3D Computer Vision Research

A Journey Through Point Clouds, 3D Reconstruction & SLAM

Point Cloud Processing

3D Reconstruction

SLAM

What is the goal?

Project Objectives:

- Implement published research papers from scratch
- Study and understand core computer vision concepts
- Present results and analysis in oral defense
- Apply algorithms to real-world use cases

Robot Navigation

Autonomous systems navigating 3D spaces

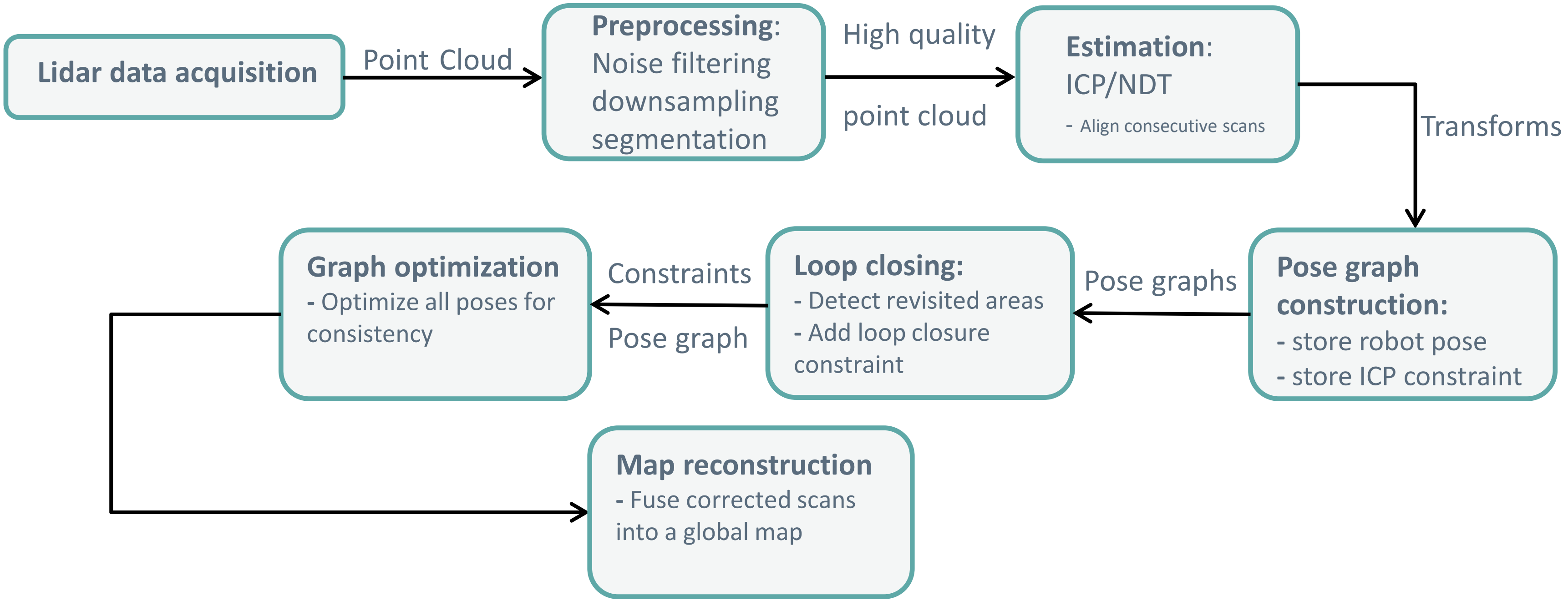
Mapping & Surveying

Large-scale 3D terrain reconstruction

Cultural Heritage

Digital preservation of monuments

(lidar) SLAM


Lidar data acquisition
Point Cloud
Preprocessing:
Noise filtering
downsampling
segmentation
High quality
point cloud
Estimation:
ICP/NDT
- Align consecutive scans
Transforms
Pose graph construction:
- store robot pose
- store ICP constraint
Pose graphs
Loop closing:
- Detect revisited areas
- Add loop closure constraint
Constraints
Pose graph
Graph optimization
- Optimize all poses for consistency
Map reconstruction
- Fuse corrected scans into a global map

Structure from motion (SfM)

Image acquisition

Images

Feature detection:
- Detect keypoints
- Extact feature descriptors

features

Feature matching:
-"where can I find feature 'x' in image 1 in image 2" (see FLANN, BFmatcher).

