

Camera parameter estimation for image based modeling

Jaechul Kim

Purpose

- Introduce a basic procedure of camera parameter estimation from multiple images and its application to image-based modeling

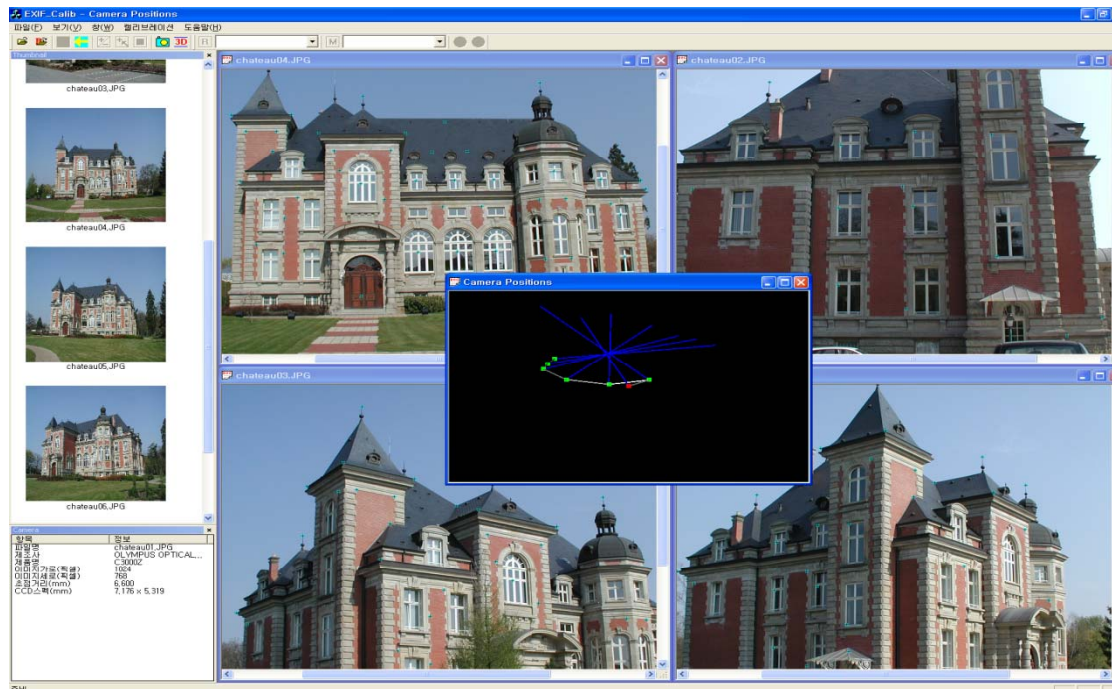
Overview of general procedure

- Step 1 : Point matches and epipolar geometry estimation (i.e. Fundamental matrix computation)



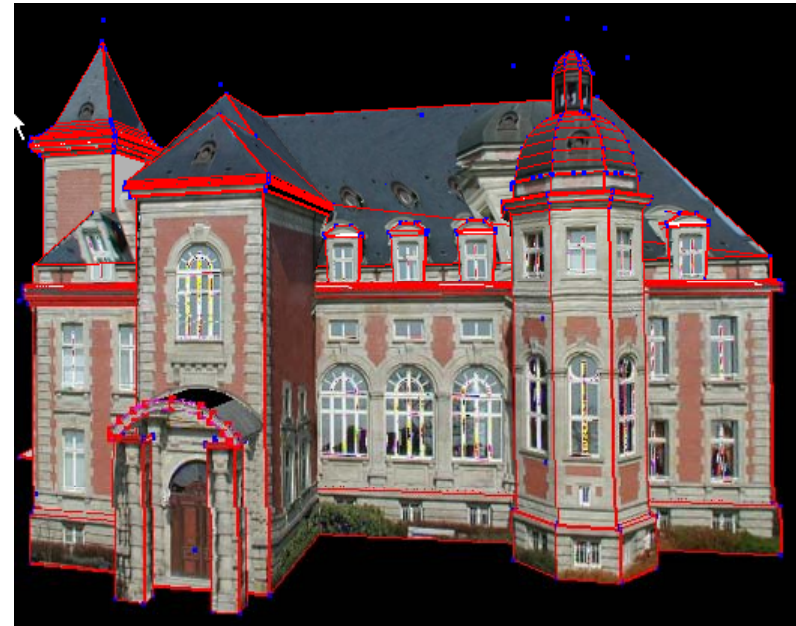
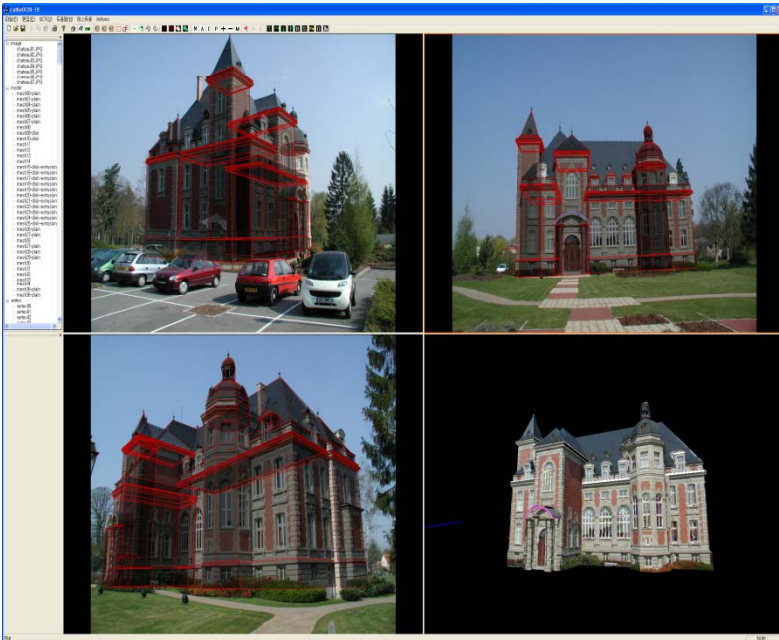
Overview of general procedure

- Step2 : Estimation of camera parameters
 - Focal length, Camera position, Viewing direction etc.



Overview of general procedure

- Step 3: 3D reconstruction & Texture mapping



Step1

Feature Points Matching & Epipolar Geometry Estimation

- General procedure
 - Find point correspondences between images
 - From point correspondences, compute fundamental matrices (F-matrices) between images
 - Outliers in point correspondences are rejected during F-matrix computation using RANSAC
- Output : F-matrix (i.e. projective reconstruction)

Step 1

Feature Points Matching

- Three methods are tested in this demo
 - Harris corner detector & Window correlation + RANSAC
 - SIFT detector & SIFT descriptor + RANSAC
 - Manual matching

