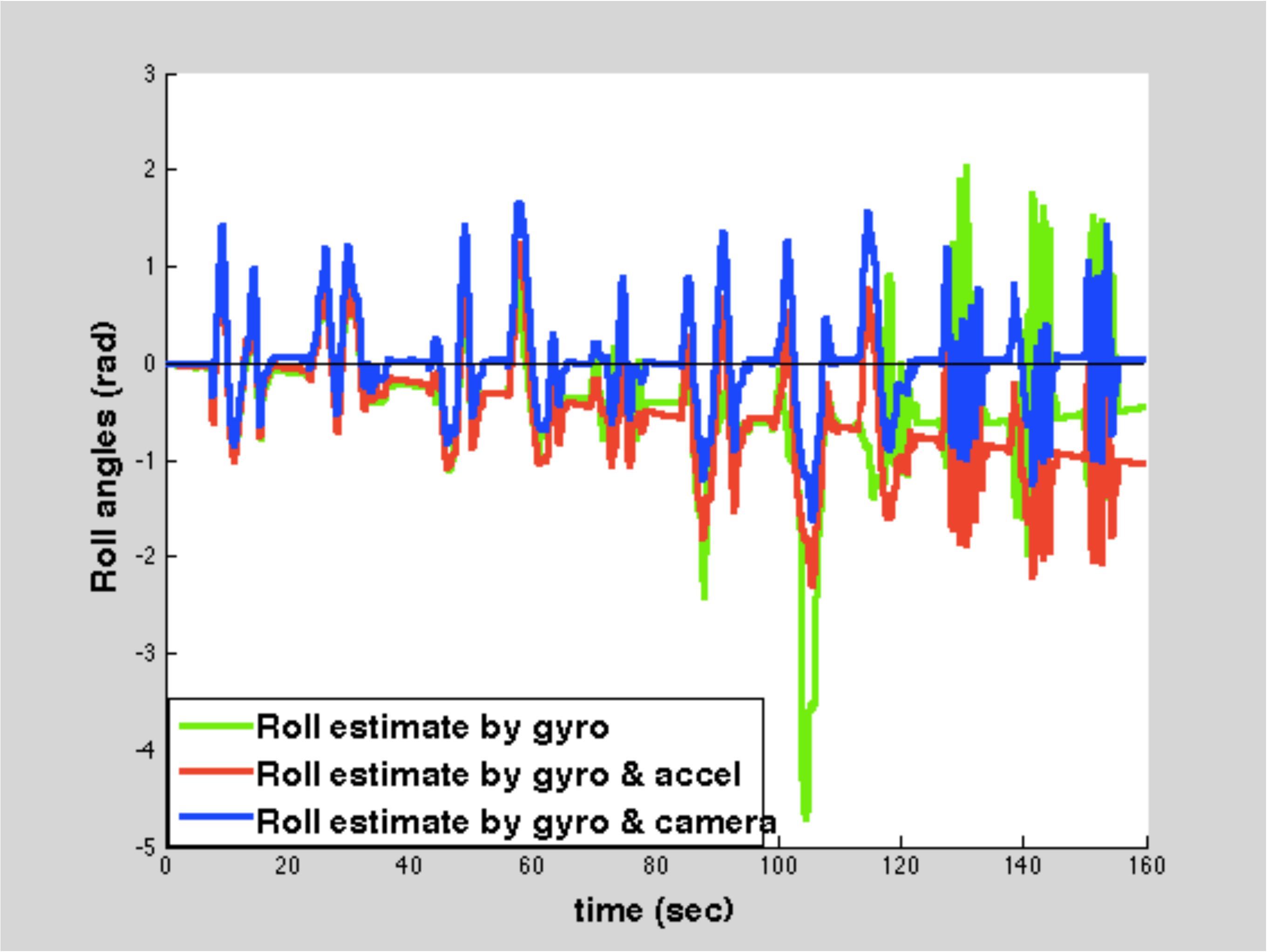
- Zero-angle test
  - Start with cell phone on a plat surface
  - Rotate cell phone at will, then put it back on the surface and stay still for several seconds
  - Repeat for ten times
  - Ground truth available naturally for pitch and roll





Rotation Estimation Accuracy

- Using raw gyro readings (with bias)



