

#### Geometry for Computer Vision Lecture 8 Rolling shutter and push-broom cameras: geometry and calibration

Per-Erik Forssén



### Overview

- What is a rolling shutter camera?
- Geometric modelling
- Readout time calibration





## What is wrong?





## What is wrong?



• Hand held  $\Rightarrow$ 

non-smooth camera path

- Geometric distortions (wobble)
- HTC desire (Q2 2010)







- To correct the video, both effects need to be considered:
- •Camera Motion
- •Geometric Distortion





#### Some current cameras





### Single lens reflex camera





#### Wafer camera



The shutter is electronic instead of mechanical!



• With a rolling shutter camera, rows are exposed sequentially



#### Static Scene

#### **Captured Image**



• With a rolling shutter camera, rows are exposed sequentially



#### **Dynamic Scene**

**Captured Image** 



















#### Sensor readout times

We obtain the readout time as  $t_r = N_r/(Tf_o)$  by imaging a flashing LED with known frequency f<sub>o</sub> and measuring the imaged period T [Geyer et al. OmniVis 2005]





#### Sensor readout times

We obtain the readout time as  $t_r = N_r/(Tf_o)$  by imaging a flashing LED with known frequency f<sub>o</sub> and measuring the imaged period T [Ringaby & Forssén IJCV 2012]





#### Sensor readout times

Device	framerate	Released	readout	
GoProHD Hero	59.94fps	Fall 2009	16.22 msec	
Kinect RGB	30fps	Nov 2010	26.11 msec	
Kinect NIR	29.97fps	Nov 2010	30.55 msec	
iPhone 4s	30fps	Oct 2011	22.08 msec	SP
AR drone v2	30fps	June 2012	24 msec	30



## Summary of the RS situation

- Rolling shutter cameras are everywhere
- A rolling shutter degrades all kinds of geometric computer vision
- A mechanical shutter solves the RS problem
- The readout time is a new camera parameter, that determines the rolling shutter speed.



### The pin-hole camera

Recap:

The camera projection operator P has the explicit form:

#### $\mathbf{P} = \mathbf{K} \left[ \mathbf{R}^T | - \mathbf{R}^T \mathbf{d} \right] = \mathbf{K} \mathbf{R}^T \left[ \mathbf{I} | - \mathbf{d} \right]$

K is the 3x3 intrinsic camera matrix

d is a translation of the origin, and R is a 3D rotation



For a moving camera, projection in frame k becomes:





For a moving camera, projection in frame k becomes:





For a moving camera, projection in frame k becomes:

 $\mathbf{x}_k \sim \mathbf{K} \mathbf{R}_k^T [\mathbf{I} | - \mathbf{d}_k] \mathbf{X} \qquad \mathbf{x}_k \sim \mathbf{K} \mathbf{R} (t_{\mathbf{x}})^T [\mathbf{I} | - \mathbf{d} (t_{\mathbf{x}})] \mathbf{X}$ 

One pose per line! For tractability, we need to parameterise d and R

The simplest option is to assume linear changes according to the image row index.

 $\mathbf{d}(t_{\mathbf{x}}) = \mathbf{d}_0(1-\lambda) + \mathbf{d}_1\lambda \quad \lambda = (t_{\mathbf{x}} - t_0)/(t_1 - t_0)$ 

...and similarly with SLeRP for the rotation (lecture 7).

More advanced modelling requires the use of splines (see lecture 7)



For a moving camera, projection in frame k becomes:

 $\mathbf{x}_k \sim \mathbf{K} \mathbf{R}_k^T [\mathbf{I} | - \mathbf{d}_k] \mathbf{X} \qquad \mathbf{x}_k \sim \mathbf{K} \mathbf{R} (t_{\mathbf{x}})^T [\mathbf{I} | - \mathbf{d} (t_{\mathbf{x}})] \mathbf{X}$ 

One pose per line! For tractability, we need to parameterise d and R

The simplest option is to assume linear changes according to the image row index.

