



# Final Project Presentation: Photorealistic 3D Scenes using SfM with Gaussian Splatting

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<https://github.com/john00003/sfm-gaussian-splatting>

**CMPUT 428 / 615 - Winter 2025**

# Overview - What is Gaussian Splatting?

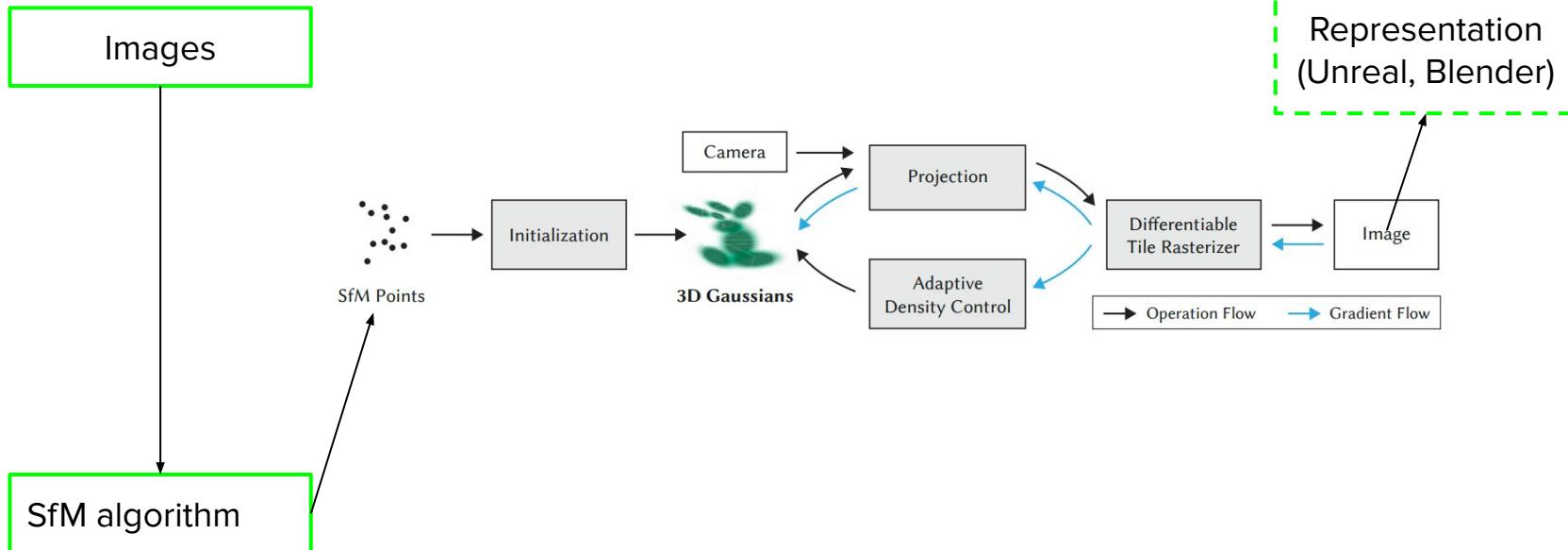
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Gaussian splatting is a method of reconstructing a 3D scene using a **dense** point cloud. This provides an alternative to meshing, texturing, and applying photorealistic rendering techniques to create a 3D scene.



# Project Overview & Goals

- Apply fundamental techniques learned throughout the semester to create our own SfM algorithm
  - ready to use with Gaussian Splatting
  - export to common 3D modelling software such as unreal engine

