

6-DoF Semantics-Aware Condition- and Viewpoint-Invariant Visual SLAM

Confirmation of Candidature

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Contents

- Introduction
- Literature Review
- Research Questions
- Research Plan
- Work Progress
- Conclusion

Introduction



Social



Domestic



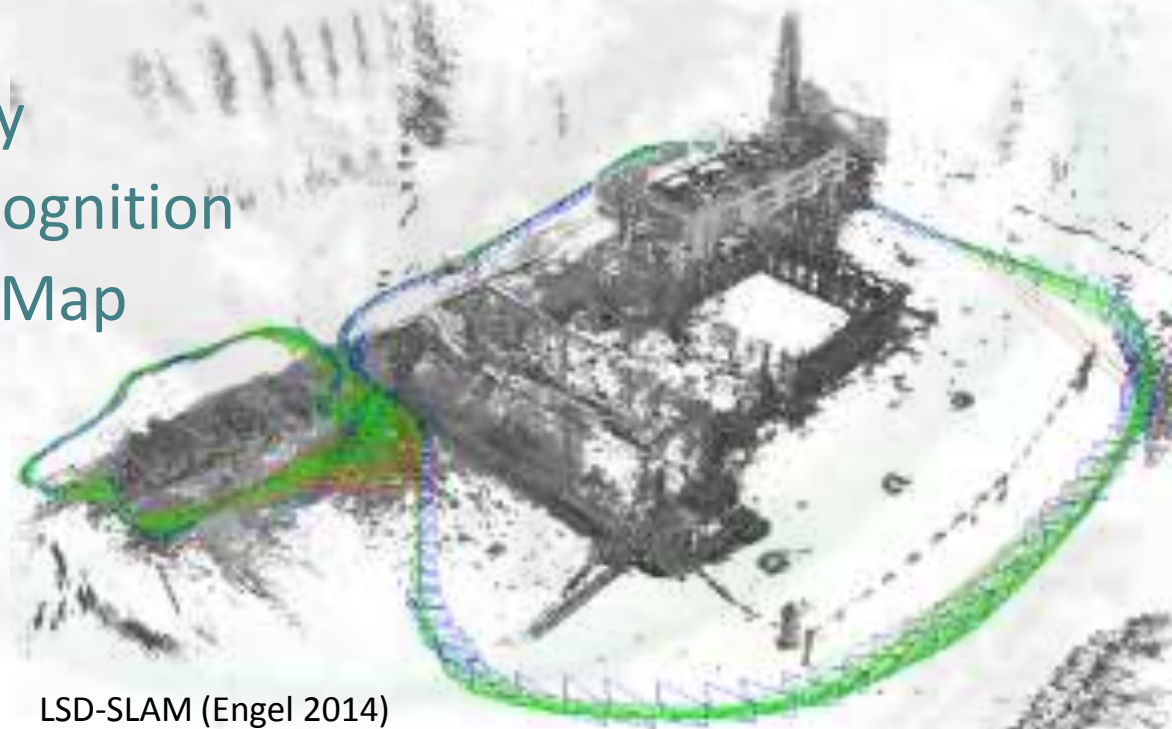
Industrial

SLAM: Is it solved?

- Simultaneous Localization and Mapping
- Solved (Thrun and Nier, 2010):
 - For Static Environments
 - Using Laser Rangefinder
- Unsolved:
 - Vision Only
 - Extreme Appearance Change
 - Dynamic Objects
 - Semantic Understanding

Visual SLAM

- Use only Visual cues
 - Monocular or Stereo Vision using Digital Cameras
- Components:
 - Visual Odometry
 - Visual Place Recognition
 - Representation Map



LSD-SLAM (Engel 2014)

Visual Place Recognition

- Image Representation
 - Local Features – SIFT, SURF, BRIEF, ORB etc.
 - Bag of Words in FAB-MAP, ORB-SLAM etc.
 - Global Representation – ConvNet, Bit-Planes, HoG etc.
 - Direct Matching in LSD-SLAM, SeqSLAM etc.
- Challenges
 - Perceptual Aliasing
 - Different places appear similar
 - Conditions Variations (Weather, Season, Time of day)
 - Same place appears different
 - Viewpoint Variations

Environmental Conditions



Seasonal Variations in Nordland (Sunderhauf 2013)

SeqSLAM - Sunny Days vs Stormy Nights (Milford 2012)

Non-linear Intensity
Deformation by
Automatic Camera
Settings (Alismail
2017)



Perceptual Aliasing



Different Places with Similar Appearance (Cummins 2007)

Place Recognition – Review

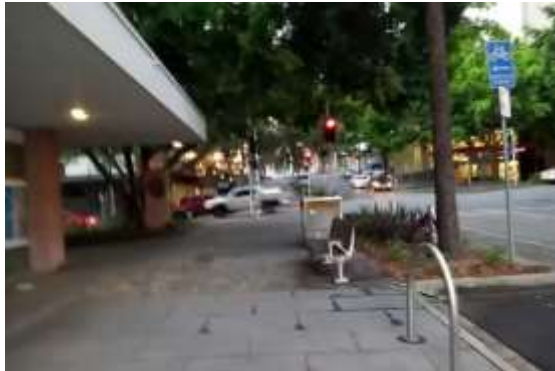
- Local Image Features
 - Robust to viewpoint changes
 - Prone to appearance variations
- Global Representations
 - Robust to appearance variations
 - Prone to viewpoint variations
- Deep-learned features
 - Robust in both cases
 - Lack relative 3D pose estimation

