





A Brief Introduction to

Structure from Motion

Zhang Yedi 2020.8.19 Wed.

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Steps





Origin: Snavely, Seitz, & Szeliski, 2006

Photo Tourism: Exploring Photo Collections in 3D

Noah Snavely University of Washington Steven M. Seitz University of Washington Richard Szeliski Microsoft Research

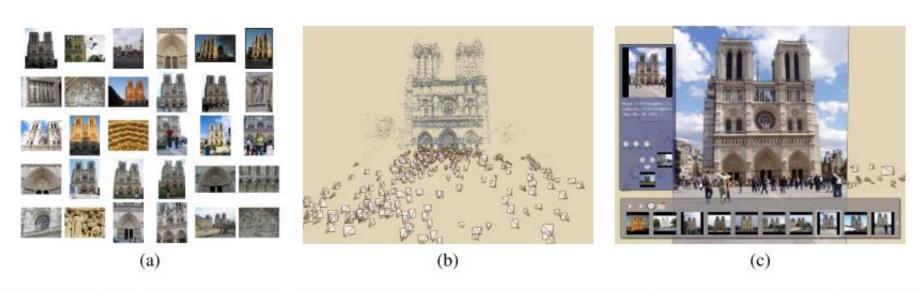
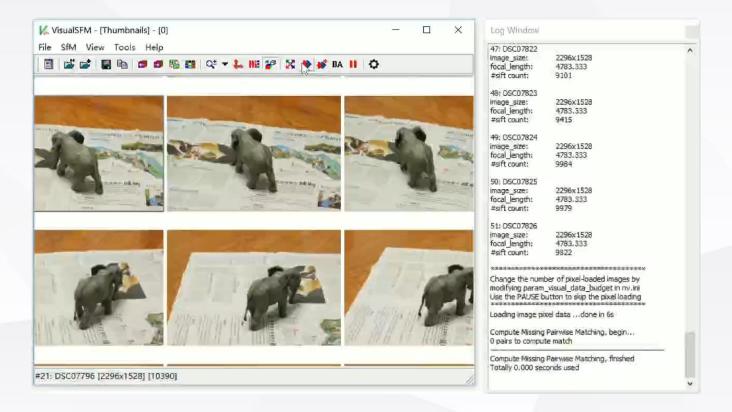


Figure 1: Our system takes unstructured collections of photographs such as those from online image searches (a) and reconstructs 3D points and viewpoints (b) to enable novel ways of browsing the photos (c).



Definition

• SfM = 利用运动的相机拍摄的图像生成稀疏3D点云



Reproduced results via Changchang Wu, VisualSFM



基本概念

- SfM = 利用运动的相机拍摄的图像生成3D点云
- 输入:
- \rightarrow 图像及匹配的一系列特征点的像素坐标 $p_{ij} = (x_{ij}, y_{ij})$
- 输出:
- \rightarrow Structure = 场景的3D点云 每个特征点 p_i 的3D坐标 X_i
- \rightarrow Motion = 相机位置和朝向相机外参 t_j , R_j , (相机内参 K_j)

Steps



具体步骤

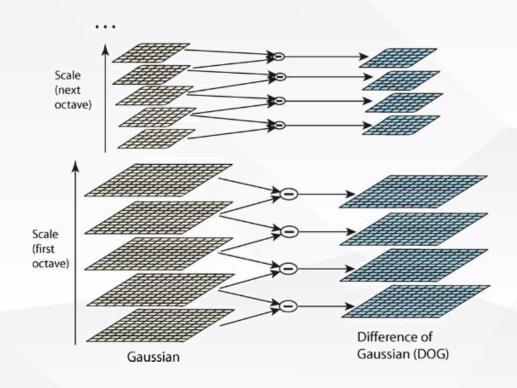
- 1 特征点检测与匹配
- 2 外极几何图构造
- 3 相机位姿和场景结构估计