 $\mathbf{d}(t_{\mathbf{x}}) = \mathbf{d}_0(1-\lambda) + \mathbf{d}_1\lambda \quad \lambda = (t_{\mathbf{x}} - t_0)/(t_1 - t_0)$ 

In practise one can compute the projection time from the row index:

 $t_{\mathbf{x}} - t_0 = x_2 / N_r \cdot t_r / T$ 





A push broom







A push-broom sensor is a 1D image sensor that acquires 2D images by moving.





#### Example: Imspec sensor used at FOI





3 or ~60 output bands from sensor, registered with a 3dof gyro signal



Data from FOI Sensor systems



#### Gyro based compensation (rotation only)





## Push-broom camera model

- Push-broom geometry can be viewed as a special case of rolling shutter geometry
- With a PB sensor, only one (very long) image is acquired
- With a general RS video camera, many frames in sequence are captured.



If we observe a point in two views, we can do triangulation (if motion is known)

 $\begin{array}{ll} \mathbf{x}_1 \sim \mathbf{K}_1[\mathbf{R}(\tau_1) | \mathbf{t}(\tau_1)] \mathbf{X} \\ \mathbf{x}_2 \sim \mathbf{K}_2[\mathbf{R}(\tau_2) | \mathbf{t}(\tau_2)] \mathbf{X} \end{array} \Rightarrow \begin{array}{l} \mathbf{0} \sim \mathbf{x}_1 \times \mathbf{P}_1 \mathbf{X} \\ \mathbf{0} \sim \mathbf{x}_2 \times \mathbf{P}_2 \mathbf{X} \end{array}$ 



If we observe a point in two views, we can do triangulation (if motion is known)

 $\begin{array}{ll} \mathbf{x}_1 \sim \mathbf{K}_1[\mathbf{R}(\tau_1) | \mathbf{t}(\tau_1)] \mathbf{X} \\ \mathbf{x}_2 \sim \mathbf{K}_2[\mathbf{R}(\tau_2) | \mathbf{t}(\tau_2)] \mathbf{X} \end{array} \Rightarrow \begin{array}{l} \mathbf{0} \sim \mathbf{x}_1 \times \mathbf{P}_1 \mathbf{X} \\ \mathbf{0} \sim \mathbf{x}_2 \times \mathbf{P}_2 \mathbf{X} \end{array}$ 

3D SaM from a rolling-shutter image pair is possible, using bundle adjustment:

[Ait-Aider&Berry ICCV09]

$$J(\{\mathbf{X}_n\}_{n=1}^N, \mathbf{R}, \mathbf{t}) = \sum_{n=1}^N ||\mathbf{x}_{1,n} - \hat{\mathbf{x}}_{1,n}||^2 + ||\mathbf{x}_{2,n} - \hat{\mathbf{x}}_{2,n}||^2$$



If we observe a point in two views, we can do triangulation (if motion is known)

 $\begin{array}{ll} \mathbf{x}_1 \sim \mathbf{K}_1[\mathbf{R}(\tau_1) | \mathbf{t}(\tau_1)] \mathbf{X} & \Rightarrow & \mathbf{0} \sim \mathbf{x}_1 \times \mathbf{P}_1 \mathbf{X} \\ \mathbf{x}_2 \sim \mathbf{K}_2[\mathbf{R}(\tau_2) | \mathbf{t}(\tau_2)] \mathbf{X} & \Rightarrow & \mathbf{0} \sim \mathbf{x}_2 \times \mathbf{P}_2 \mathbf{X} \end{array}$ 

Each correspondence gives us 4 equations (Why?)

Assuming that R,t change linearly with time, we have 5+3N unknowns for N correspondences. Thus we need

$$4N \ge 5 + 3N \quad \Rightarrow \\ N \ge 5$$



Degenerate motion [Ait-Aider&Berry ICCV09]:





Degenerate motion [Ait-Aider&Berry ICCV09]:



Illustration by Ait-Aider and Berry



- Under degeneracy, motion and structure can be interchanged freely.
- Special case: known motion, no degeneracy.
- If one of the cameras has a global shutter, both structure and motion can be determined [Ait-Aider&Berry ICCV'09]
- If multiple frames are used, rolling shutter structure from motion (SfM) is stable in practise [Hedborg et al. CVPR'12].