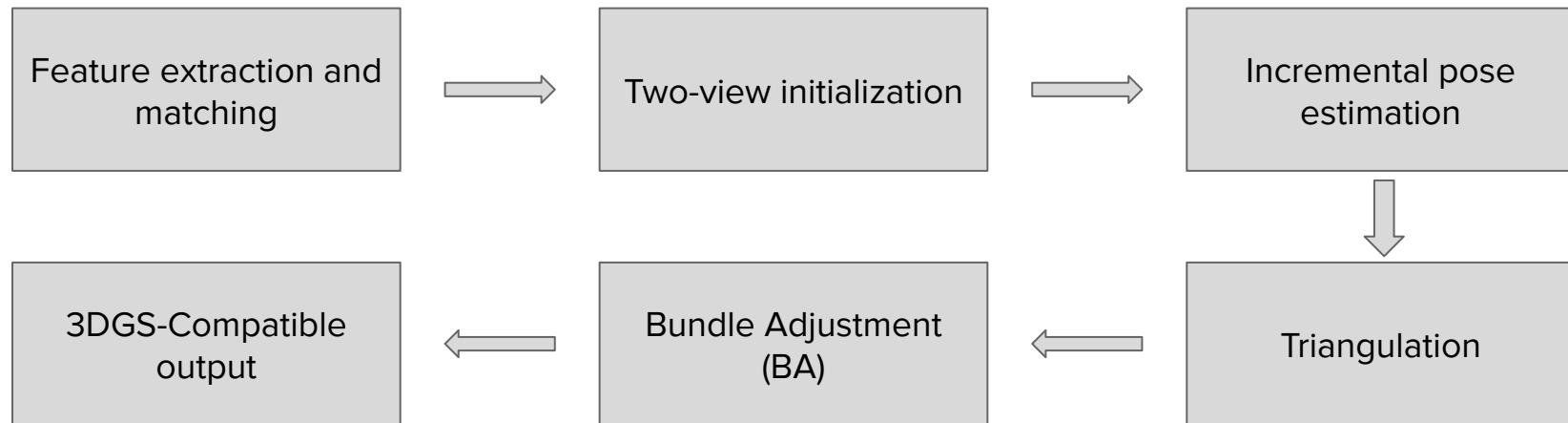


# Our Work - SfM Algorithm Overview

Incremental Structure-from-Motion System

Goal: Reconstruct 3D scene structure and camera poses from a set of images.

A 6-step implementation:



# SfM - Feature Extraction

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## Image Loading & Intrinsic Extraction

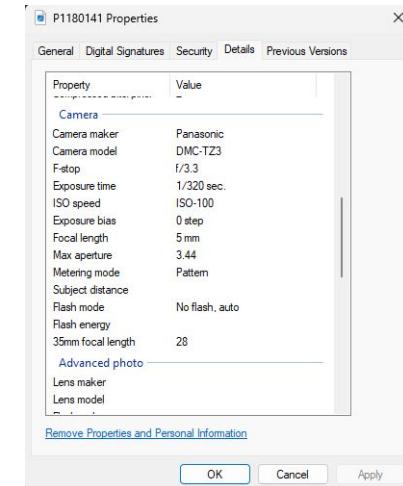
Load images and extract EXIF intrinsics or use hardcoded values

Intrinsics matrix built per image

## SIFT Keypoint Extraction (CPU)

Detect and compute keypoints per view

Attach RGB color to each keypoint for visualization



# SfM - OpenCV Matching Interface and SIFT

## Scale Invariant Feature Transform

- select points to search for correspondences in other images

```
struct View {  
    int id = -1;  
    bool registered = false;  
    std::string image_path;  
    cv::Mat image;  
    cv::Mat K;  
    std::vector<cv::KeyPoint> keypoints;  
    std::vector<cv::Vec3b> colors; // a parallel array with keypoints  
    cv::Mat descriptors;  
    std::map<int, std::vector<std::vector<cv::DMatch>>> matches_map;  
    std::vector<std::pair<int, int>> points_3d;  
    Eigen::Matrix4d pose = Eigen::Matrix4d::Identity();  
};
```



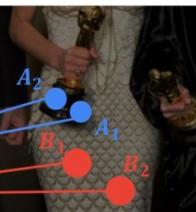
# SfM - GPU Feature Matching

## CUDA Brute-Force Matcher

GPU-accelerated descriptor matching

KNN with Lowe's Ratio Test

Full / Sequential / Windowed match strategies



$AA_1 = 20$  - The best match

$AA_2 = 80$  - The second best match

$BB_1 = 10$  - The best match

$BB_2 = 25$  - The second best match

True

False

*if*  $20 < 0.6 \cdot 80$   
 $20 < 48$

*if*  $10 < 0.6 \cdot 25$   
 $20 < 15$

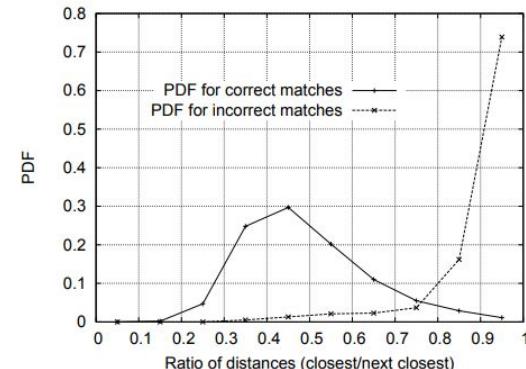


Figure 11: The probability that a match is correct can be determined by taking the ratio of distance from the closest neighbor to the distance of the second closest. Using a database of 40,000 keypoints, the solid line shows the PDF of this ratio for correct matches, while the dotted line is for matches that were incorrect.