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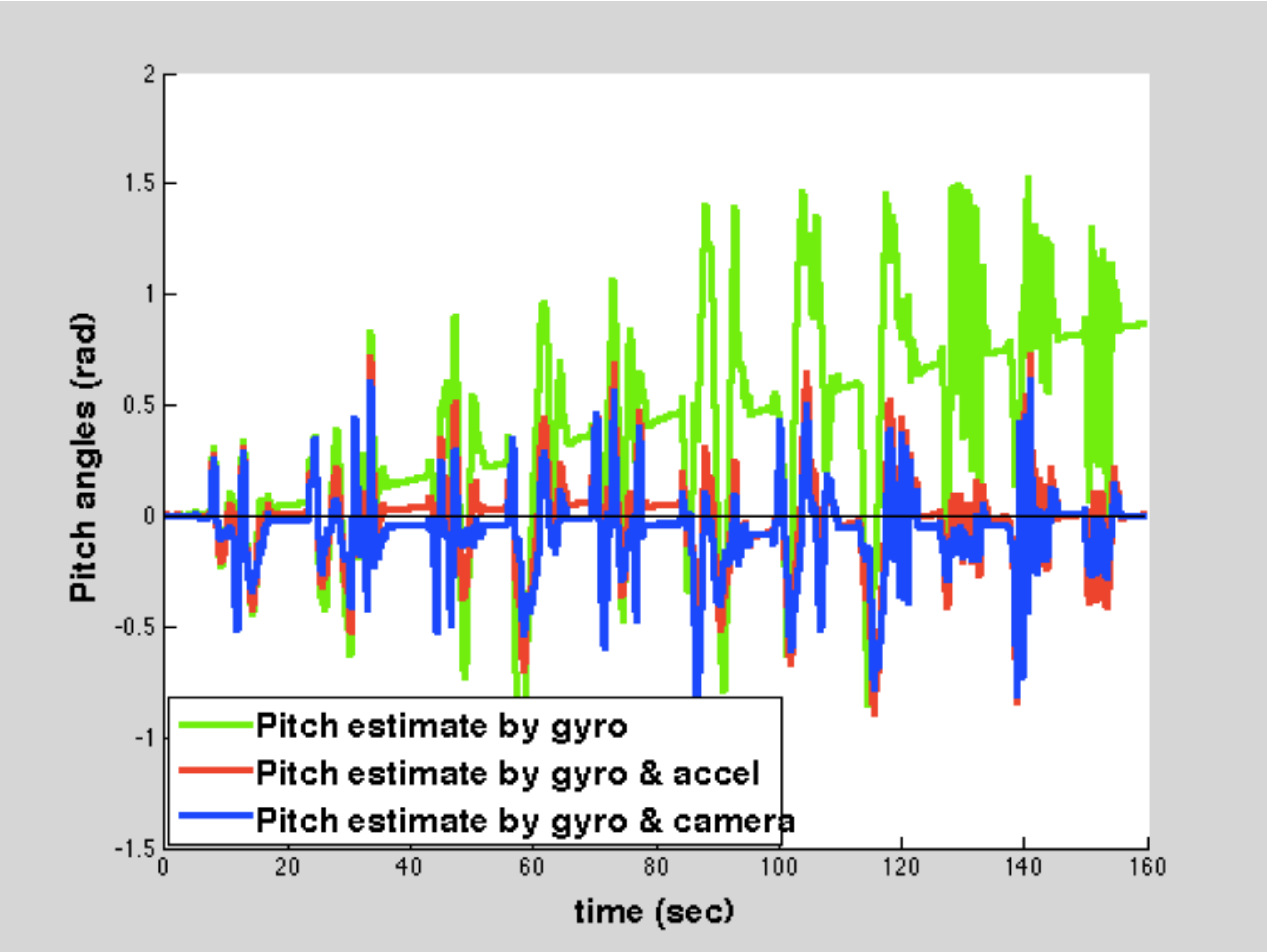
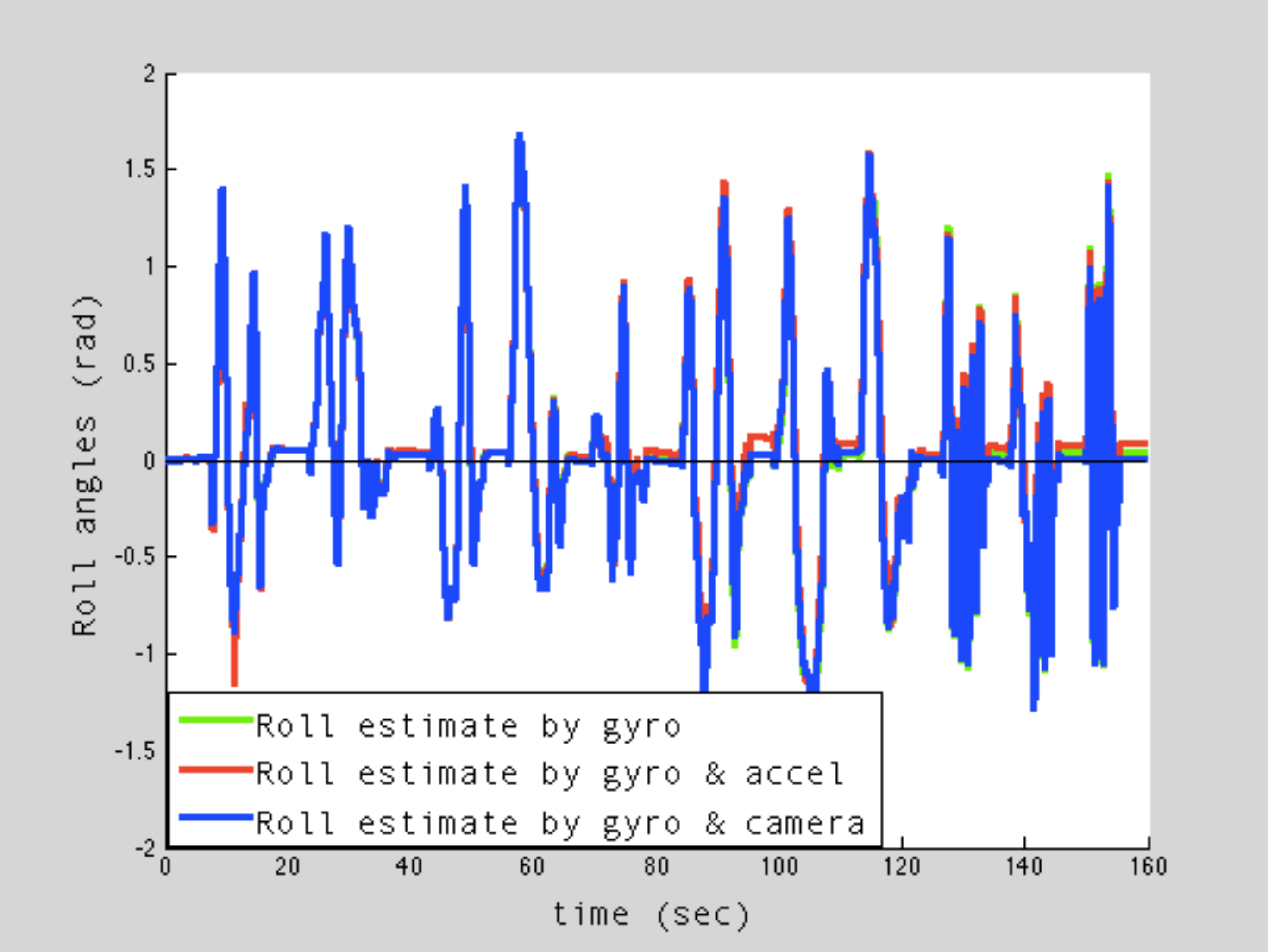