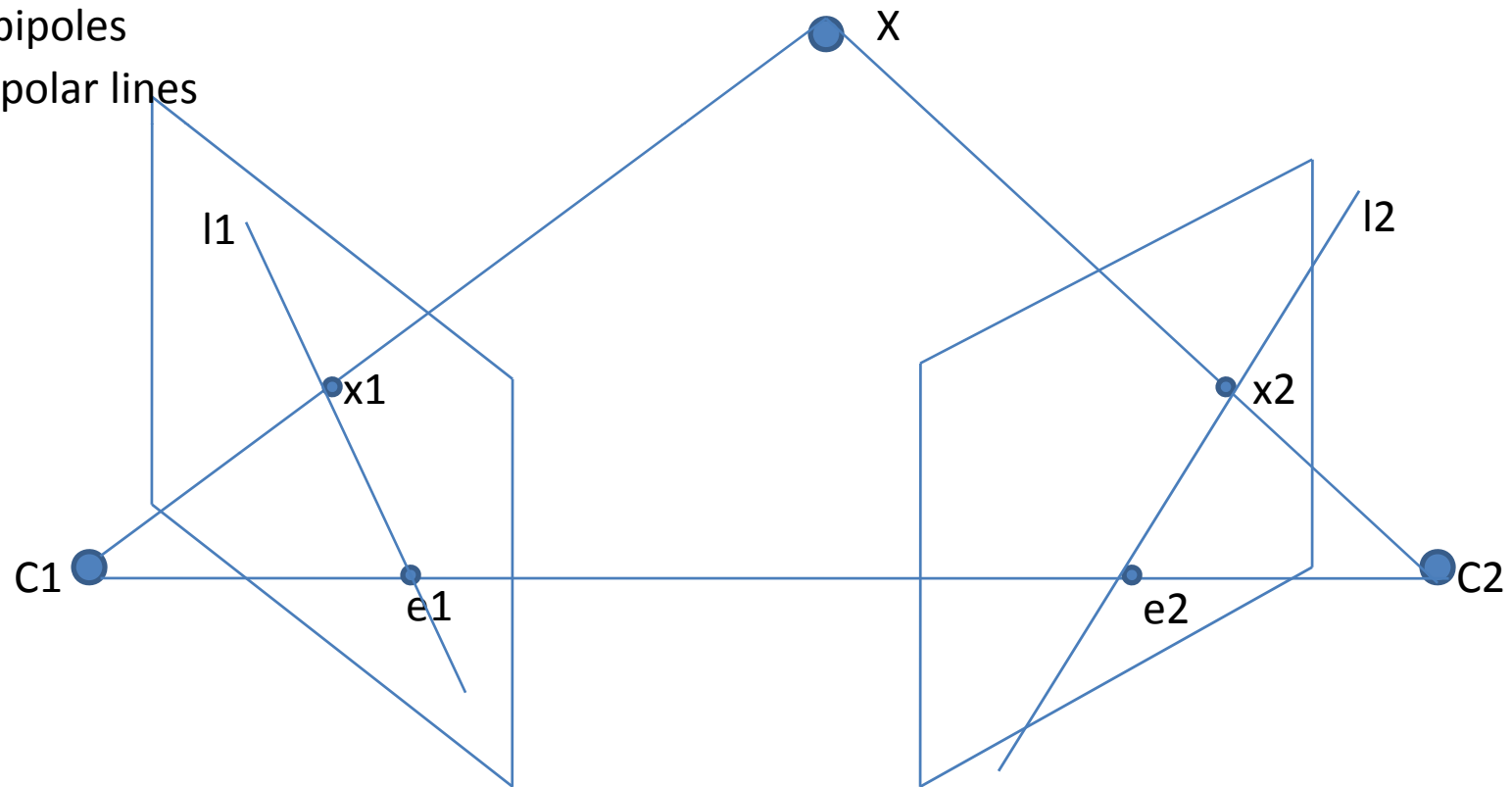
Step1

Epipolar geometry

- Projective geometry between two views

e_1, e_2 : epipoles

l_1, l_2 : epipolar lines



Step1

Fundamental matrix

- Encode epipolar geometry between two views
- Rank-2 matrix ($\det(F) = 0$) that can be computed from at least 7-point correspondences

$$\mathbf{x}_2^T \mathbf{F} \mathbf{x}_1 = 0$$

- Define epipolar line for a given point \mathbf{x}_1 or \mathbf{x}_2

$$\mathbf{l}_2 = \mathbf{F} \mathbf{x}_1$$

$$\mathbf{l}_1 = \mathbf{F}^T \mathbf{x}_2$$

Step1

RANSAC (RANdOm SAmple Concensus)

- Robust estimation technique under the presence of outliers
- Algorithm outline
 - Given putative correspondences, sample 7 or 8 correspondences and then compute the Fundamental matrix
 - Using the computed Fundamental matrix, count the number of inliers
 - If the number of inlier is a maximum among iterations, store the Fundamental matrix and inliers.
 - Repeat the sampling.

Step 1

Feature point detection & matching

Harris corner + Window correlation + RANSAC

- Harris corner detector

$$A = \sum_u \sum_v w(u, v) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} = \begin{bmatrix} \langle I_x^2 \rangle & \langle I_x I_y \rangle \\ \langle I_x I_y \rangle & \langle I_y^2 \rangle \end{bmatrix},$$

$$M_c = \lambda_1 \lambda_2 - \kappa (\lambda_1 + \lambda_2)^2 = \det(A) - \kappa \text{trace}^2(A)$$

– Parameters to be used

- Harris threshold, M_c , is 500
- Kappa is set to 0.04
- Gaussian smoothing with sigma 1 is applied to image before corner detection
- Window size (u,v) is 1

Step1

Feature point detection & matching

Harris corner + Window correlation + RANSAC

- Windows correlation
 - For a detected corner point (x,y) in the image 1, search the corner point (x',y') in the image 2 with the minimum SSD error
 - Parameter to be used
 - Correlation window size 15
 - Search area in the image 2 is set to 300 by 300 (1/4 size of the image) centered to (x,y)

Step1

Feature point detection & matching
Harris corner + Window correlation + RANSAC

- Harris corner detection



Initially detected corner points

Step1

Feature point detection & matching

Harris corner + Window correlation + RANSAC

- Window correlation + RANSAC



Putative matches (626)

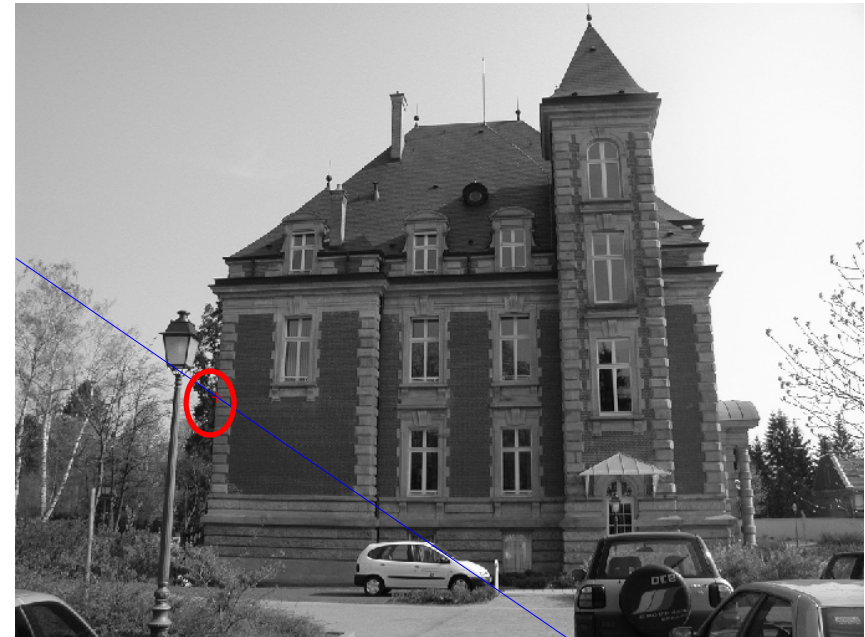


Inliers after RANSAC (23, 4%)