Matched features

Motion estimation:
-like the ICP step, but for features using epipolar geometry to get the transform

Transform

Triangulation

Point cloud

Incremental Reconstruction:
-add new images sequentially

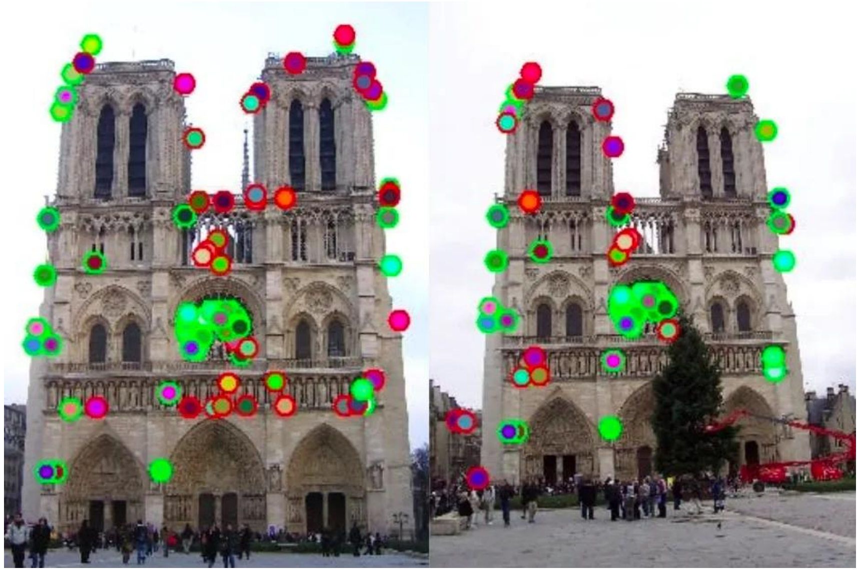
Global point cloud

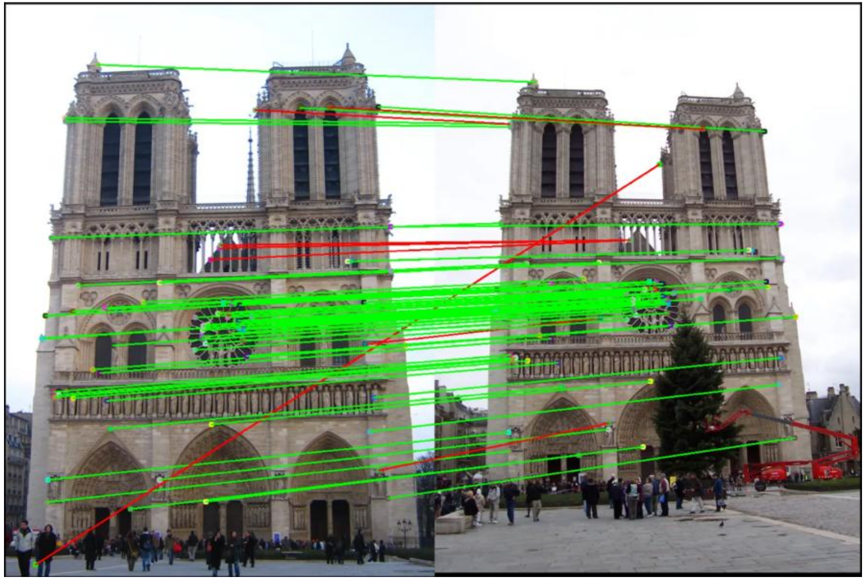
Loop closing:
-detect loops (netVLAD)
- Add constraints

Global point cloud

Constraints

Bundel adjustments:
-optimize based on constraints, poses and points





8 Research Papers We'll Explore

Cutting-edge algorithms from computer vision conferences

PICP
Probability Iterative Closest Point for robust registration

IMLS-SLAM
LiDAR SLAM with implicit surfaces

Photometric Stereo
Uncalibrated shape recovery

Loop Closure
Video sequence merging

Segmentation based classification
Multi-scale point cloud segmentation

FPFH
Fast Point Feature Histograms

GOOD
3D shape descriptor

Fast ICP
Variant of ICP made for speed

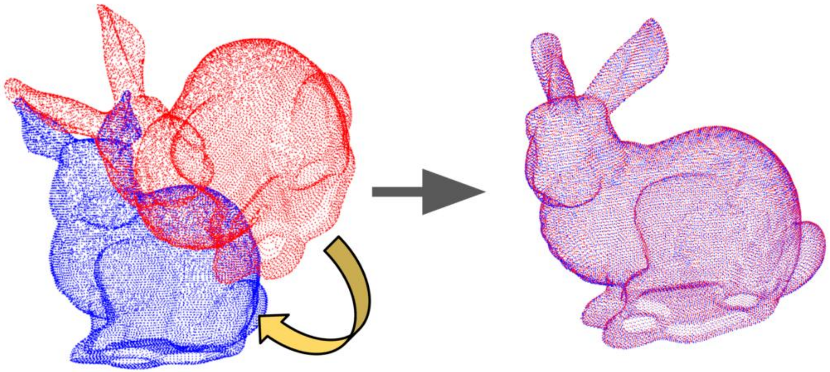
PICP: Probability Iterative Closest Point