## Structure from motion

For RS aware SfM, we define reprojection errors again using interpolated key poses (translations and rotations)





## Cost Function, BA

Cameras:  $\mathbf{C}_j, j = 1..J.$  3D points:  $\mathbf{X}_k, k = 1..K$ 

 $\mathbf{C}_j = \mathbf{R}_j^T [\mathbf{I}| - \mathbf{d}_j]$ 

 $\operatorname{proj}(\mathbf{C}_j, \mathbf{X}_k)$  where  $\operatorname{proj}: (\Re^{3 \times 4}, \Re^3) \to \Re^2$ 

$$\min_{\mathbf{C},\mathbf{X}} \frac{1}{2} \sum_{j=1}^{J} \sum_{k \in \mathcal{V}_j} ||\mathbf{p}_{j,k} - \operatorname{proj}(\mathbf{C}_j, \mathbf{X}_k)||_2^2$$

 $\mathcal{V}_j$  is the set of visible points in camera j



## Cost Function, RSBA

Cameras:  $\mathbf{C}_j(y), j = 1..J.$  3D points:  $\mathbf{X}_k, k = 1..K$ 

$$\mathbf{C}_{j}(y) = \mathbf{R}_{j,j+1}^{T}(y)[\mathbf{I}| - \mathbf{d}_{j,j+1}(y)]$$

 $\operatorname{proj}(\mathbf{C}_j(y), \mathbf{X}_k)$  where  $\operatorname{proj}: (\Re^{3 \times 4}, \Re^3) \to \Re^2$ 

T

$$\min_{\mathbf{C},\mathbf{X}} \frac{1}{2} \sum_{j=1}^{J} \sum_{k \in \mathcal{V}_j} ||\mathbf{p}_{j,k} - \operatorname{proj}(\mathbf{C}_j(y_k), \mathbf{X}_k)||_2^2$$

 $\mathcal{V}_j$  is the set of visible points in camera j



## Structure from motion

In RSBA, we also need rolling-shutter aware versions of PnP and Triangulation.





## Rolling Shutter PnP

Simultaneous Object Pose and Velocity Computation Using a Single View from a Rolling Shutter Camera

Omar Ait-Aider, Nicolas Andreff, Jean Marc Lavest and Philippe Martinet, ECCV 2006



Non-linear least squares on the following cost function:

K

# $\min_{\mathbf{R},\mathbf{d},\mathbf{\Omega},\mathbf{v}} \sum_{k=1}^{n} ||\mathbf{x}_k, \operatorname{proj}(\mathbf{C}_j(t), \mathbf{X}_k)||^2$



## Rolling Shutter PnP

Parallel Tracking and Mapping on a camera phone Georg Klein and David Murray, **ISMAR 2009** 

- Ported PTAM (parallel tracking and mapping) to the CMOS camera of the Iphone 3G
- System Initialization: find planar structure and do homography estimation
- Then a rolling shutter aware perspective-n-point method



## Rolling Shutter PnP

Parallel Tracking and Mapping on a camera phone Georg Klein and David Murray, **ISMAR 2009** 

Solve the velocity of the camera

Then compensate for the RS-distortion

$$\begin{bmatrix} \mathbf{J}_1 \\ \vdots \\ \mathbf{J}_n \end{bmatrix} \dot{\boldsymbol{\mu}} = \begin{bmatrix} \dot{\mathbf{m}}_1 \\ \vdots \\ \dot{\mathbf{m}}_n \end{bmatrix}, \ \mathbf{m'}_i = \mathbf{m}_i - \mathbf{J}_i \dot{\boldsymbol{\mu}} \delta t$$



Rotation homography approximation:

 $\begin{array}{ll} \mathbf{x}_1 \sim \mathbf{K} \mathbf{R}(t_1) \mathbf{X} \\ \mathbf{x}_2 \sim \mathbf{K} \mathbf{R}(t_2) \mathbf{X} \end{array} \implies \begin{array}{l} \mathbf{x}_1 \sim \mathbf{H} \mathbf{x}_2 \\ \mathbf{H} \sim \mathbf{K} \mathbf{R}(t_1) \mathbf{R}(t_2)^T \mathbf{K}^{-1} \end{array}$ 