Step1

Feature point detection & matching
Harris corner + Window correlation + RANSAC

- Examples of false matches



Step1

Feature point detection & matching
Harris corner + Window correlation + RANSAC

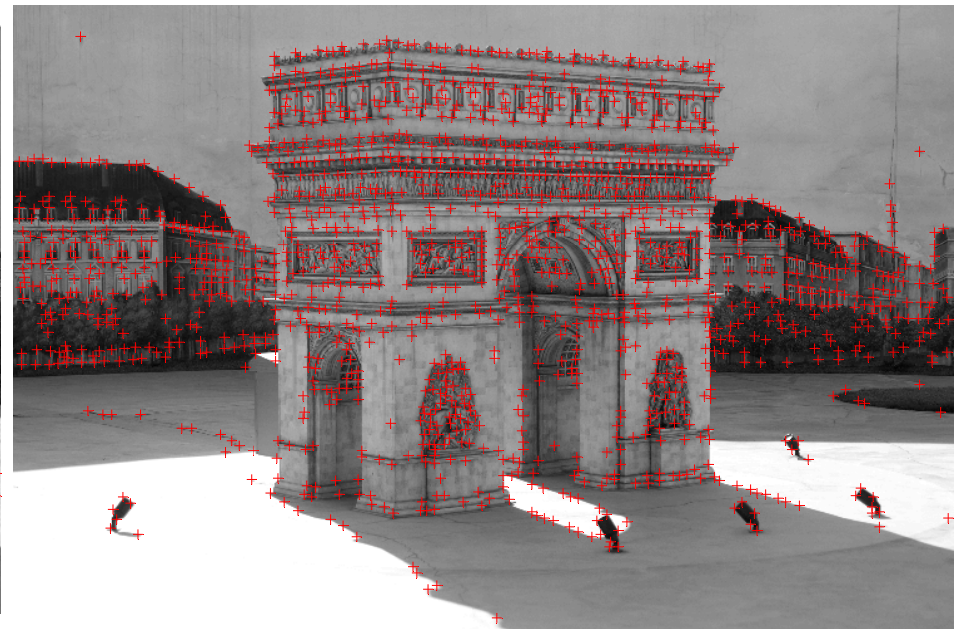
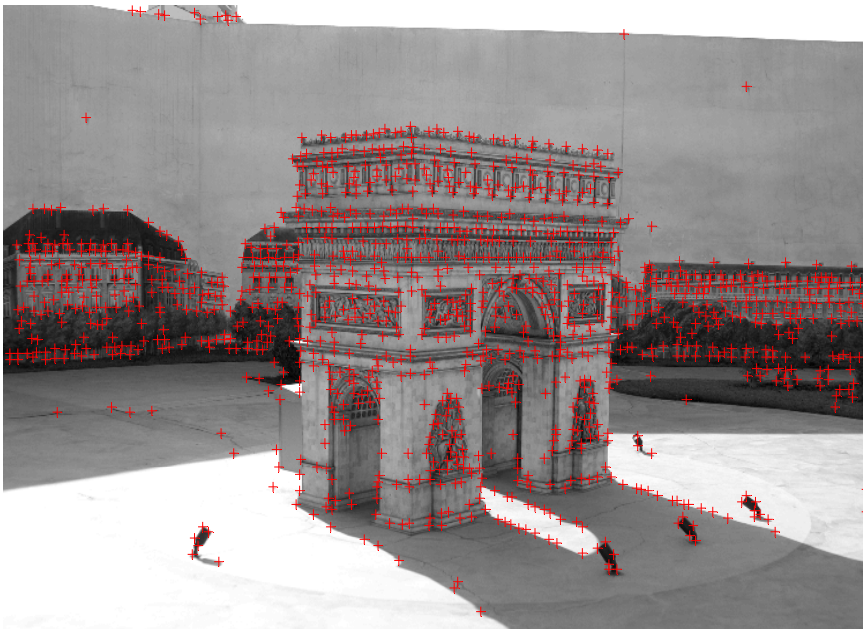
- Examples of false matches



Step1

Feature point detection & matching
Harris corner + Window correlation + RANSAC

- More examples (Harris + RANSAC)



Initially detected corner points

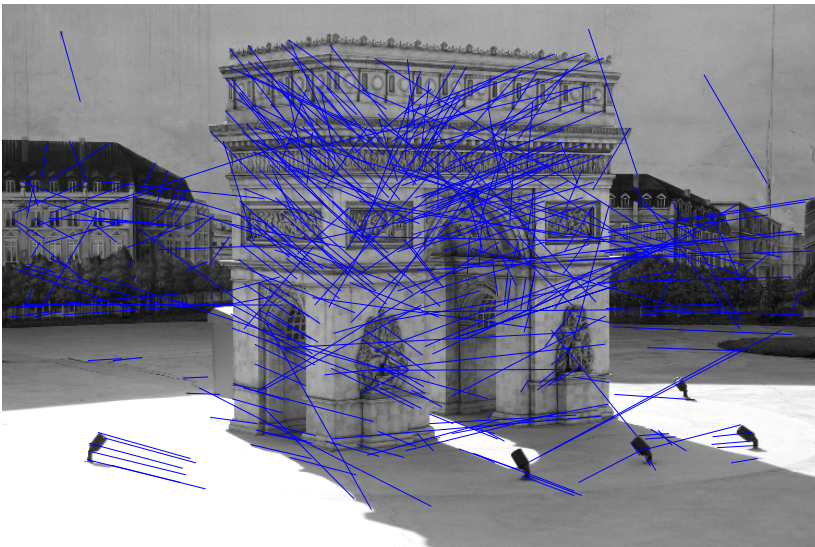
Demo presentation - Visual recognition and
search, Mar 21, 2008

Step1

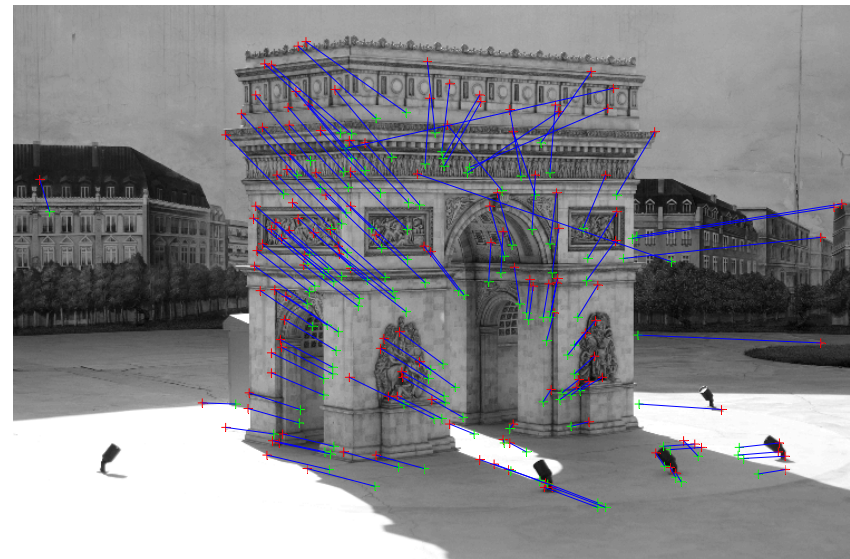
Feature point detection & matching

Harris corner + Window correlation + RANSAC

- More examples (Harris + RANSAC)



Putative matches (386)

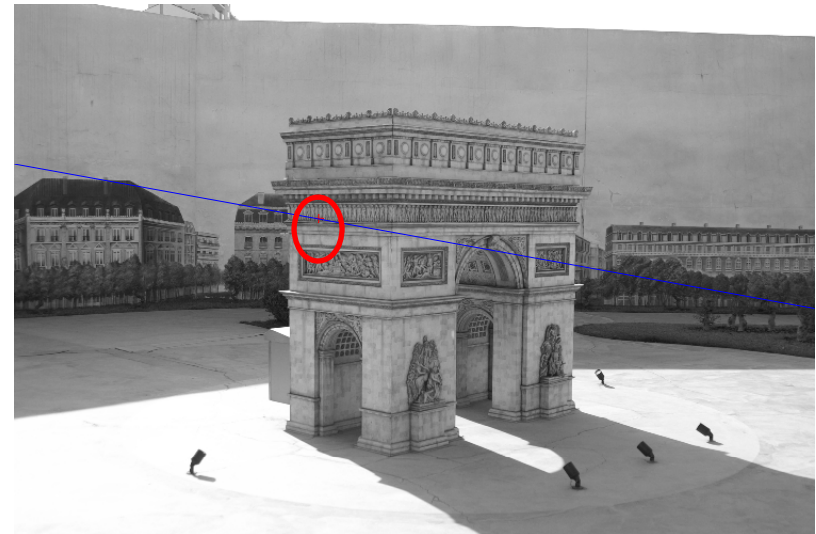
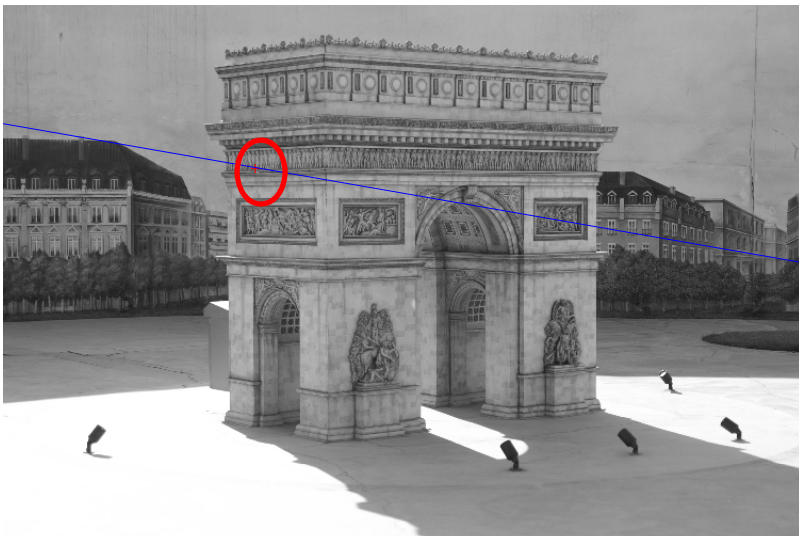