The Big Idea

- Traditional ICP fails with noise and outliers
- PICP uses probabilistic weighting for robust registration
- Variance annealing: starts global, refines locally
- Achieves better accuracy on noisy datasets

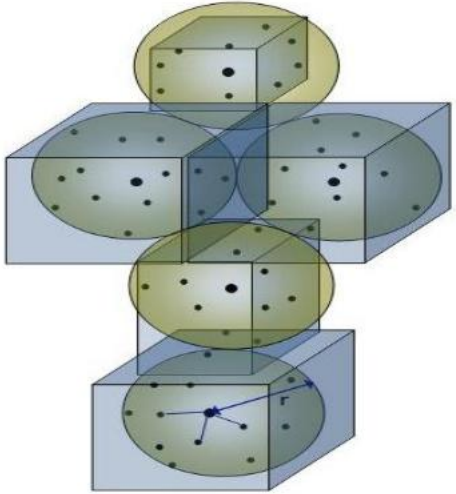
Key Features:

- Gaussian Probability Model
- Global-to-Local Strategy
- One-to-One Correspondence



Segmentation Based Classification of 3D Urban Point Clouds

Groups the point cloud into supervoxels and classifies urban elements



Key Innovations:

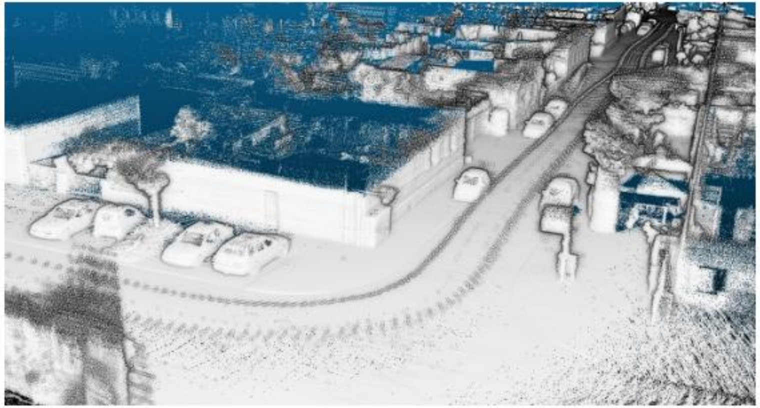
- Group points into voxels
- Groups voxels into supervoxels by link chain method
- Classification using geometric models

IMLS-SLAM: Implicit Moving Least Squares SLAM

Match to smooth IMLS surfaces built from accumulated scans instead of raw noisy points

Core Innovations:

- IMLS Surface Model: Smooth surfaces handle noise naturally
- Scan-to-Model: Current scan → 100 previous scans
- Intelligent Sampling: 900 optimal points from 13,000
- Low Drift: Only 0.40-0.69% error over km trajectories
- Real-Time: 10 Hz operation on standard CPU



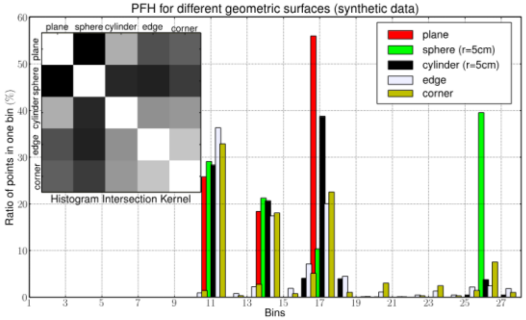
Fast Point Feature Histograms (FPFH)

For 3D Registration

FPFH creates rotation-invariant geometric 'fingerprints' for 3D points that are faster to compute than the original PFH, enabling real-time point cloud registration.

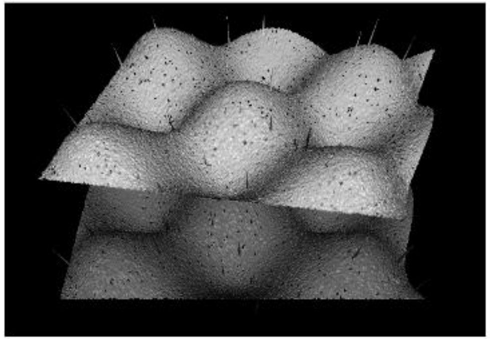
How It Works:

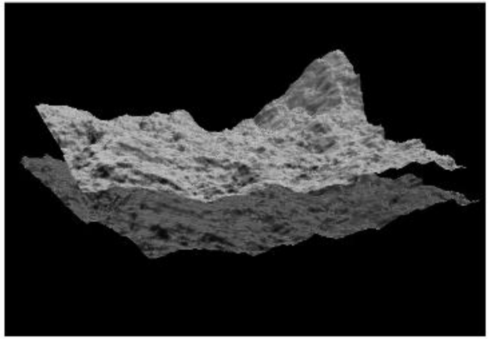
- Describes local 3D geometry via angular relationships between surface normals
- Used for finding corresponding points between overlapping 3D scans
- 33× speedup: Computes features only between each point and neighbors
- Reweights with neighboring histograms to recover geometric information



Fast ICP

ICP variant based on uniform sampling of space normals





Key Difference:

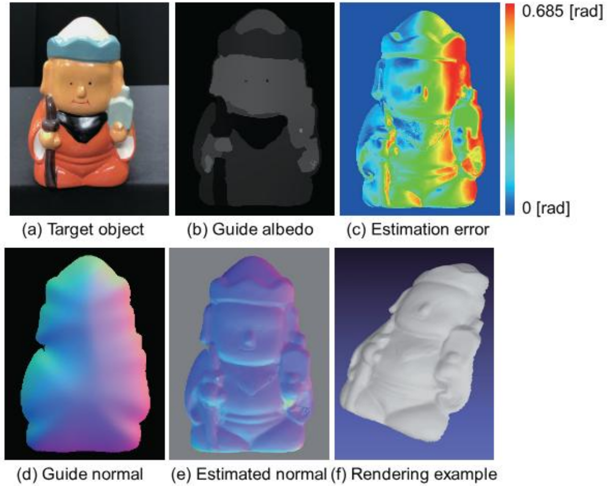
- Test of multiple ICP algorithms to check speed
- Introduction of a new ICP algorithm
- Combination of multiple ICP algorithms optimized for high speed

Uncalibrated Photometric Stereo

Shape from shading algorithm given only image sequence (no light calibration needed)

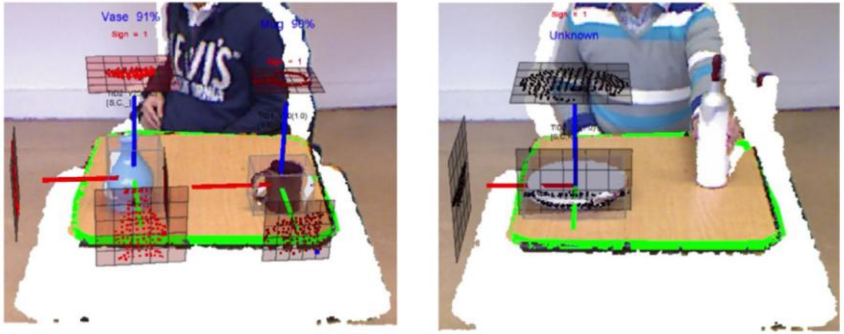
Key Difference:

- Normal Shape from Shading: Requires known light direction
- Uncalibrated: Works without knowing lights or camera!
- Uses intrinsic reflectance and bilateral filtering
- Resolves ambiguity with guide normals from silhouette



Global orthographic object descriptor for 3D recognition

Creates a compact, fast, and pose-invariant 3D shape descriptor for real-time object recognition and manipulation



Key Difference:

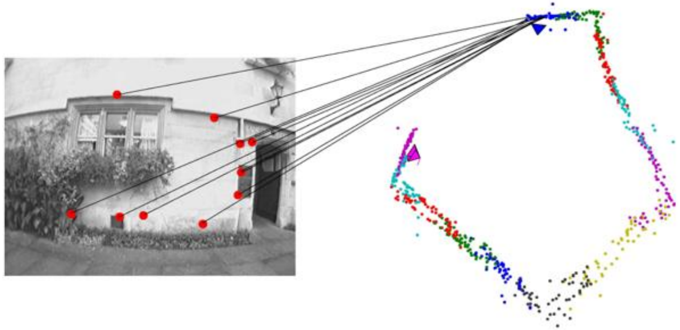
- **Existing 3D descriptors are too slow** for real-time robotics
- **Large memory footprint** makes them impractical for embedded systems
- **Sensitivity to noise and point cloud density**

Loop Closure Detection

Detect similarity of images to use loop closure and correct accumulated drift

The Problem:

- Accumulating drift causes errors in SLAM algorithms
- Loop closure detects when robot returns to previous location
- Optimizes path by detecting similar images (similar positions)
- Corrects the path based on loop closure constraints
- Uses vocabulary trees for fast image similarity matching



LOOP CLOSURE DETECTION

CLOSED LOOP

For questions: Bilal.Moussa.Fares@vub.be

Ready to Dive In?

Rank your most to least favorite project

Each project will consist of 3 people

Deadline is next Tuesday

Good luck!

Research paper selection – Fill out form