# SfM - Matching Acceleration and Algorithm



Brute Force (repeat process on each image)



Sequential Search

# SfM - Matching Acceleration and Algorithm



Windowed Sequential Search

Sequential Search with Anchor



# SfM - Two-View Initialization

Select the Best Initial Pair

Two images with the most strong feature matches

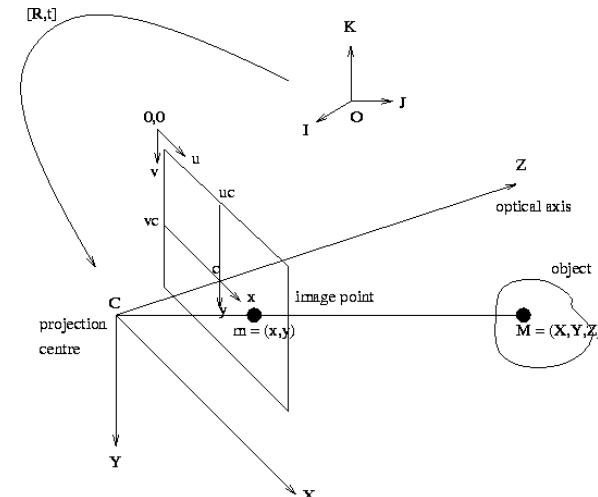
KNN + Lowe's ratio test to filter high-confidence matches

Estimate Relative Camera Pose

Find essential matrix using matched keypoints

Decompose E into rotation (R) and translation (t)

OpenCV's recoverPose to extract relative  
camera motion



# SfM - Two-View Initialization

## Two-View Initialization

Triangulate Initial 3D Points

Back-project 2D matches into 3D space

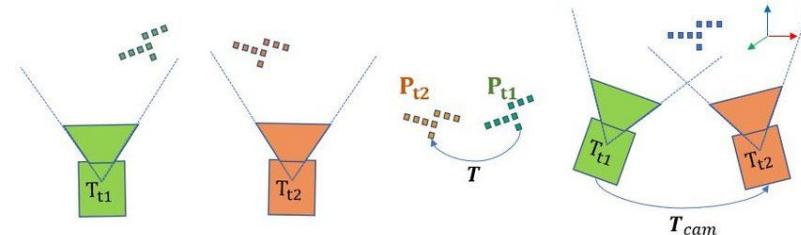
Filter points using reprojection error and depth checks

Store these as the first 3D landmarks (tracks)

Then we got:

Two images now have known poses

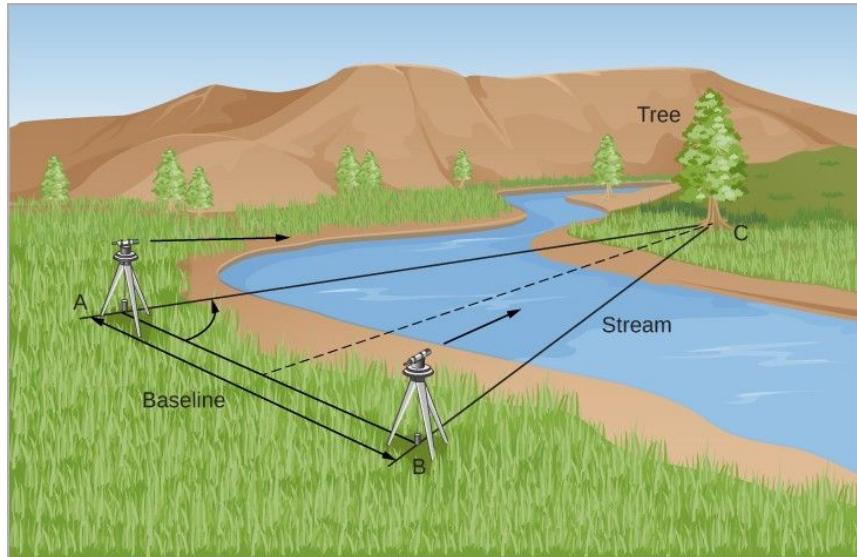
A small set of 3D points are initialized



# SfM - Two-View Initialization

Triangulation in surveying - same logic!

<https://courses.lumenlearning.com/suny-astronomy/chapter/surveying-the-stars/>



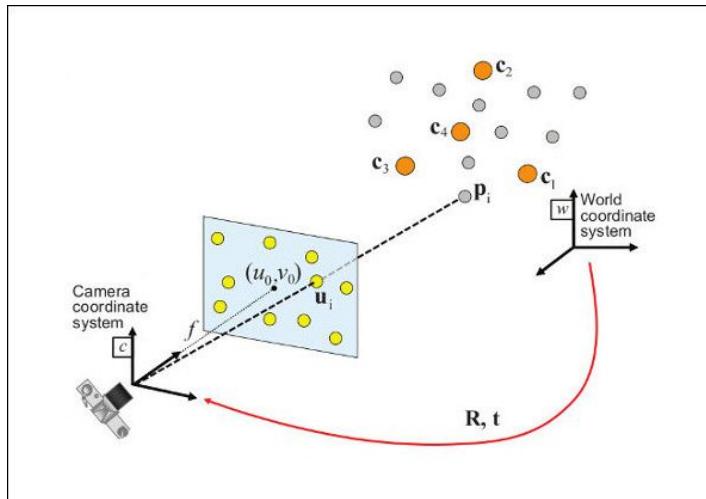
# SfM - Registering New Views

We need to estimate the pose of a new image using known 3D points.