Inliers after RANSAC (141, 37%)

Step1

Feature point detection & matching
Harris corner + Window correlation + RANSAC

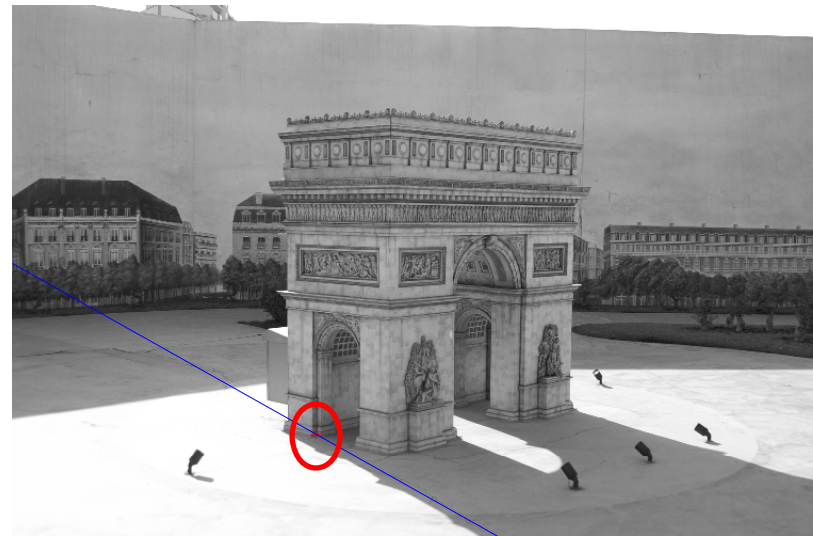
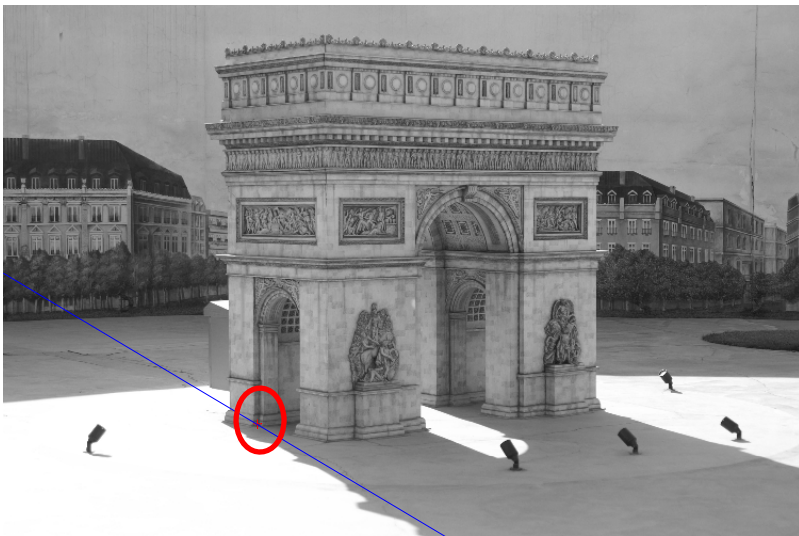
- More examples (Harris + RANSAC) :Good result



Step1

Feature point detection & matching
Harris corner + Window correlation + RANSAC

- More examples (Harris + RANSAC) : Good result



Step1

Feature point detection & matching

Harris corner + Window correlation + RANSAC

- Harris + RANSAC - Conclusion
 - Weak to matching two images with large viewpoint change
 - Confusion in repetitive textures
 - Some of image pairs have incorrect F matrices
 - Harris corner detection seems to be more proper to video based camera parameter tracking where image change between consecutive frames is small

Step1

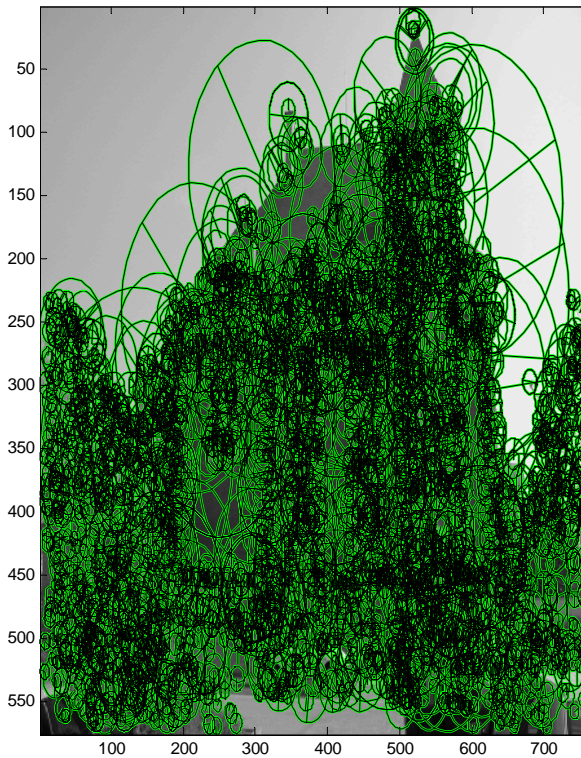
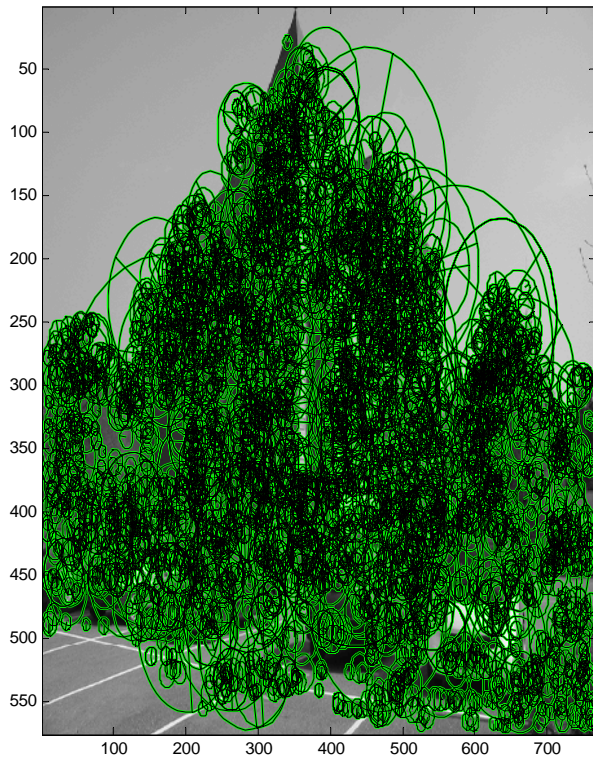
Feature point detection & matching SIFT + RANSAC

- SIFT + RANSAC
 - Parameter to be used
 - Sigma : 0.5
 - Number of octaves : 6
 - Number of levels per octave: 3
 - SIFT descriptor : 128 dimensions
 - Putative matches are found using nearest neighbor between the SIFT descriptors

Step1

Feature point detection & matching SIFT + RANSAC

- SIFT + RANSAC

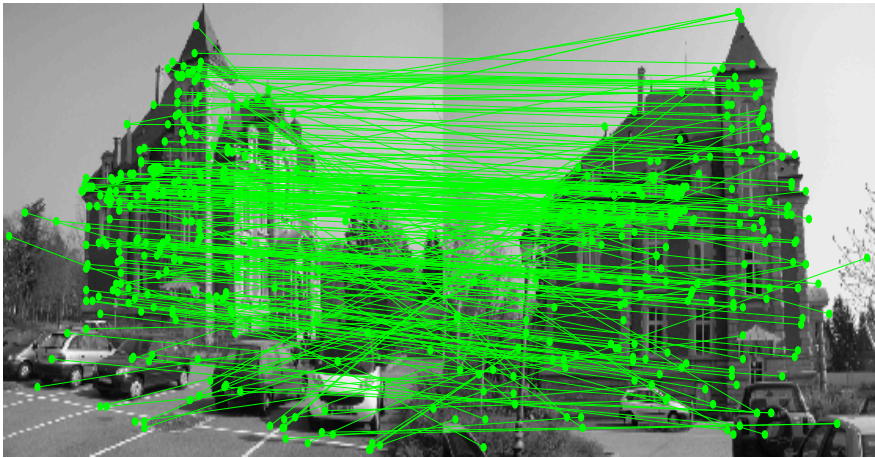


Initially detected SIFT feature points

Step1

Feature point detection & matching SIFT + RANSAC

- SIFT + RANSAC



Putative matches (258)