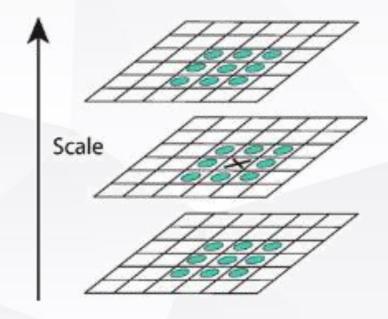
步骤1: 特征点检测与匹配

- •特征点检测: SIFT, SURF, FAST, BRIEF, ORB, etc
- ①建立高斯差分金字塔

②确定关键点位置

Steps



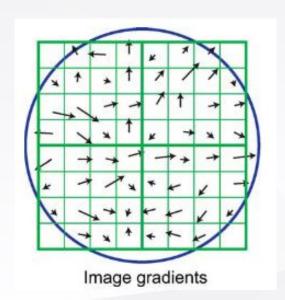


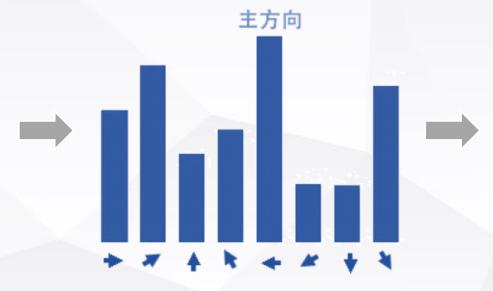
Steps

步骤1: 特征点检测与匹配

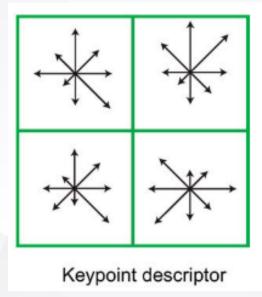
•特征点检测: SIFT, SUFT, FAST, ORB, etc

③确定关键点方向





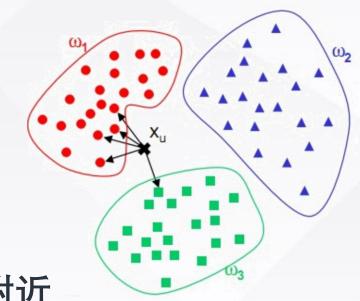
4创建关键点描述符





步骤1:特征点检测与匹配

- •特征点匹配: 2张图片间的匹配
- ≻以KD树为数据结构,计算最近邻
- ▶比值约束:最近邻/次近邻小于一定阈值
- ▶ 外极几何约束: 匹配特征点在对应的外极线附近





• 目的:确定步骤3 (摄像机位姿和场景结构估计)的初值

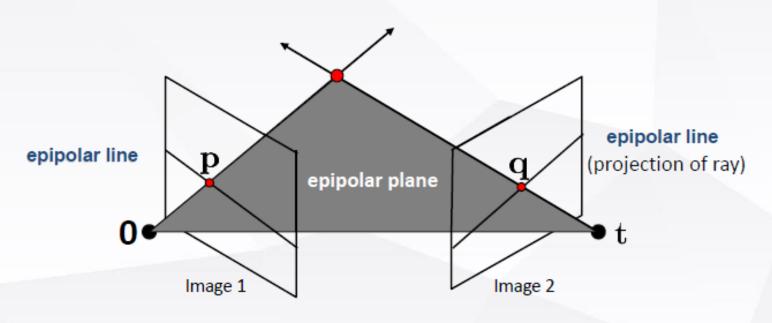
•初值:通过重建2张图片,粗略给出3D点坐标 X_i 和相机参数 R_i, t_i, K_i