Find 2D-3D correspondences

Match the new image's keypoints to already-triangulated 3D tracks

For each matched keypoint, find the corresponding 3D point

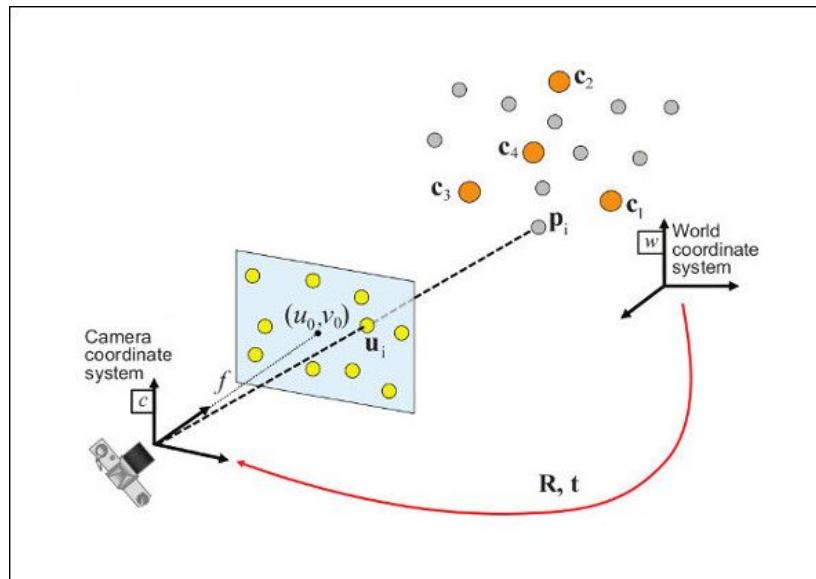


# SfM - Registering New Views

Solve camera pose

Use OpenCV's solvePnP Ransac to estimate camera pose

Accept the pose only if enough inliers are found

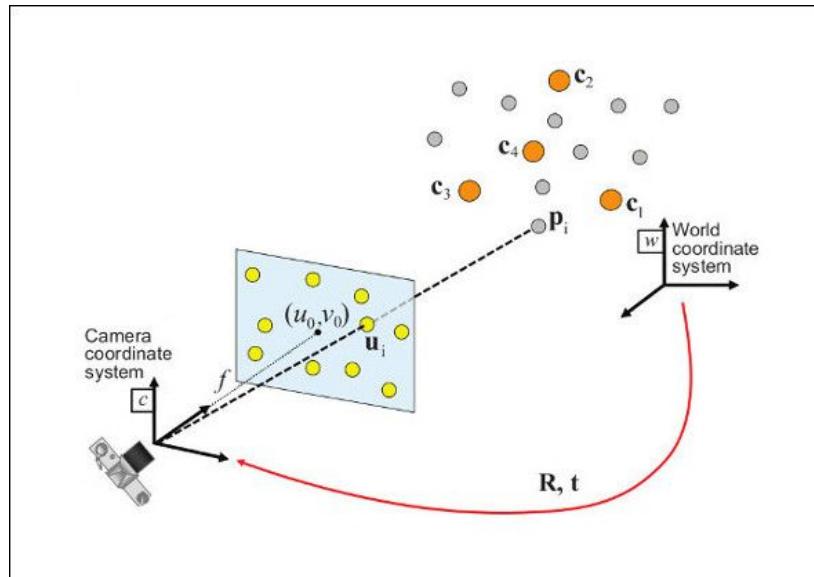


# SfM - Registering New Views

Add new view to the system

If successful, mark the view as “registered”

It can now contribute to further triangulations and BA



# SfM - Triangulating New Points

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When a new view is registered

- Match it to all previously registered views

For each match:

- Check if the matched keypoints are not already used in a 3D track

- Use known camera poses to triangulate a new 3D point



# SfM - Triangulating New Points

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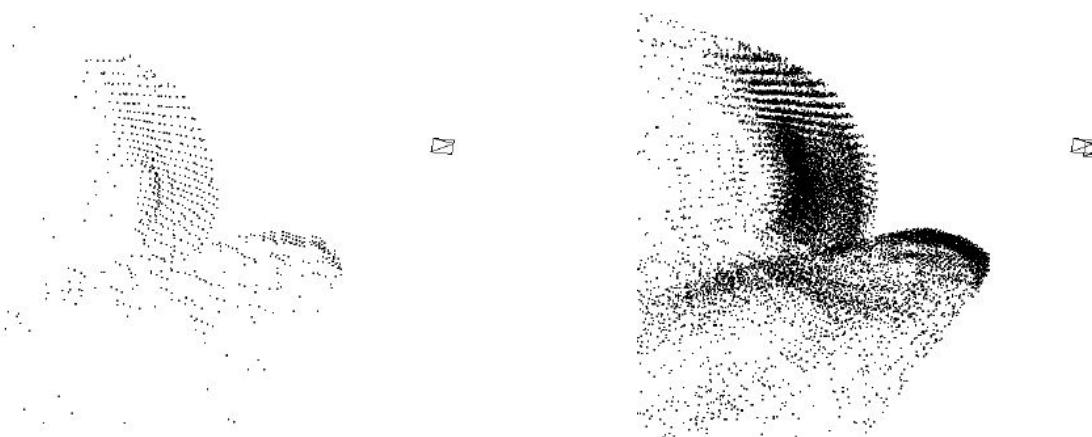
Validation:

- Reprojection error must be low

- Depth must be positive and not too far

- Add to global track list only if valid

Result:



# SfM - Bundle Adjustment (BA)

Purpose:

Refine all camera poses and 3D points to reduce projection error

Global BA:

Run after many views are registered

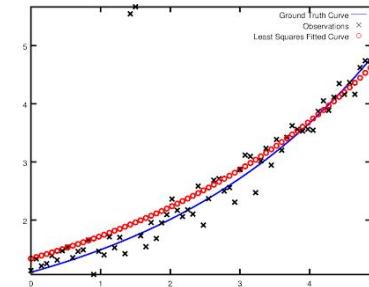
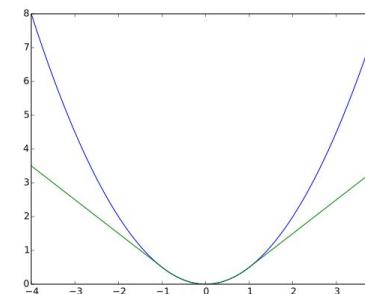
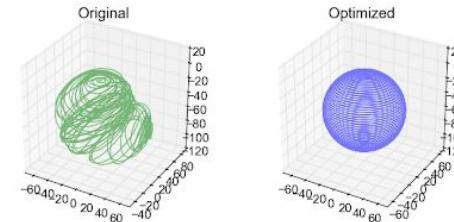
Optimizes:

All camera poses

All 3D point positions

Ceres Solver with EigenSparse backend

Robust to outliers using Huber loss



# SfM - Bundle Adjustment (BA)

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## Local BA

Run after each new view is added

Optimizes:

The latest 3 views (sliding window)

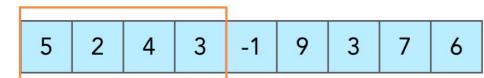
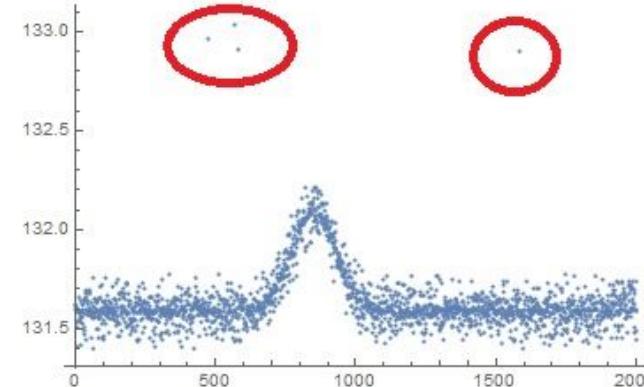
Their shared 3D tracks

Much faster than global BA

Keeps structure accurate during expansion

Final Step:

Remove outlier points with large reprojection error



Sliding window → →

# SfM - Output Formatting

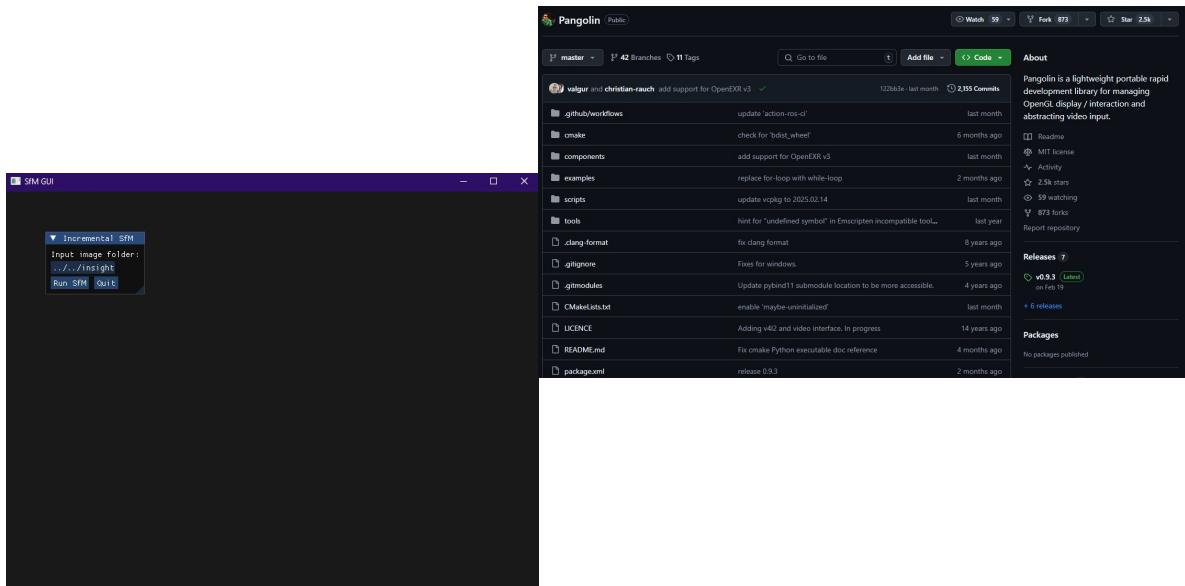
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- cameras.txt
  - encode intrinsic matrix of all cameras used to photograph scene
- images.txt
  - encode each key point seen from each view
- points3D.txt
  - encode the 3D coordinates of each point, and the keypoint in any view that observes this point