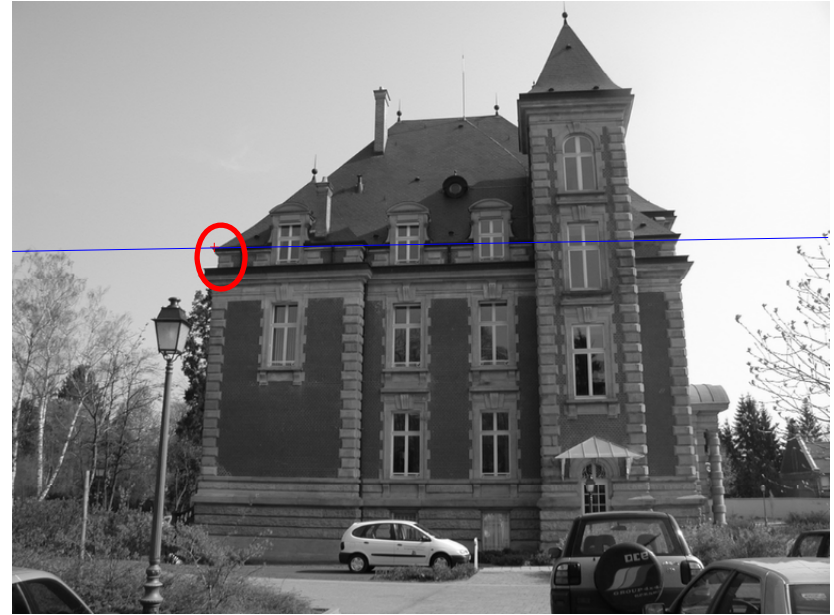
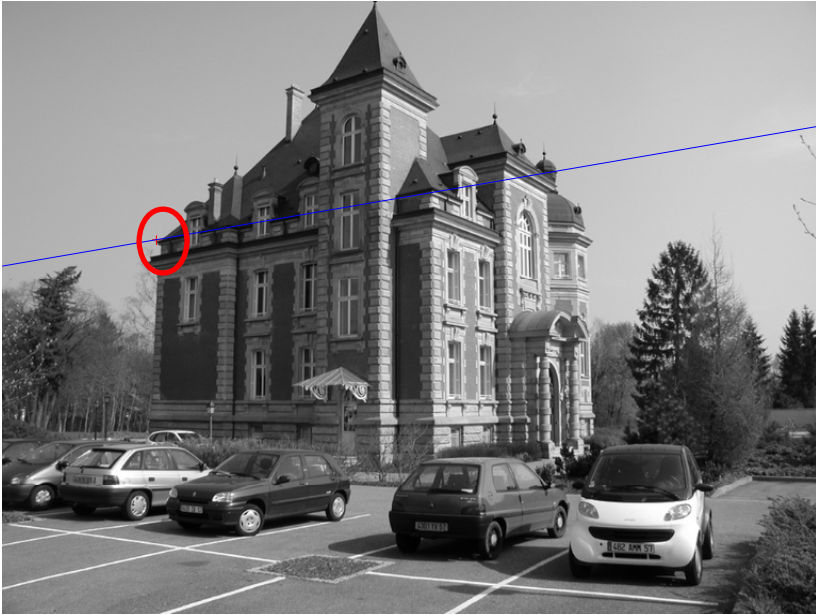


Inliers after RANSAC (133, 52%)

Step1

Feature point detection & matching SIFT + RANSAC

- SIFT + RANSAC : Good result



Step1

Feature point detection & matching SIFT + RANSAC

- SIFT + RANSAC : Good result



Step1

Feature point detection & matching SIFT + RANSAC

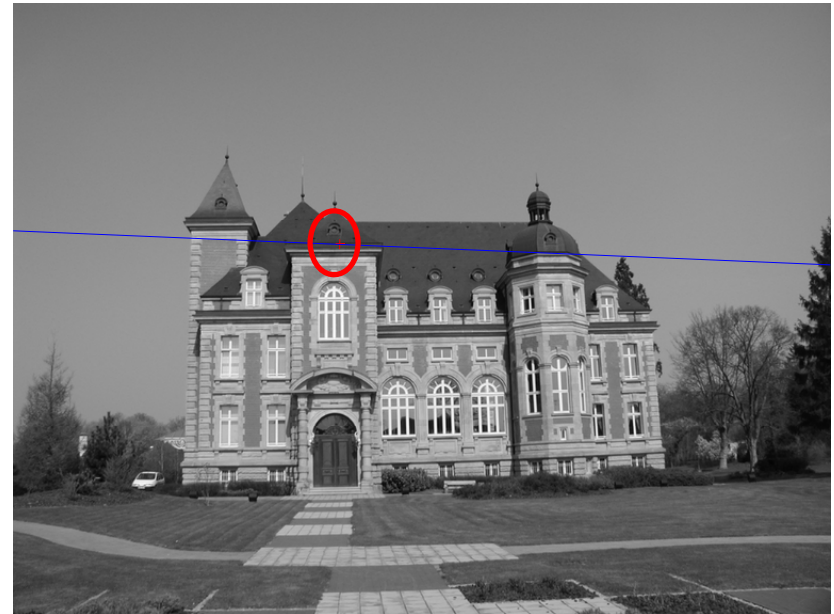
- Failure examples (SIFT + RANSAC)



Step1

Feature point detection & matching SIFT + RANSAC

- Failure examples (SIFT + RANSAC)



Step1

Feature point detection & matching

SIFT + RANSAC

- SIFT + RANSAC – Conclusion
 - More robust to the viewpoint variance than Harris corner
 - In some cases, automatic matching using SIFT provides a reliable F-matrix
 - But, it still invokes false matches in repetitive textured areas
 - For bag-of-features, this may be not a critical problem
 - But, for F-matrix computation, the accurate location between matches is very important

Step1

Feature point detection & matching Conclusion

- Automatic feature matching for F-matrix computation
 - Both Harris + RANSAC and SIFT + RANSAC don't provide the reliable results persistently over many images taken from the wide range of imaging conditions in practice
 - But, SIFT+RANSAC is more powerful
 - If many of images with similar appearances are given, SIFT+RANSAC can provide reliable F-matrices estimation
 - Or, some progressive way like the one used in reading assignment paper could fix the problem
 - The higher the inlier rate is, the more reliable the match result is.

Step1

Feature point detection & matching Conclusion

- Manual assignment of correspondences
 - In all of my trials, automatic matches fail to provide a convergent estimation of camera parameters
 - Therefore, all experiments on camera parameter estimation are performed on the dataset with manually assigned correspondences

Step2


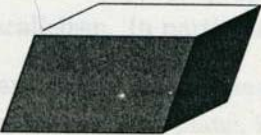


Camera parameter estimation

- The implemented method
 - EXIF information based parameter initialization +
Parameter optimization using Bundle adjustment

Why need camera parameters?