Rotation Estimation Accuracy

- Using unbiased gyro readings



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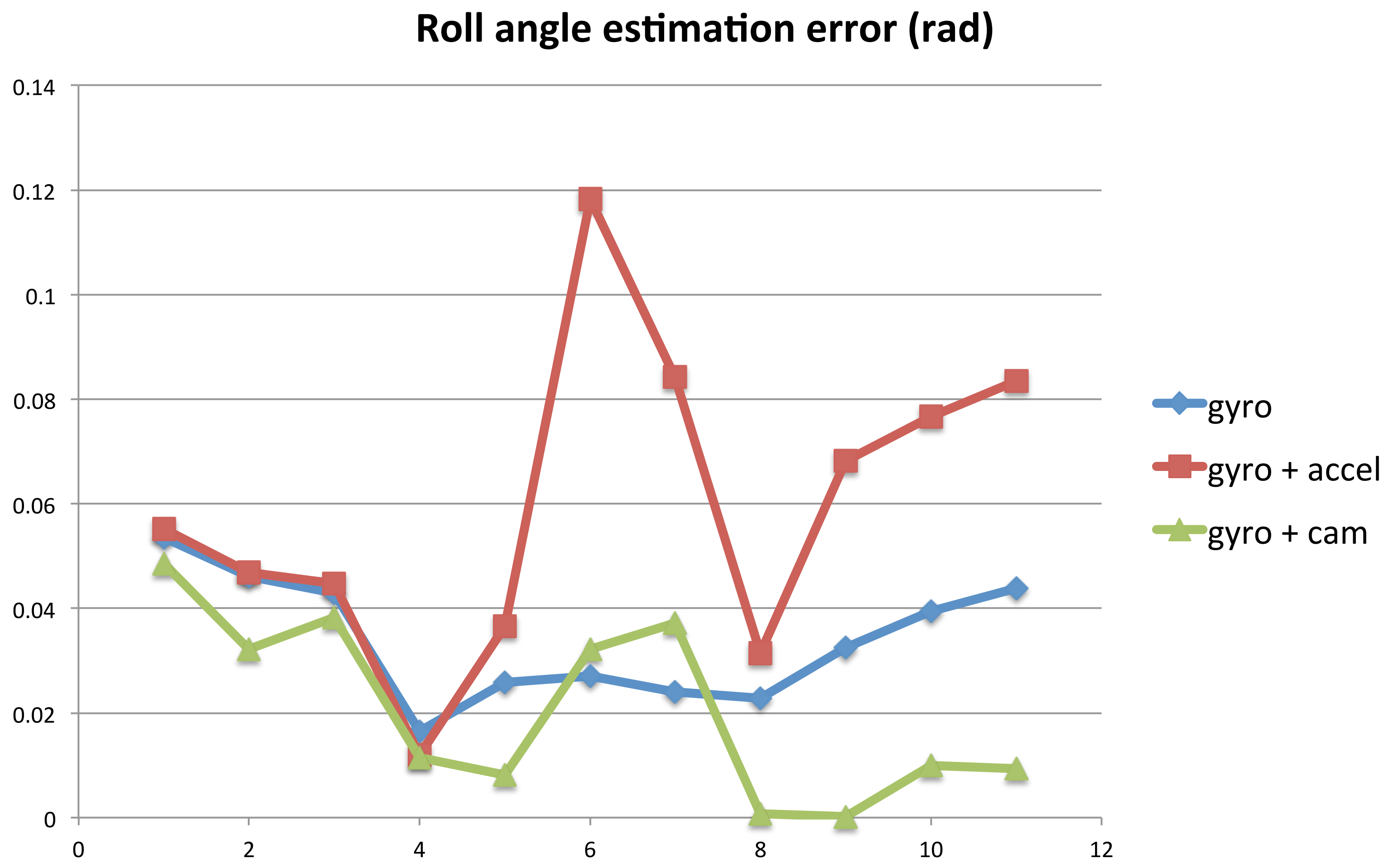