Valid if the distance to imaged objects is large compared to the baseline



Rotation homography approximation:

$$\begin{array}{ll} \mathbf{x}_1 \sim \mathbf{K} \mathbf{R}(t_1) \mathbf{X} \\ \mathbf{x}_2 \sim \mathbf{K} \mathbf{R}(t_2) \mathbf{X} \end{array} \Rightarrow \begin{array}{l} \mathbf{x}_1 \sim \mathbf{H} \mathbf{x}_2 \\ \mathbf{H} \sim \mathbf{K} \mathbf{R}(t_1) \mathbf{R}(t_2)^T \mathbf{K}^{-1} \end{array}$$

Valid if the distance to imaged objects is large compared to the baseline



For hand-held motion rotation is typically the dominant source of distortions



Rotation homography approximation:

 $\begin{array}{ll} \mathbf{x}_1 \sim \mathbf{K} \mathbf{R}(t_1) \mathbf{X} \\ \mathbf{x}_2 \sim \mathbf{K} \mathbf{R}(t_2) \mathbf{X} \end{array} \Rightarrow \begin{array}{l} \mathbf{x}_1 \sim \mathbf{H} \mathbf{x}_2 \\ \mathbf{H} \sim \mathbf{K} \mathbf{R}(t_1) \mathbf{R}(t_2)^T \mathbf{K}^{-1} \end{array}$ 

Valid if the distance to imaged objects is large compared to the baseline

Allows estimation of rotations across a sequence of frames given correspondences, using BA (see next discussion paper)

$$J = \sum_{k=1}^{K} d(\mathbf{x}_{1,k}, \mathbf{H}\mathbf{x}_{2,k})^2 + d(\mathbf{x}_{2,k}, \mathbf{H}^{-1}\mathbf{x}_{1,k})^2$$



Once we know the rotations R and the intrinsics K, rectification from a single frame is possible  $\mathbf{x}' \sim \mathbf{KR}(t_{\mathrm{mid}})\mathbf{R}(t_{\mathbf{x}})^T\mathbf{K}^{-1}\mathbf{x}$ 

This is forward interpolation, which in this case is slightly more accurate than regular inverse interpolation





### Rectification

Each line is rectified with a separate homography

 $\mathbf{x}' \sim \mathbf{KR}(t_{\text{mid}})\mathbf{R}(t_{\mathbf{x}})^T \mathbf{K}^{-1} \mathbf{x}$ 





### Readout calibration

Luc Oth, Paul Furgale, Laurent Kneip, Roland Siegwart, *Rolling Shutter Camera Calibration*, CVPR'13

Checkerboard calibration, using known intrinsics K.

$$J(t_r, \mathbf{R}_1, \mathbf{d}_1, \dots, \mathbf{R}_N, \mathbf{d}_N) = \sum_n \sum_k d^2(\mathbf{x}_{k,n}, \mathbf{K}\mathbf{R}(t_{k,n})^T [\mathbf{I}] - \mathbf{d}(t_{k,n})]\mathbf{X}_k)$$

True reprojection error is used:

- Time at reprojection  $t_{k,n}$  insead of
- Time at observation t<sub>x</sub>

Requires iteration, as camera pose R(t),d(t) now depends on t, and t depends on R(t),d(t) !



### Readout calibration

Luc Oth, Paul Furgale, Laurent Kneip, Roland Siegwart, *Rolling Shutter Camera Calibration*, CVPR'13

Checkerboard calibration, using known intrinsics K.

$$J(t_r, \mathbf{R}_1, \mathbf{d}_1, \dots, \mathbf{R}_N, \mathbf{d}_N) = \sum_n \sum_k d^2(\mathbf{x}_{k,n}, \mathbf{K}\mathbf{R}(t_{k,n})^T [\mathbf{I}] - \mathbf{d}(t_{k,n})]\mathbf{X}_k)$$

True reprojection error is used:

- Time at reprojection  $t_{k,n}$  insead of
- Time at observation  $t_x$

Requires iteration, as camera pose R(t),d(t) now depends on t, and t depends on R(t),d(t) !

Also uses a split criterion, to iteratively add new poses where needed.



#### Papers to discuss next week...

E. Ringaby and P-.E. Forssén. *Efficient* Video Rectification and Stabilisation for Cell-Phones, IJCV'12