Projective ambiguity

- Projective Geometry - Hierarchy of transformations

| Group | Matrix | Distortion | Invariant properties |
|----------------------|--|---|---|
| Projective 15 dof | $\begin{bmatrix} \mathbf{A} & \mathbf{t} \\ \mathbf{v}^T & v \end{bmatrix}$ |  | Intersection and tangency of surfaces in contact. Sign of Gaussian curvature. |
| Affine 12 dof | $\begin{bmatrix} \mathbf{A} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$ |  | Parallelism of planes, volume ratios, centroids. The plane at infinity, π_∞ , (see section 2.5). |
| Similarity 7 dof | $\begin{bmatrix} s\mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$ |  | The absolute conic, Ω_∞ , (see section 2.6). |
| Euclidean 6 dof | $\begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$ |  | Volume. |

General Imaging

Orthographic camera

Fronto-parallel viewing camera

Fully calibrated camera
 $\{\mathbf{PH}, \mathbf{H}^{-1}\mathbf{X}\}$

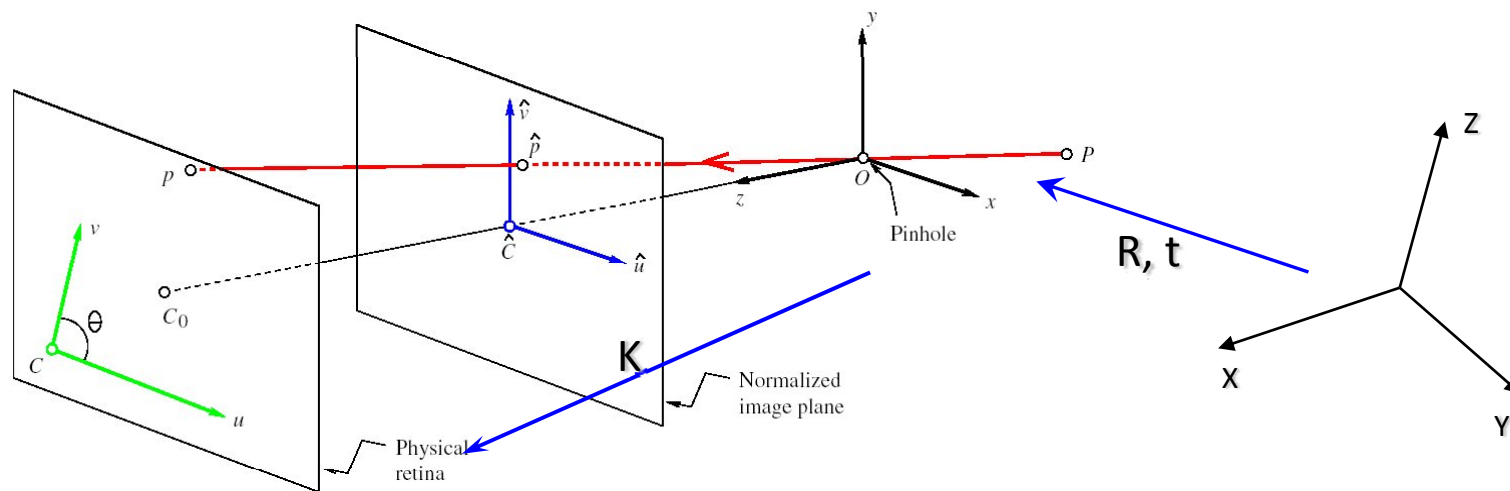
Increasing focal, increasing distance
Camera calibration

From "Multiple-view geometry in Computer Vision", 1st ed. pp.59)

Step2

Camera parameter estimation

- Camera model : Pin-hole projection + CCD model



$$\mathbf{x}_3 = \mathbf{K}[\mathbf{R} \mid \mathbf{t}]\mathbf{X}_4 \rightarrow \text{Homogeneous coordinate (linear)}$$

$$\mathbf{X}_{3c} = \mathbf{R}\mathbf{X}_{3w} + \mathbf{t}, \mathbf{x}_3 = \mathbf{K}\mathbf{X}_{3c} \rightarrow \text{Non-homogeneous coordinate}$$

Step2

Camera parameter estimation

- Intrinsic parameters : CCD

$$\mathbf{K} = \begin{bmatrix} \alpha f & s & o_x \\ 0 & f & o_y \\ 0 & 0 & 1 \end{bmatrix}$$

- Extrinsic parameters : coordinate transformation
 - R, t

Step2

Camera parameter estimation

- EXIF information
 - Meta-file information stored in image file by digital cameras
 - Contains focal length, f-number, white balance, model name, maker name, etc

Step2

Camera parameter estimation

- How to initialize a camera using EXIF
 - Get a focal length f (mm) from EXIF information
 - e.g. 10mm
 - Estimate a CCD size from model name in EXIF information
 - e.g. 20mm by 20mm for canon EOS 300d
 - Convert the unit of focal length from mm to pixels
 - e.g. image size 1000 by 1000, then $1\text{pixel} = 20/1000$ mm, $f = 10\text{mm} = 10 / (20/1000) = 500$ pixels
 - For more accurate computation, we can consider the number of effective pixels
 - e.g. if 10M pixels Digital camera has 8M effective pixels, then CCD size should be considered using the reduced size by 8/10.

Step2

Camera parameter estimation

- Parameter optimization using bundle adjustment
 - Initialize the internal parameters using EXIF information
 - Initialize the external parameters using F-matrix and the initialized internal parameters
 - Given, F and internal parameters, camera motion can be computed via linear equation.
 - Minimize the re-projection errors using non-linear least square optimization

Step2

Bundle adjustment

- Iterative non-linear least square technique to fit the model to the measurement
 - Levenberg-Marquardt algorithm is generally used.

$$\min \sum_i \sum_j (\mathbf{x}_{i,j} - \mathbf{P}_i \mathbf{X}_j)^2$$

- Variables : 3D reconstructed points + Camera projection matrices
- Measurement : 2D point correspondences
- Error measure : re-projection error of 3D reconstructed points from 2D observed points

Step2

Bundle adjustment

- Speed-up via using a sparseness

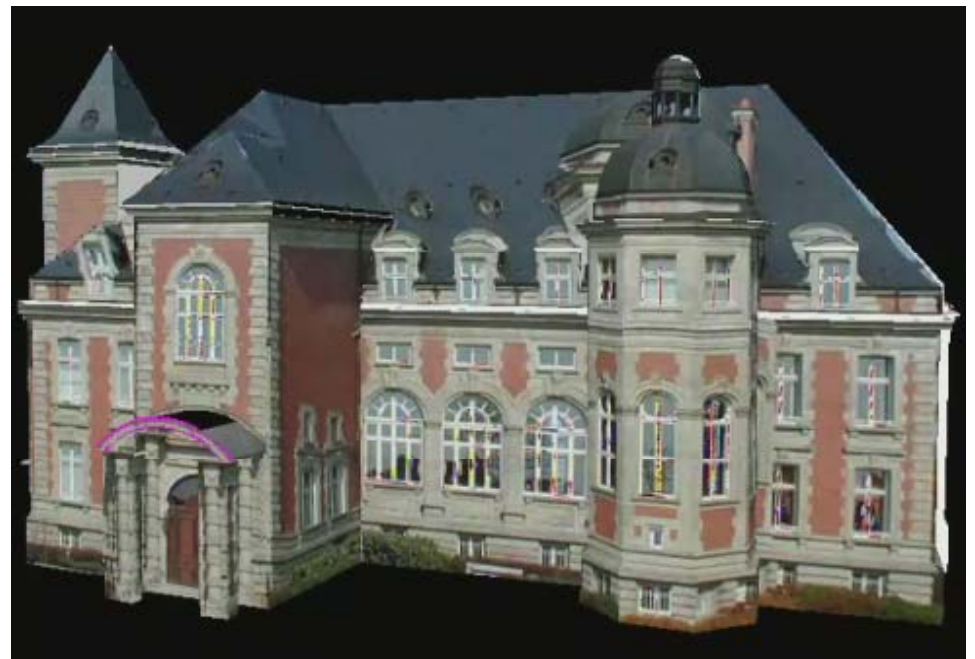
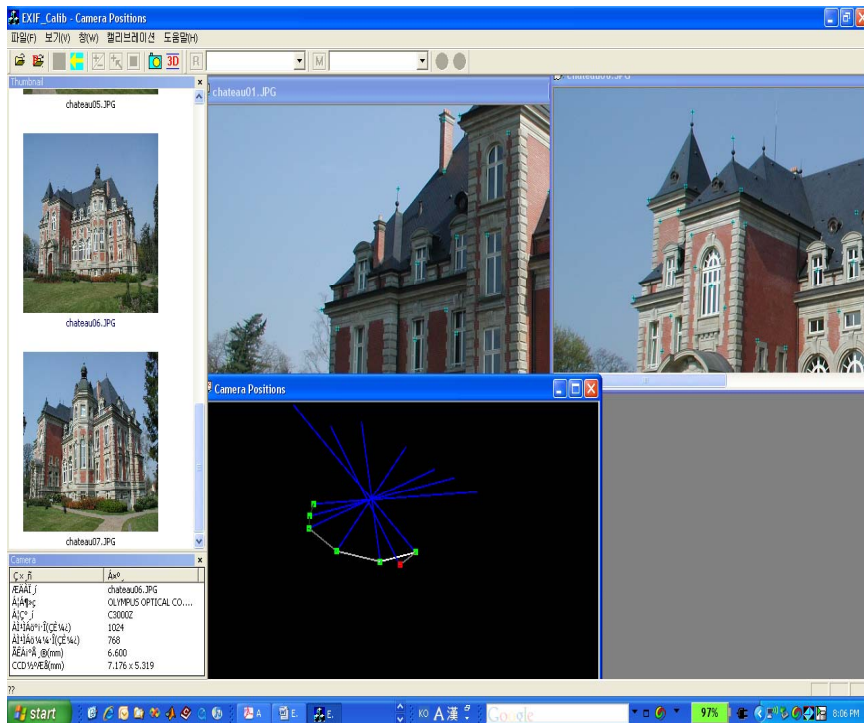
$$(\mathbf{J}^T \mathbf{J} + \lambda \mathbf{I}) \Delta = -\mathbf{J}^T \boldsymbol{\varepsilon}$$