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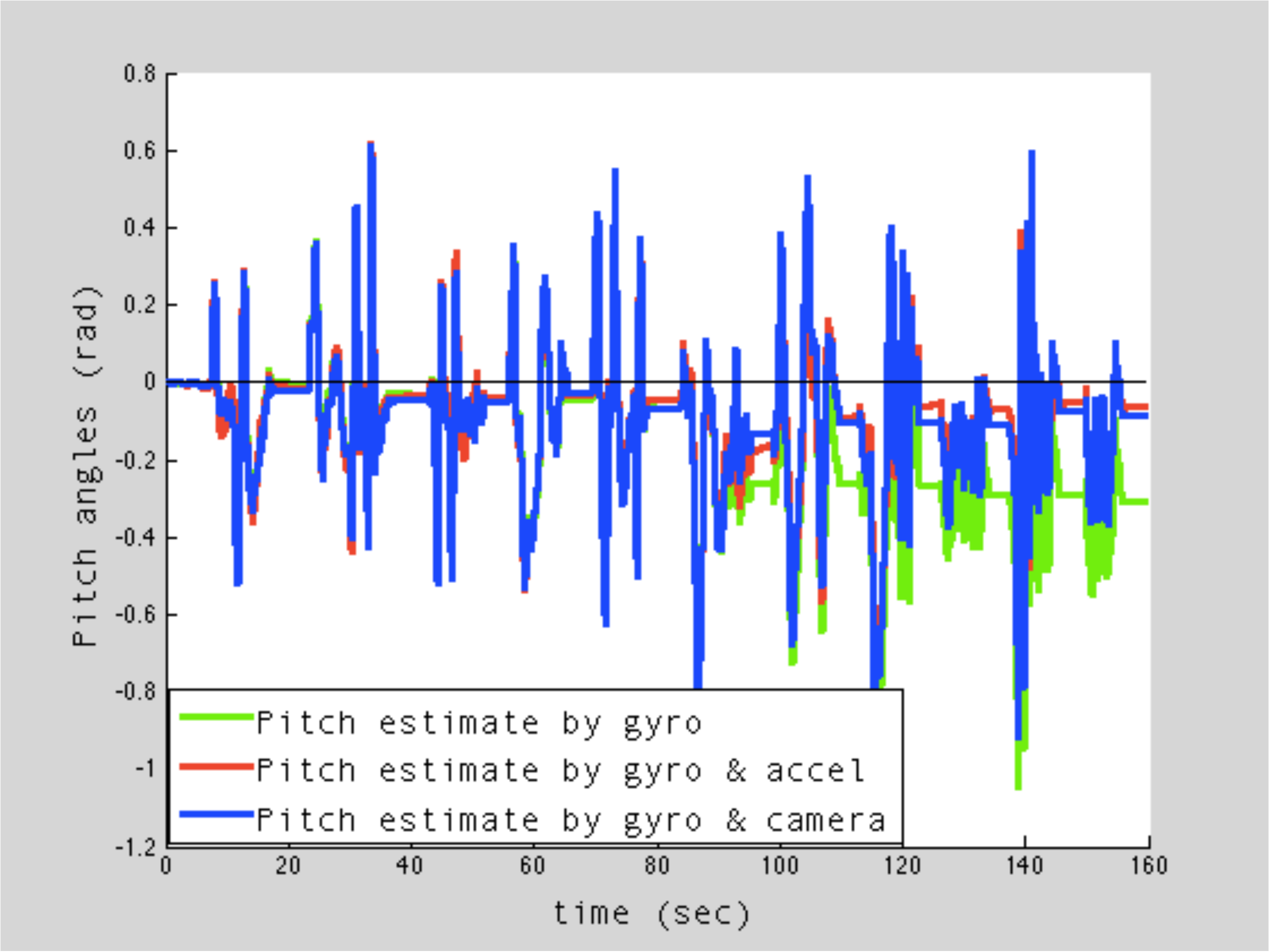