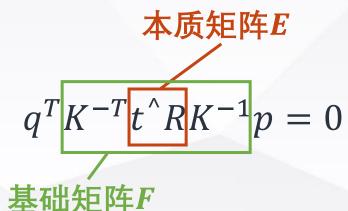
Steps



•初值:通过重建2张图片,粗略给出3D点坐标 X_i 和相机参数 R_j, t_j, K_j

•求解: 8点法求本质矩阵E, SVD分解出R, t, 三角化求出 $3D点坐标X_i$





性质: $q^T K^{-T} E K^{-1} p = 0$

带入8对特征点求解本质矩阵

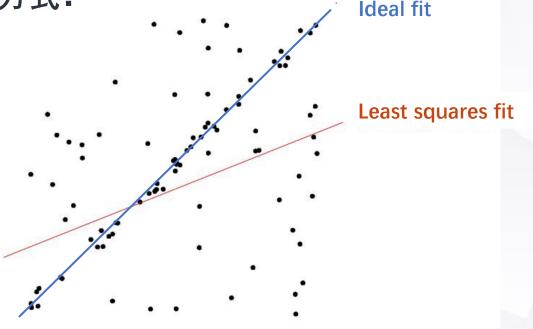


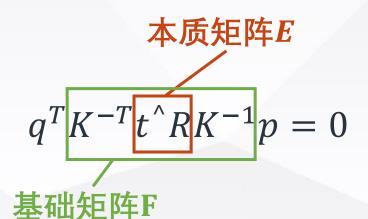
•初值:通过重建2张图片,粗略给出3D点坐标 X_i 和相机参数 R_j, t_j, K_j

•求解: 8点法求本质矩阵E, SVD分解出R, t, 三角化求出 $3D点坐标X_i$

挑选8个点的方式:

RANSAC





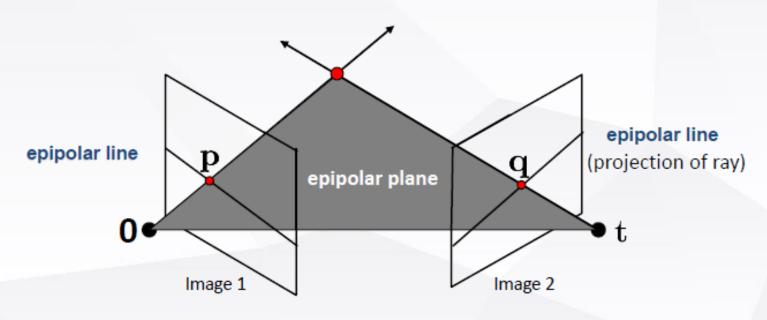
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带入8对特征点求解本质矩阵



•初值:通过重建2张图片,粗略给出3D点坐标 X_i 和相机参数 R_j, t_j, K_j

•求解:8点法求本质矩阵E,SVD分解出R,t,三角化求出3D点坐标 X_i



本质矩阵: $E = t^R$

SVD分解: $E = U\Sigma V^T$

其中奇异值矩阵:

 $\Sigma = diag(\sigma, \sigma, 0)$

则得相机位姿:

$$t^{^{\wedge}} = Ur\Sigma U^T$$

$$R = Ur\Sigma V^T$$

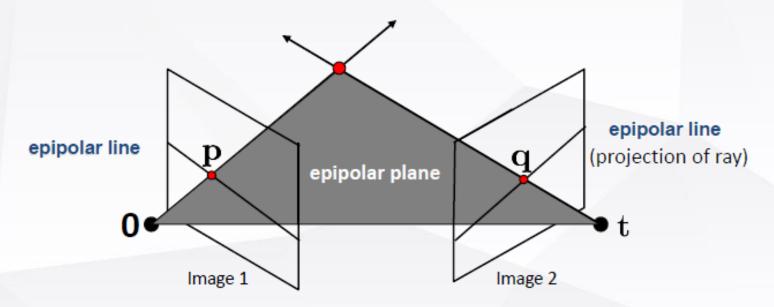
Steps



步骤2: 外极几何图构造

•初值:通过重建2张图片,粗略给出3D点坐标 X_i 和相机参数 R_j, t_j, K_j

•求解: 8点法求本质矩阵E, SVD分解出R, t, 三角化求出3D点坐标 X_i



一对特征点的坐标满足:

$$d_1p = d_2Rq + t$$

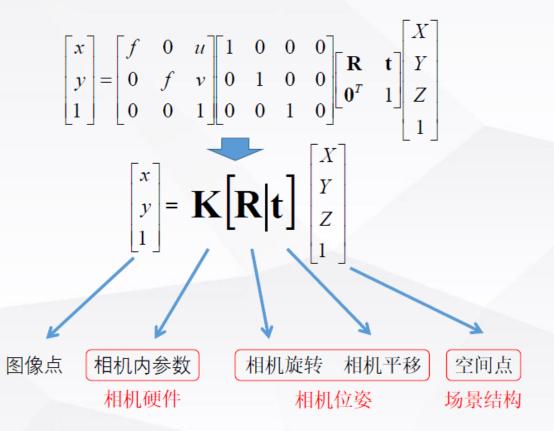
t,R已知。则由

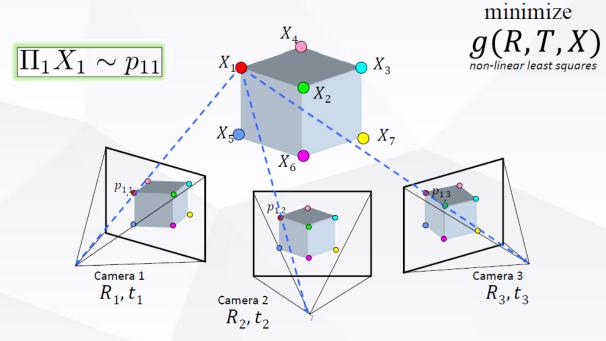
$$d_1p^{\hat{}}p = 0 = d_2p^{\hat{}}Rq + p^{\hat{}}t$$

求得深度,从而获知3D点坐标



• 问题的描述: 最小化重投影误差

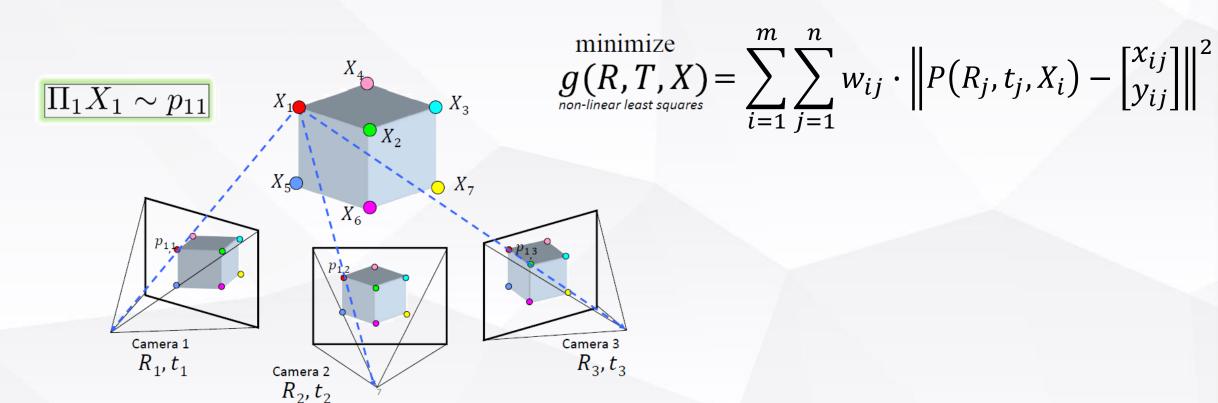




Steps

步骤3: 摄像机位姿和场景结构估计

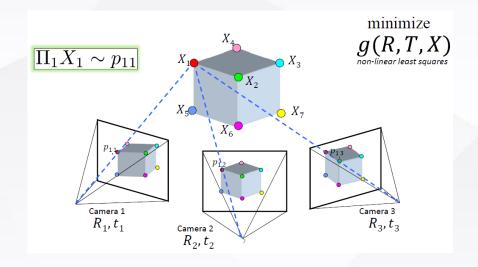
• 问题的描述: 最小化重投影误差





• 问题描述: 最小化重投影误差

$$g(R,T,X) = \sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} \cdot \left\| P(R_j, t_j, X_i) - \begin{bmatrix} x_{ij} \\ y_{ij} \end{bmatrix} \right\|^2$$



- 问题规模: $[n \times (3+3+3+2) + m \times 3]$ 个自变量
- 高维非线性最小二乘问题,做非线性优化
- 求解工具: Levenberg-Marquardt迭代法