| | P1 | P2 | P3 | X1 | X2 | X3 |
|-----|----|----|----|----|----|----|
| X11 | ■ | | | ■ | | |
| X12 | ■ | | | | ■ | |
| X13 | ■ | | | | | ■ |
| X21 | | ■ | | ■ | | |
| X22 | | ■ | | | ■ | |
| x23 | | ■ | | | | ■ |
| x31 | | | ■ | ■ | | |
| X32 | | | ■ | | ■ | |
| X33 | | | ■ | | | ■ |

Step2

Camera parameter estimation

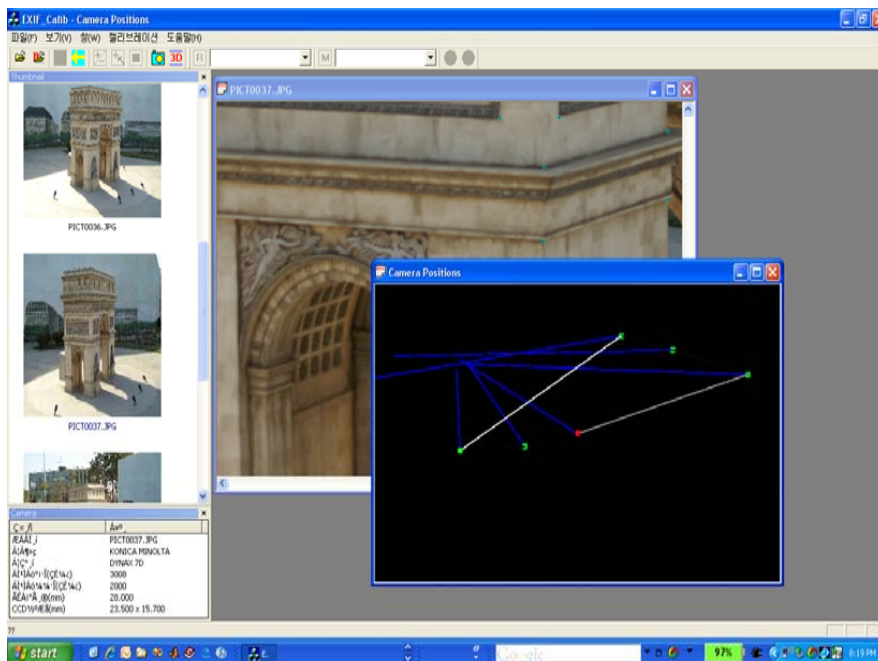
- Result 1 – Chateau cattle images (7 images)



Step2

Camera parameter estimation

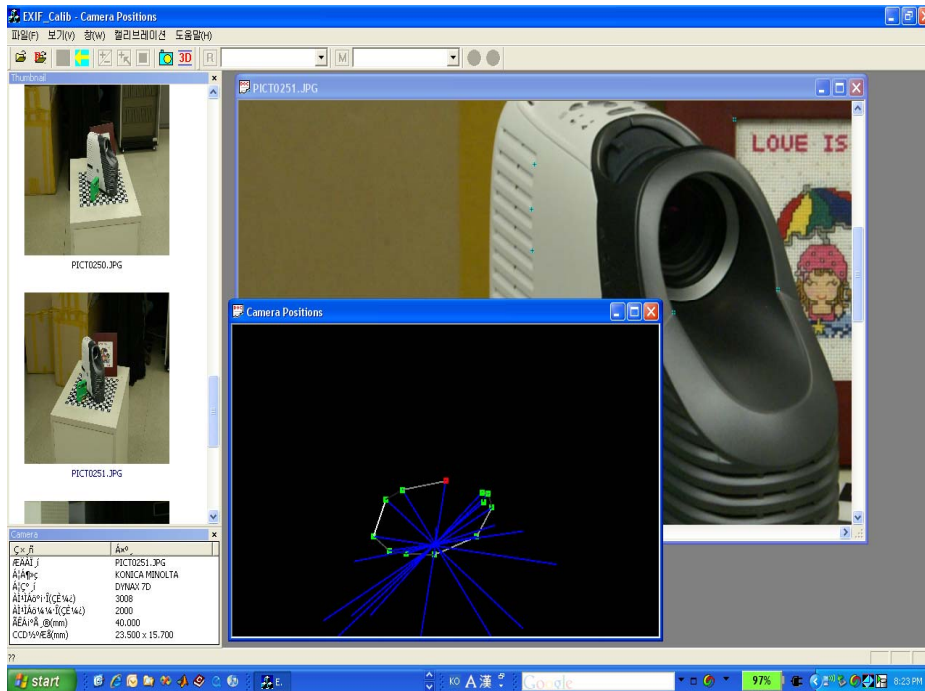
- Result2 - Triumphal Arch images (6 Images)



Step2

Camera parameter estimation

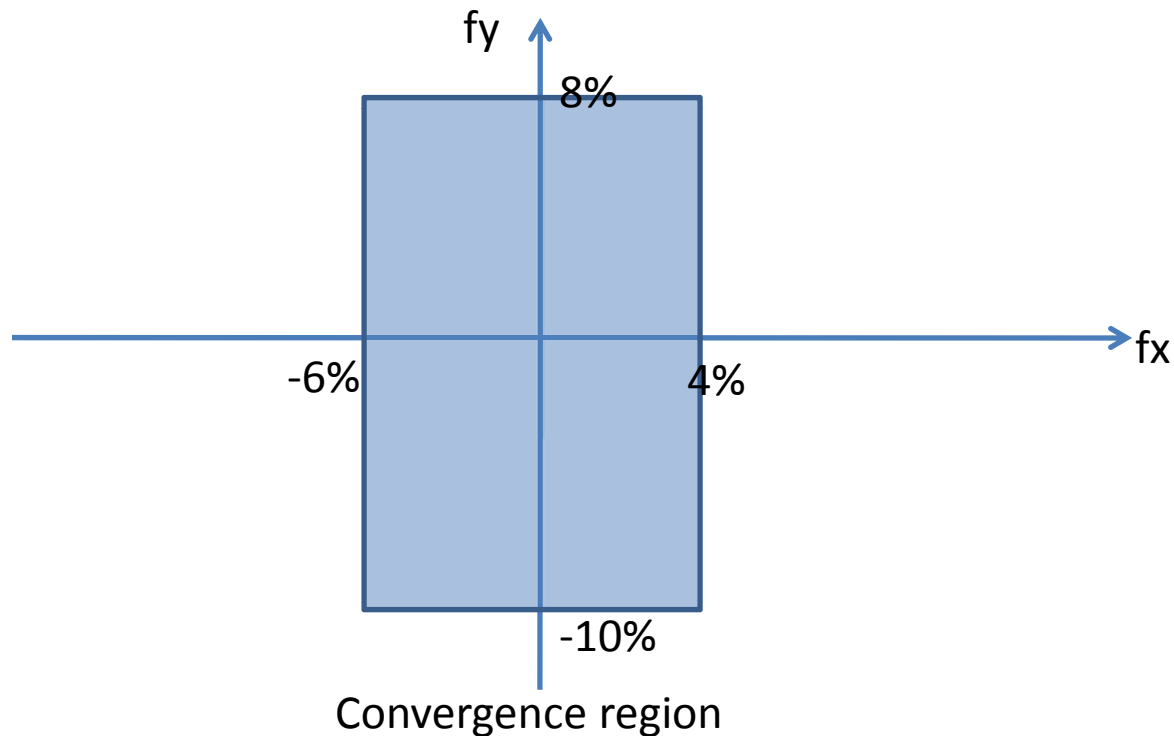
- Result3 – Projector images (12 images)