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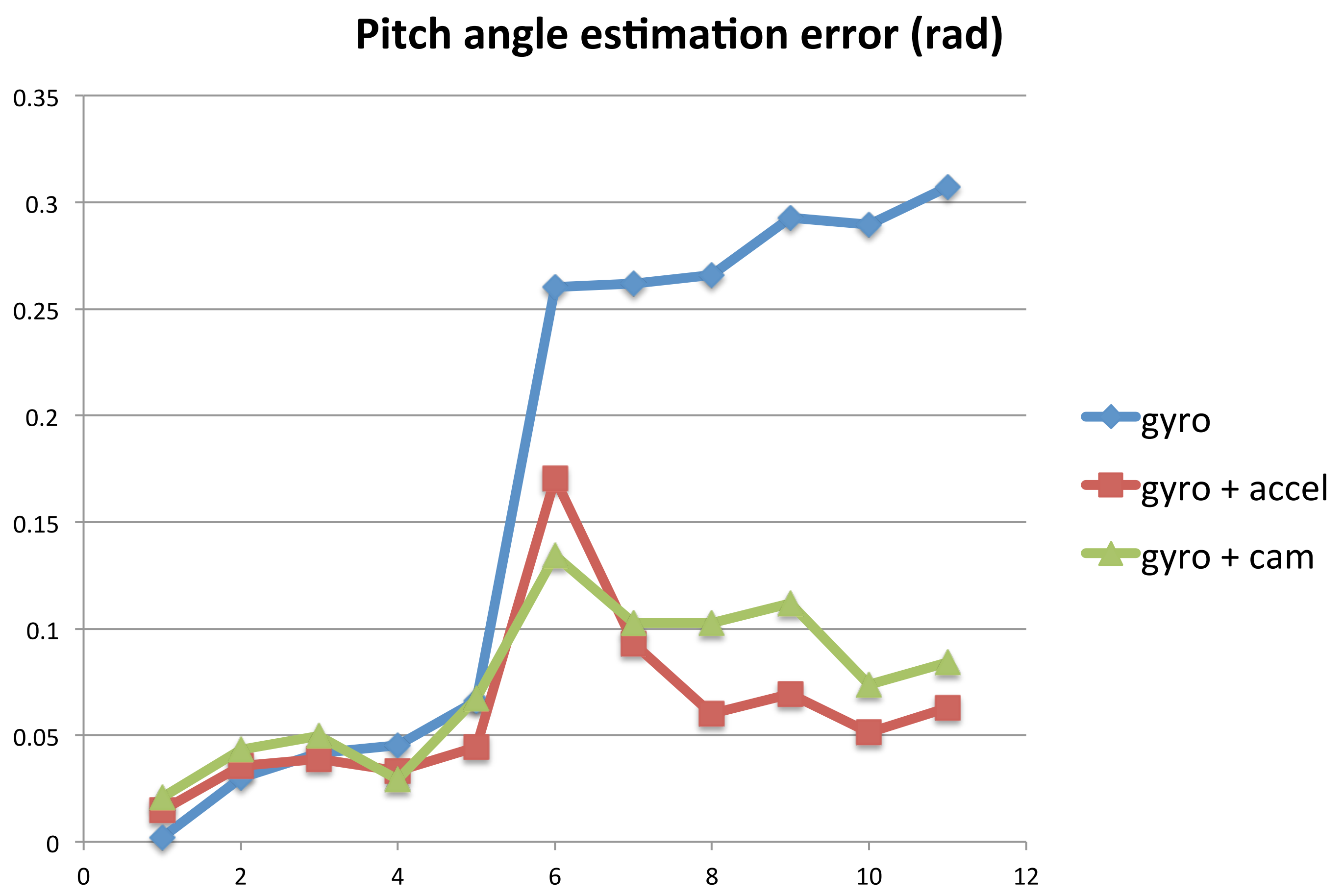
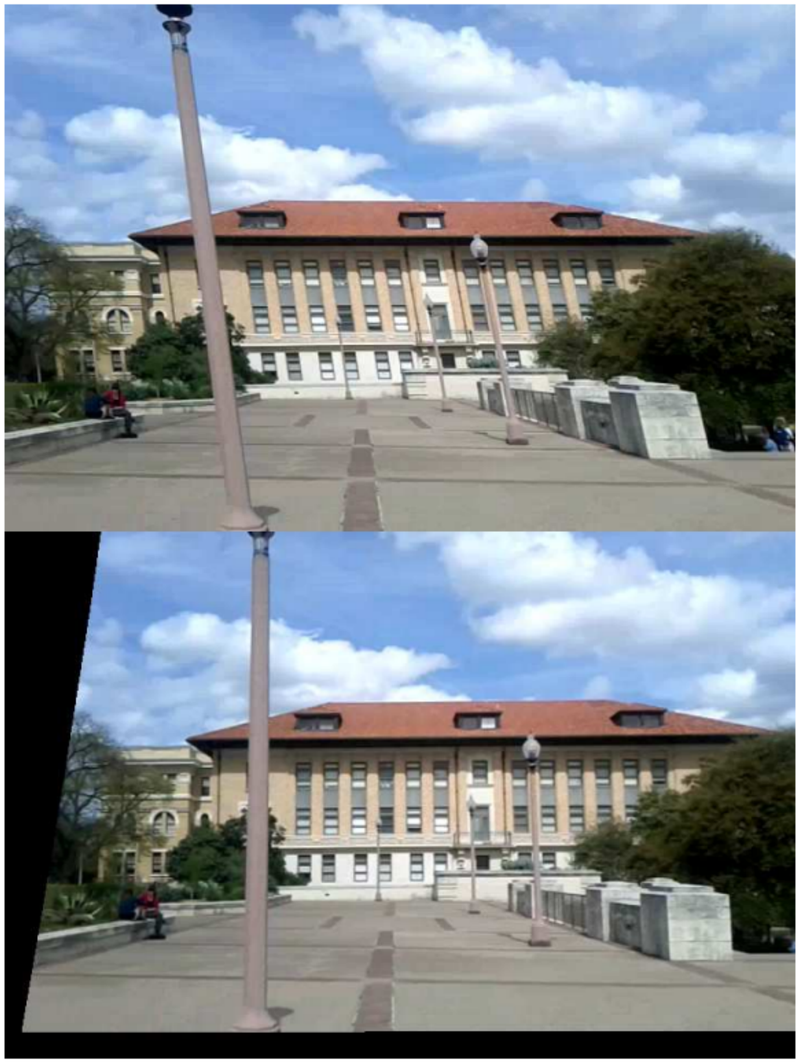