 cameras	2025-04-06 9:01 PM	Text Document	1 KB
 images	2025-04-06 9:01 PM	Text Document	15,195 KB
 points3D	2025-04-06 9:01 PM	Text Document	29,657 KB

 cameras.bin	2025-04-06 9:01 PM	BIN File	1 KB
 images.bin	2025-04-06 9:01 PM	BIN File	16,343 KB
 points3D.bin	2025-04-06 9:01 PM	BIN File	1 KB

# SfM - 3D Point Cloud Visualizer and GUI



# Incremental SfM

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Keep registering new cameras + keep adding new point clouds  
Builds the entire scene bit by bit!

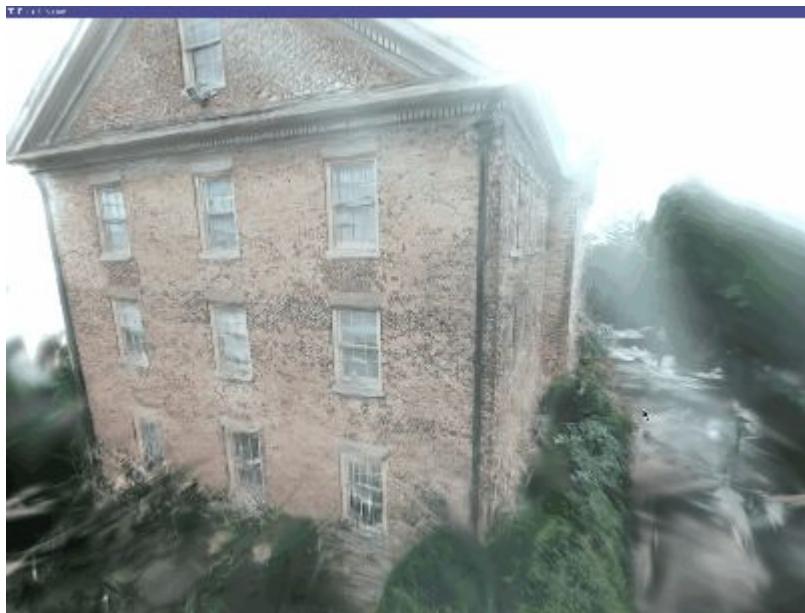


Image source:

<https://capsulesbot.com/blog/2019/03/12/apolloscape-sfm.html>

# Results - South Building at UNC Chapel Hill

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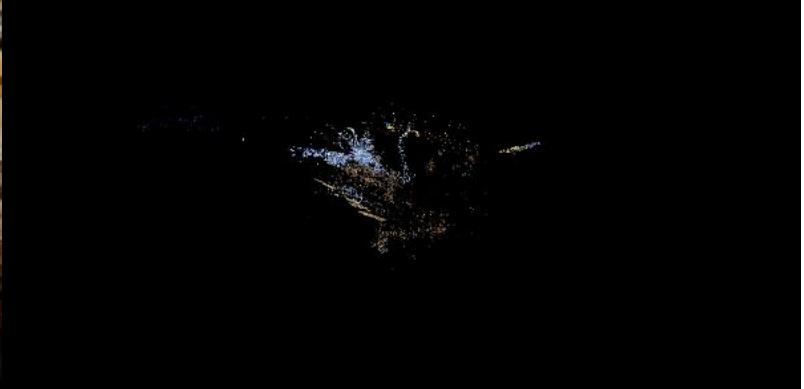
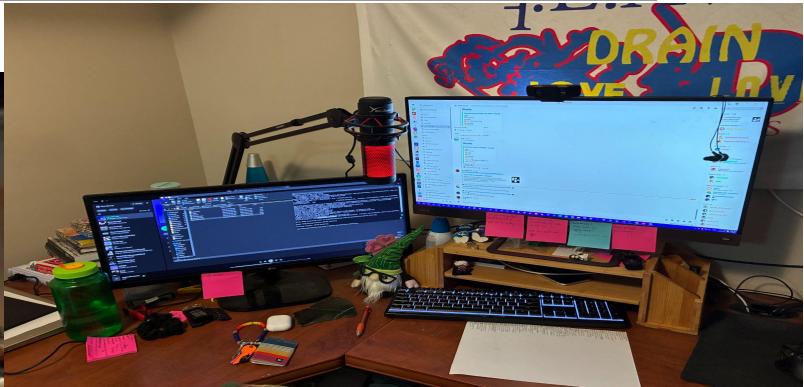
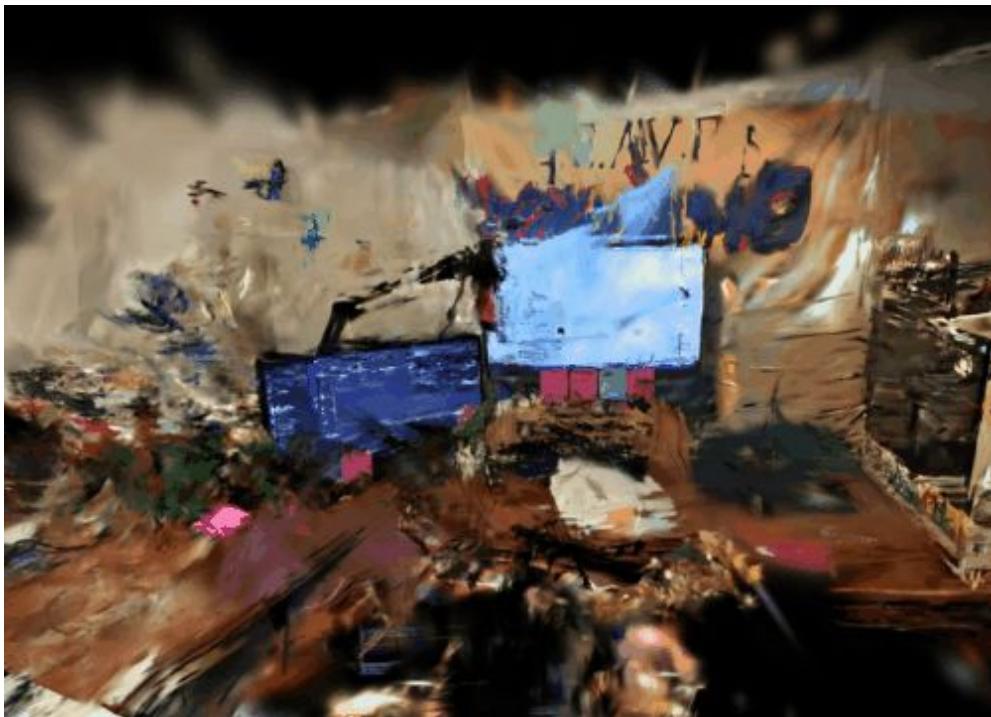


# Results - Insight Medical Clinic

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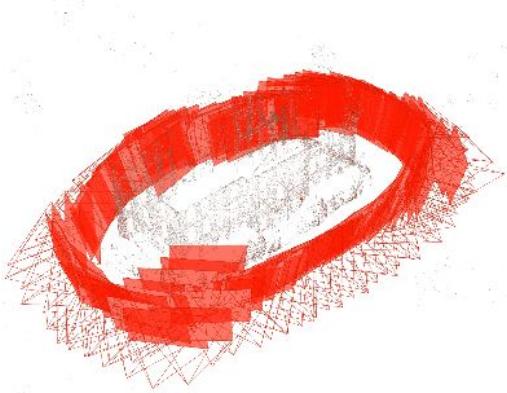