- 求解工具: Levenberg-Marquardt迭代法
- 首先介绍Gauss-Newton迭代法

$$g(R,T,X) = \sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} \cdot \left\| P(R_j, t_j, X_i) - \begin{bmatrix} x_{ij} \\ y_{ij} \end{bmatrix} \right\|^2 = \sum_{i,j} e_{ij}^2(R,T,X)$$

$$g(R,T,X) = \sum_{i,j} [e_{ij}(P_0) + J_{ij}\Delta]^2 \approx c + 2b^T \Delta + \Delta^T H \Delta$$

- •对 Δ 求偏导并置为0,即: $H\Delta + b = 0$
- 赋值 $P \leftarrow P + \Delta$, 进行下一轮迭代



- 求解工具: Levenberg-Marquardt迭代法
- · Gauss-Newton迭代法与梯度下降法的综合

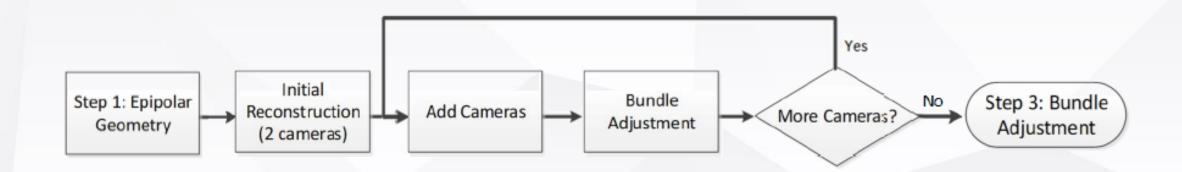
$$g(R, T, X) = \sum_{i=1}^{m} \sum_{j=1}^{n} w_{ij} \cdot \left\| P(R_j, t_j, X_i) - \begin{bmatrix} x_{ij} \\ y_{ij} \end{bmatrix} \right\|^2 = \sum_{i,j} e_{ij}^2(R, T, X) \approx c + 2b^T \Delta + \Delta^T H \Delta$$

- •对 Δ 求偏导,加入阻尼系数,再置为0,即: $(H + \lambda I)\Delta + b = 0$
- •若误差 \bigcirc ,接受 \triangle 同时减小 λ ;若误差 \bigcirc ,不接受 \triangle 同时增大 λ
- 赋值 $P \leftarrow P + \Delta$, 进行下一轮迭代



· 光束平差法(Bundle Adjustment): 增量式,全局式,混合式

Steps





与开源API

- SIFT (SURF, FAST, BRIEF, ORB ···)
- RANSAC
- Bundle adjustment (SBA, PBA, G2O, Ceres…)

与Simultaneous Localization and Mapping (SLAM)

- · VSLAM: 对具有时间先后顺序的图像序列实时求解SfM问题
- 侧重点不同,故优化的方向不同
- ·数据源可能不同,单目、双目、RGB-D



三维重建的开源与商业软件

- ✓开源SfM软件
- OpenMVG 3030 ☆
- Colmap 2.3k☆
- OpenSfM (Python) 1.8k☆
- Bundler 1.2k☆
- MVE 669 ★
- TheiaSfM 615☆
- MICMAC 292☆
- MAP-Tk

✓商业软件

- Pix4DMapper
- ContextCapture
- PhotoMesh
- Photoscan
- Streetfactory
- RealityCapture



内容小结

- 简介
- 具体步骤 特征点检测与匹配 外极几何图构造

相机位姿和场景结构估计

• 相关内容 与SLAM的关联 相关开源与商业软件



参考论文

- Snavely, Noah, Steven M. Seitz, and Richard Szeliski. "Photo Tourism: Exploring Photo Collections in 3d."
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其他参考资料

- 《视觉SLAM十四讲: 从理论到实践》, 高翔、张涛等著
- 《基于图像点特征的多视图三维重建》,康来著
- CCCV2017讲习班《基于图像的大规模场景三维重建》,中科院申抒含、崔海楠
- 浙江大学谭平老师课程《计算机视觉》
- B站up主会飞的吴克







Thank you!

Zhang Yedi 2020.8.19 Wed.