COLMAP

<u>SFM</u> → 3D Reconstruction + 2D Images from diff views.

3 Majors step.

1. Keypoints detection & Matching
2. Reconstruction → 3D Model
3. Bundle Adjustment → Refining Camera & Structure.

<u>Detection & Matching</u>

Feature Extraction → Keypoints & Descriptor.

1.) SIFT / ORB / SURF

*

Feature Matching → 1.) Brute Force Matching
*2.) Vocabulary Trees
3.) ANN (Approx. Near. Neig.)

Geometric Verification : → epipolar geometry
*Essential Matrix (E), *Fundamental Matrix (F) & Homography (H)

RANSAC → to filter out wrong matched.
ir

→ Scene graph augment

Scene graph.

output after D/M → image as nodes & Verified images as edges.

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Input → Scene graph

Reconstruction

1. Initial Image pair → then add incren.
registered using *PnP (perspective n point)

• Initial from dense location result for pose estimation
accurate reconstruction.

* Triangulation → to Compute 3D points.

* Outlier filtering → removes inconsistent points

Bundle Adjustment

1) Refines Camera pose & 3D points to minimize *projection error

2) * Schur Complement trick

3. global BA (all image), local BA (new images)

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1) Scene graph Augmentation F, H, E
prevents incorrect Camera pose & improve robustness.

2) Next Best View Selection
→ Multi resolution Pyramid based selection Strategy.

* Standard Triangulation has feature tracking error
RANSAC → finds robust inlier Correspondence
→ recovers multiple independent 3D points per feature
→ reduce error caused by incorrect track Matches.

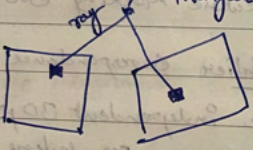
(Instead of running BA only once)

Bundle adjustment → Pre BA re-triangulation
→ Post BA re-triangulation (to refine point positions after optimization)
→ Iterative BA-RT Cycles.

Efficient Bundle Adjustment by grouping similar image into clusters.

PnP (perspective n point) → to estimate the camera pose from n known 3D points and their Correspond 2D projection images.

Triangulation → estimating the 3D points position given its 2D projection in multiple views.



Triangulation finds the 3D point where they intersect

1) Linear Triangulation

2.) Non-Liner Triangulation → Bundle Adjustment to refine.

3.) Mid-point Method. → Mini Reprojection error.

Scene graph Augmentation

1.) Validate Image pair
2.) Classify Transformation (general motion, panorama, planar).
3.) Detect Incorrect Correspondence. (watermark, timestamp).

→ Fundamental Matrix Estimation epipolar geometry b/w two uncalibrated images.
→ RANSAC
→ N_F inliers are found, the image pair is geometric verified.

Homography Estimation → planar transformation.

if $N_H / N_F < \epsilon_{HF}$ general

$>$ planar or panoramic

Estimated Essential Matrix (for Calibrated Images)

If Images are Calibrated, the E is calculated

if $N_E / N_F > \epsilon_{EF}$, then camera Calibr Consider Correct.

If Calibration is Correct, then perform triangulation
$N_H/N_F < \epsilon_{HF}$

→ median triangulation angle α_m. (distinguish)
using α_m → pure rotation
↳ planar scene

Valid Images are label in the scene graph - general motion, Panoramic, planar.

* → avoid starting from paranomic pair (they are difficult to reconstruct)

Next Best View Selection

a wrong choic can lead to Cascading errors in pose estimation & faulty triangulation.

a poorly chosen view can degrade the Based Camera registration.

Ensure Completeness.

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Strategy for choosing

① Most visible points strategy → highest no. of already triangulated 3D points.

② uncertain Driven approach.

③ Feature Distribution Based Selection

→ uniformly distributed improves stability in pose estimation.

an efficient approx. of uncertainity - driven NBV selection using → multi - reso image partitions.

① graph based feature tracking

② ** Avoiding Exhaustive Covariance propagation

③ Image grid partitioning → $K_l \times K_l$ bins

→ Empty (no - feature Detected)

→ Full (at least one feature point detected)

If new - feature appears in Empty bin, the score S_i of the image is ↑ by weight w_l.

⇒ We prioritize evenly distributed images

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outlier- dosn't fit the expected Model in estimation

If no of visible points is Small, multi-grid will fail.

Multi-resoultion pyromind → partition image progress finer grids at multiple level. $K_l = 2^l$.
to handle Sparse & dense feature.

<u>Robust & Efficient Triangulation</u>

Problem

- Many SFM dataset are Sparse, not all scene points appear in imultiple images.

- Approx. Feature Matching favors image pair with Small baseline.

→ Small baseline Cause poor depth estimation, lead to high uncertainity in triangulation.

→ Two view Matches often Contain errors due to repeated texture, diff points mistakenly grouped

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Solution ⇒ RANSAC {.

① randomly select two obs. (T_a, T_b) & triangulate a 3D point X_{ab}.

quality is checked using ① - Triangulation angle

$$\cos\alpha = \frac{(t_a - X_{ab})(t_b - X_{ab})}{\|t_a - X_{ab}\|\|t_b - X_{ab}\|}$$

α b/w Camera rays should be large.

② cheirality constraint. Depth must be +ve.

<u>Bundle Adjustment</u> non-linear optimization technique that refines estimated camera pose, intrinsic parameter & 3D points location, to minimize reprojection error.

$$\sum_{i,j} \rho(\|x_{ij} - \pi(X_j, P_j, K)\|)^2$$

projection func^n depends on camera pose P & intrinsic K.

2D project of 3D point X_j in i-image

robust loss func to handle outliers.

(cauchy loss)