# Results - John's Desk

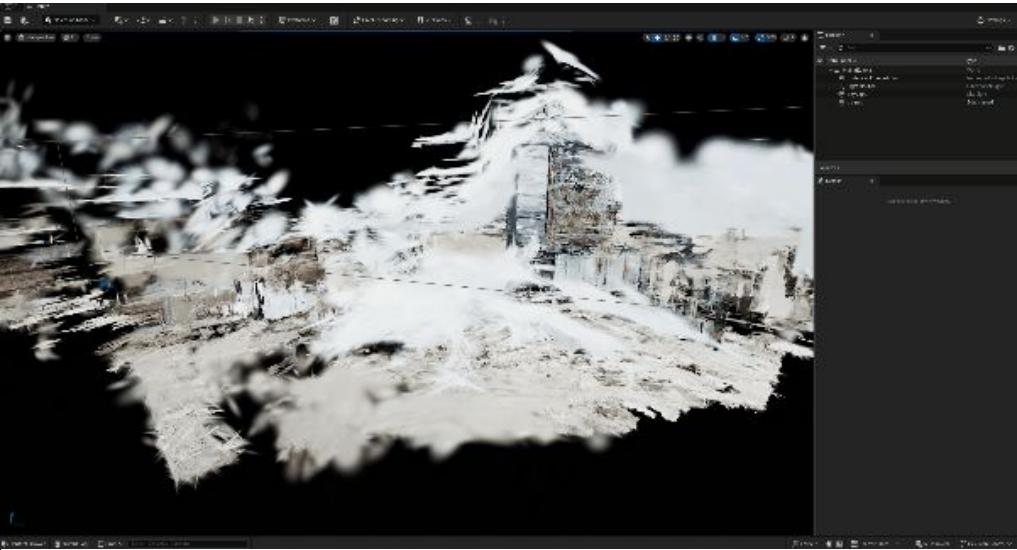
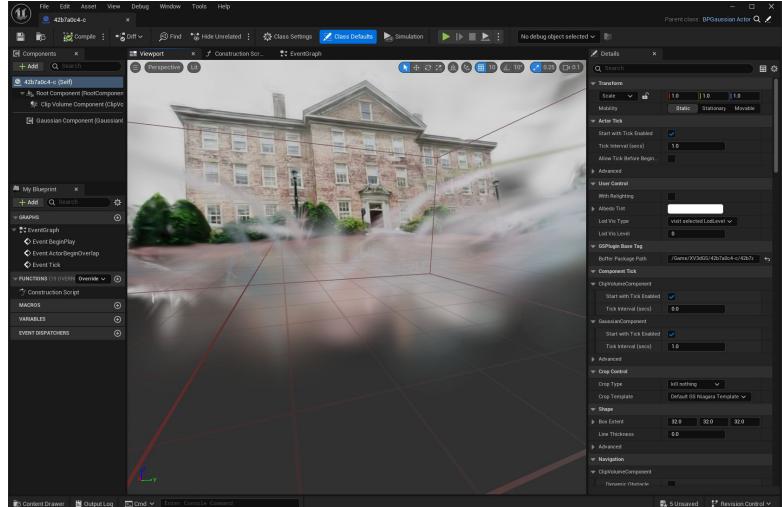


# Results - COLMAP vs Ours

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# Results - Visualized in Unreal Engine



# Challenges - Package Dependencies

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- Some of our imported libraries (in order from hardest to easiest to install):
  - OpenCV with Cuda module
  - Google's Ceres Solver
  - Gaussian Splatting repository
  - Cuda
- A docker container, and conda environment (for gaussian splatting) is desirable.



kwunglerat 2025-03-25 1:16 PM

wow nice!

i am setting up the gaussian splatting right now. it's giving me a lot of difficulties. it seems to have complicated dependencies that are hard to make work



kwunglerat 2025-03-25 3:36 PM

i think i finally got it working... only took me like6 hours LOL

# Challenges - Matching Techniques

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- Which matching technique should we use?
  - tradeoff: accuracy/completeness of feature correspondences vs. computational requirements
  - $O(n^2)$  vs.  $O(n)$  many matches. days of computation vs hours.
- Is sequential matching sufficient?
  - did pretty good for one input, but then lost track
  - sequential matching only gives a few views for a given view to register with
    - smart next view/registration selection?
    - “Choosing the next best view is critical, as every decision impacts the remaining reconstruction. A single bad decision may lead to a cascade of camera mis-registrations and faulty triangulations” [1].



# Challenges - Loop Detection

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- Good 3D structure, but once view wraps around...
  - sequential matcher fails!
    - loop detection?
  - smart selection for next view to register?



# Challenges - Outlier Filtering

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- Good 3D structure, but what is that point over there?
  - some are detecting irrelevant features of the background
  - others are very inaccurate points from 3D structure in foreground
- Can we filter out these unnecessary points based on their (x,y,z) magnitude?
  - why aren't they being filtered by the reprojection error during triangulation?



# Challenges - Input Considerations

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- Too many images: SfM takes way too long
- SIFT feature detection likes edges, corners, and textured material
  - buildings do especially well
- Need to produce good SfM to get good Gaussian Splatting
  - not what we initially expected - authors reported good results with random initialization



# Extensions and Future Work - Feature Matching

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- Feature matching is slow
  - can we use Cuda to program better feature matching algorithms? simple heuristics like start searching other image from position of keypoint in initial
- Why do a brute force search when we could use trackers for feature correspondences?

# Extensions and Future Work - 3 View Triangulation

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- COLMAP uses a 3 view triangulation algorithm
  - likely more accurate

# Extensions and Future Work - Next View Selection

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- “Choosing the next best view is critical, as every decision impacts the remaining reconstruction. A single bad decision may lead to a cascade of camera mis-registrations and faulty triangulations” [1].
  - likely a source of error/outliers/loop closure problems
- Is there a better ordering for next view registration?
  - Can only triangulate with already registered views
- Can we create an iterative algorithm that re-registers a view?

# Questions