Rolling Shutter Rectification



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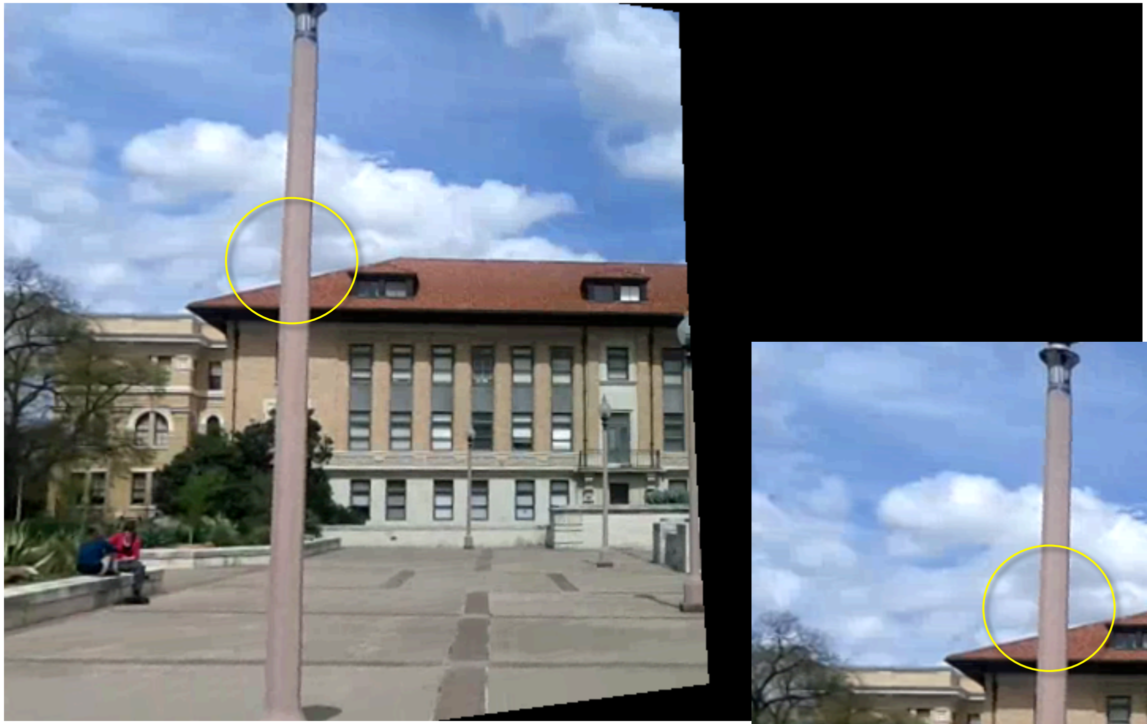
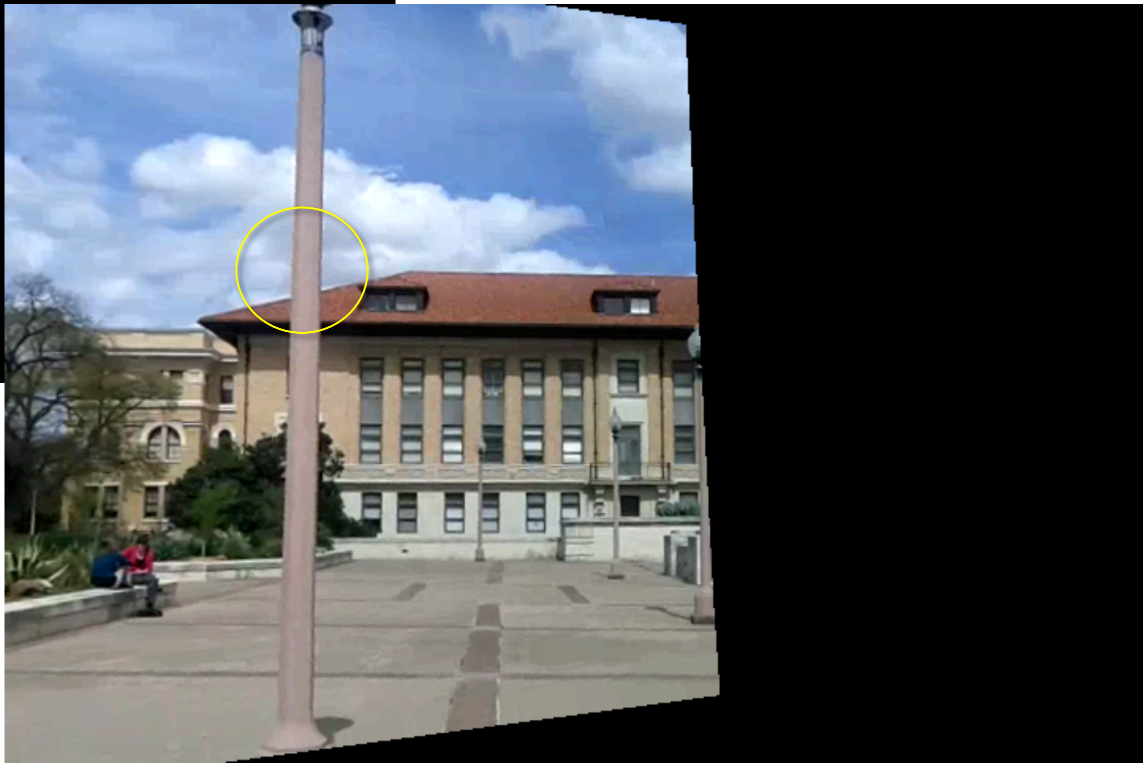
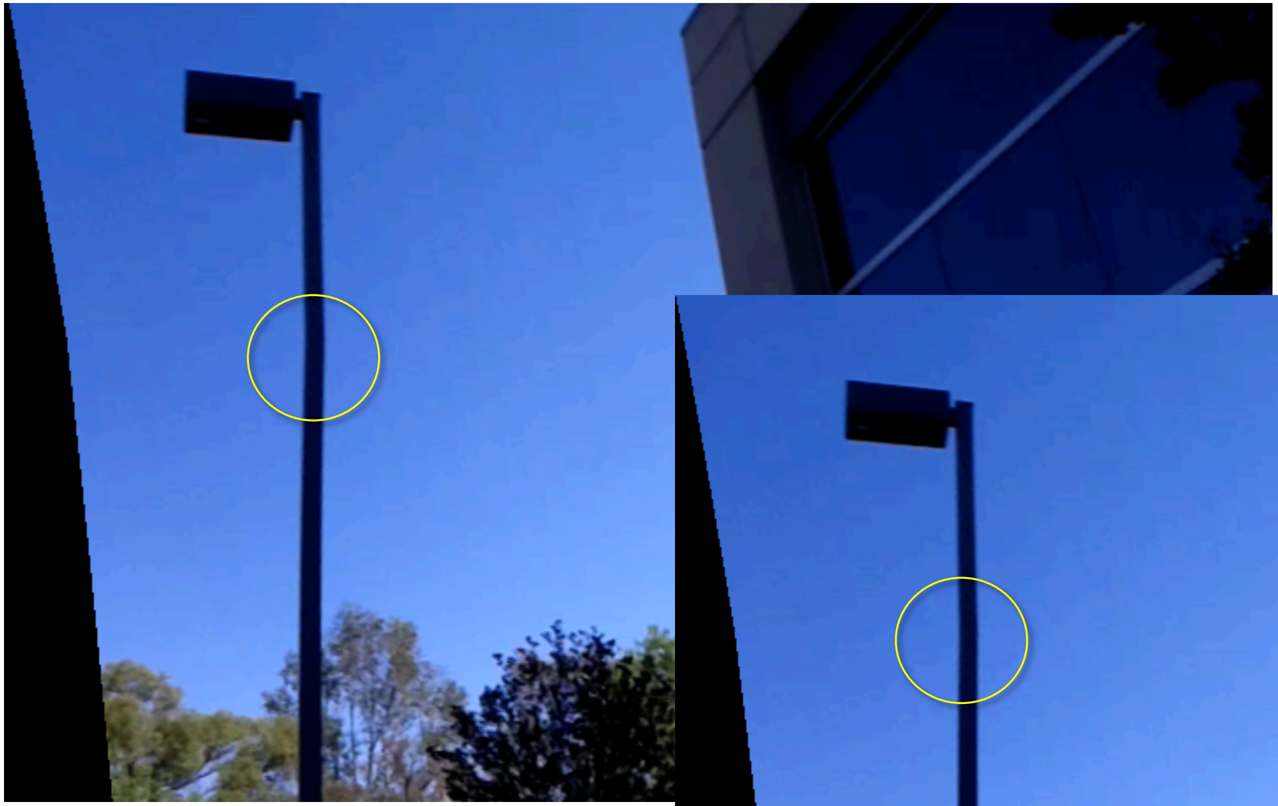