Step2

Camera parameter estimation

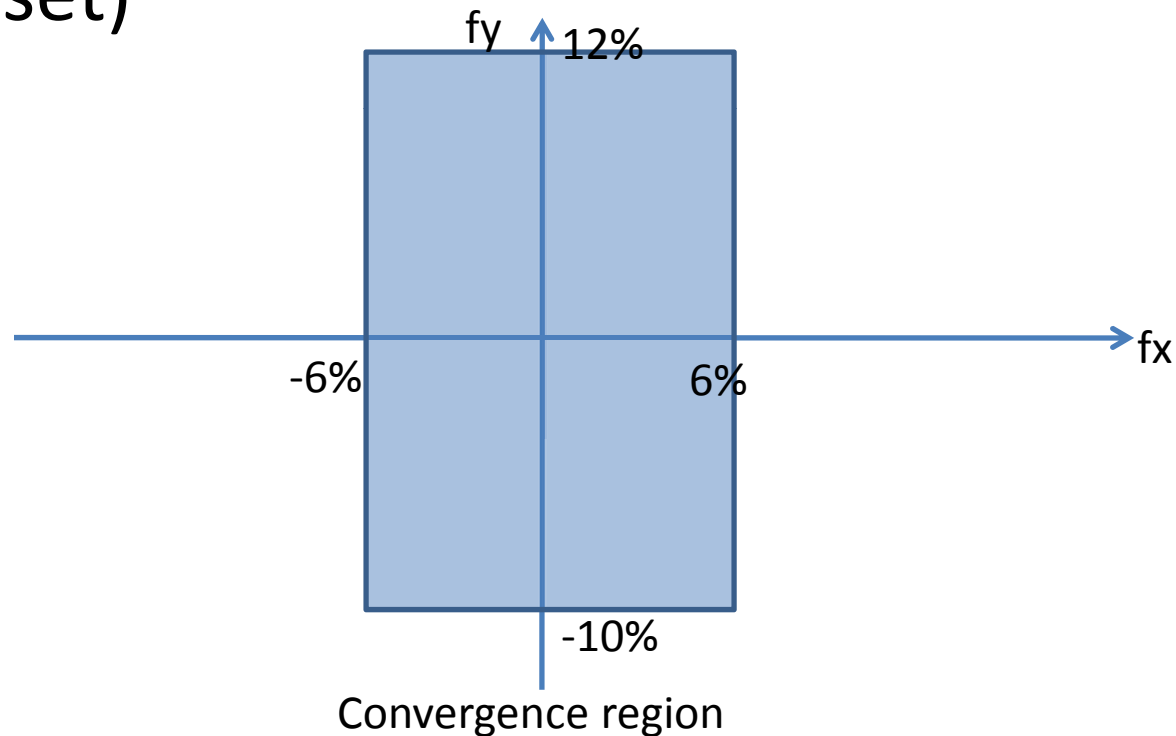
- Sensitivity to initialization (projector dataset)



Step2

Camera parameter estimation

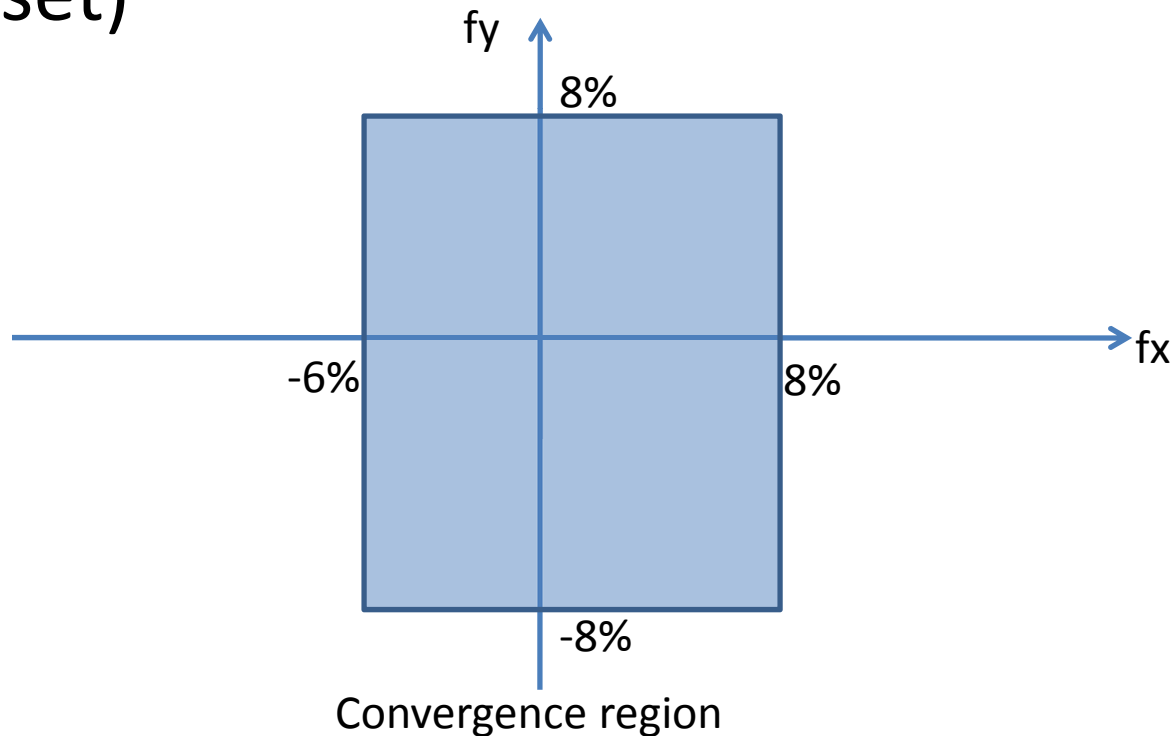
- Sensitivity to initialization (Chateau cattle dataset)



Step2

Camera parameter estimation

- Sensitivity to initialization (Triumphal Arch dataset)



Step2

Camera parameter estimation

Conclusion

- EXIF based approach
 - Provide a practical way to initializing camera parameters
 - Initialization is very important to Bundle adjustment, i.e. non-linear optimization
 - Cost function in the bundle adjustment is non-linear, and non-convex.
 - When initial parameters are distorted, it does not converge to the solution any more.

Conclusion

- SIFT outperforms Harris corner under the large view-point changes
- But, automatic matching doesn't provide consistently reliable result in practice
- Camera parameter estimation is a non-linear, non-convex problem
 - Good initialization is very important.
 - EXIF information is a practical way to initialize camera parameters.

References

- Harris corner detector and RANSAC - Matlab
 - <http://www.csse.uwa.edu.au/~pk/research/matlabfns/>
- Epipolar geometry computation - Matlab
 - <http://www.robots.ox.ac.uk/~vgg/hzbook/code/>
- SIFT – Matlab
 - <http://vision.ucla.edu/~vedaldi/code/sift/sift.html>
- Linear algebra (GSL) - C++
 - <http://www.gnu.org/software/gsl/>
- Bundle adjustment - C++
 - <http://www.ics.forth.gr/~lourakis/sba/>
- EXIF parser – C++
 - <http://www.codeproject.com/KB/graphics/cexif.aspx>
- Multiple View Geometry in Computer Vision 1st ed, Richard Hartley and Andrew Zisserman
- Chateau cattle dataset are obtained from the tutorial images used in ImageModeler S/W by REALVIZ.