gyro



gyro + cam

Rolling Shutter Rectification



gyro

gyro + cam

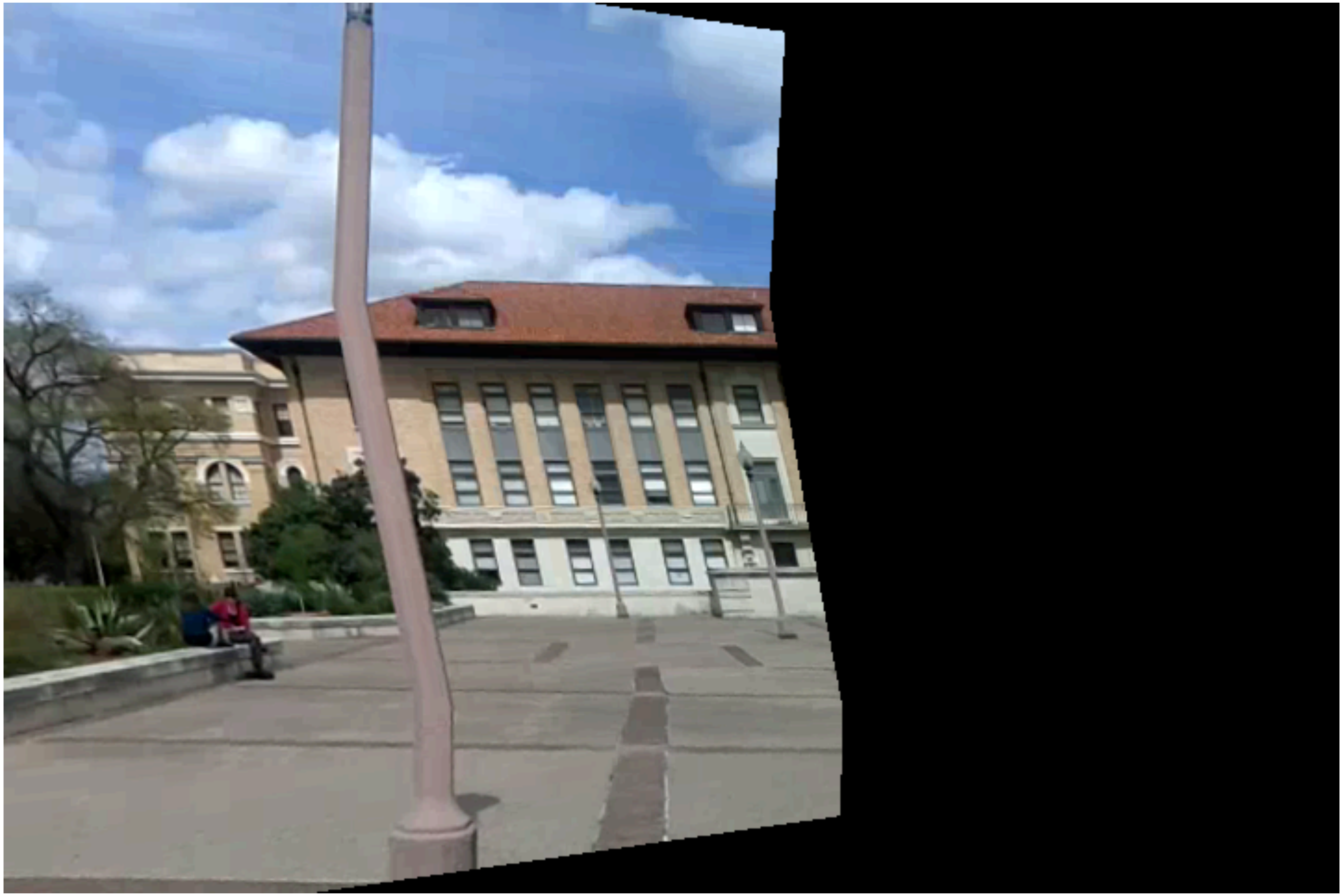
Rolling Shutter Rectification

gyro

gyro + cam

Rolling Shutter Rectification

- Complete failure using gyro + accel



Numerical Comparison

- No ground truth → no-reference method
- Vanishing point check
  - Lines detected manually
  - Find vanishing point by least-square

Average Euclidean distance from the lines to the vanishing point (in pixel)