Visual Odometry

- Matching consecutive images for Egomotion estimation
- Methods
 - Local Feature Tracking
 - FAST, SIFT, ORB etc. based feature correspondence
 - Direct Whole Image Matching
 - Deep VO
 - PoseNet, Deep Tracking, Sfm-Net etc.
- Challenges
 - Local Appearance variations
 - Low light environment
 - Rapid Camera Motion
 - Motion Blur
- VO Failure is catastrophic for Visual SLAM

Some Challenges in Visual Odometry

Motion Blur



Low Light Environment



Illumination Variation



(Alismail 2016)

Representation Map

- Types of Maps
 - Topological, Metric or Topometric
- 3D Reconstruction of Environment
 - 6-DoF Visual SLAM systems
 - Sparse, Semi-Dense or Dense Reconstruction
- Semantics in Maps
 - Meaningful interaction with environment
- Aim: Metric Map with Semantic Topology



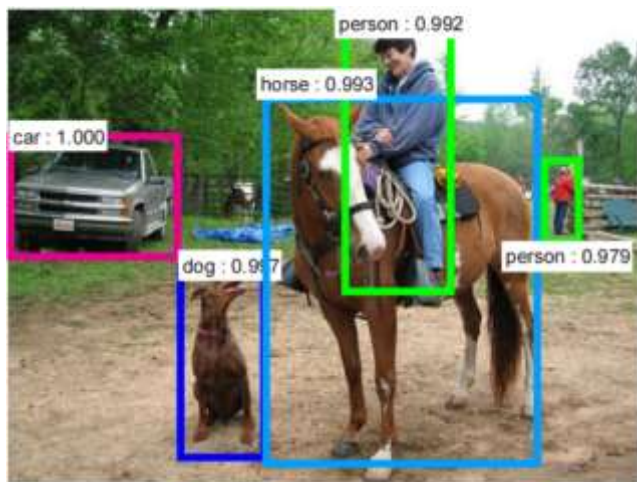
Probabilistic Semi-Dense Mapping
(Mur-Artal 2015)



Place Categorization and Semantic Mapping
(Sunderhauf 2016)

Semantics in Visual SLAM

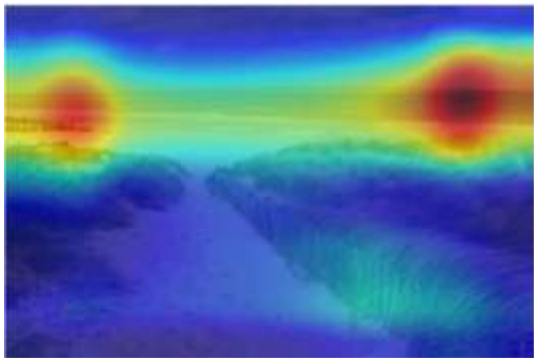
- Semantics within an Image
 - Object-Oriented
 - Deep-learned Object Recognition
 - Sparse or Dense Object Segmentation
 - Semantic Structures like wall, ceiling, floor etc.
- Place Semantics
 - Place-centric vs Object-centric Approach
 - Place Categories and Attributes
 - Structural – Train Station, Kitchen, Bedroom etc.
 - Transient – Night, Rain, Snow etc.



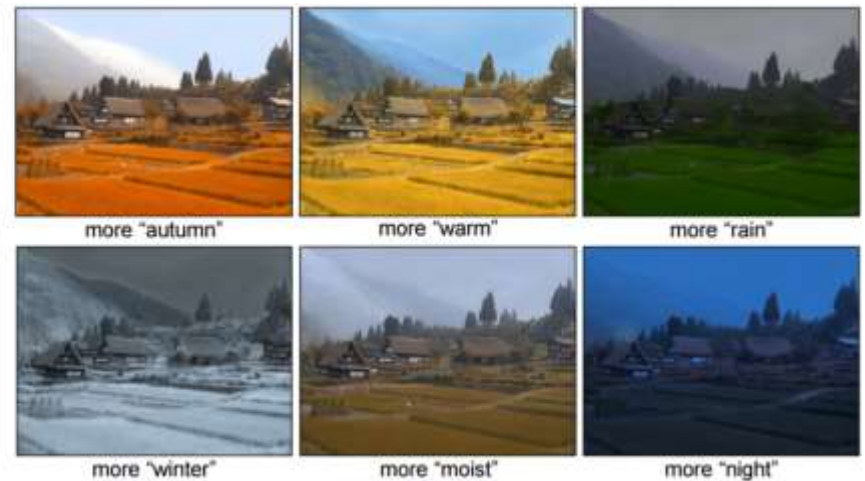
Object Detection Using Faster R-CNN
(Ren 2015)



Multi-Object SLAM (Dharmasiri 2016)



Scene Recognition Using Places
Database (Zhou 2014)



Transient Attributes for Outdoor Scene Editing
(Laffront 2014)

Research Gap

- Place Recognition
 - Viewpoint- and Condition-Invariance
 - With 3D Relative Pose Estimation
- Visual Odometry
 - Robustness to Environmental Conditions
 - Hybrid Approach for Rapid Camera Motion
- Representation Map
 - Semantic Maps on top of Geometric Maps
- Semantics in Visual SLAM
 - An integrated system where both can benefit

Problem Statement

How can we develop a general purpose
**6-DoF semantics-aware condition- and
viewpoint-invariant visual SLAM system?**

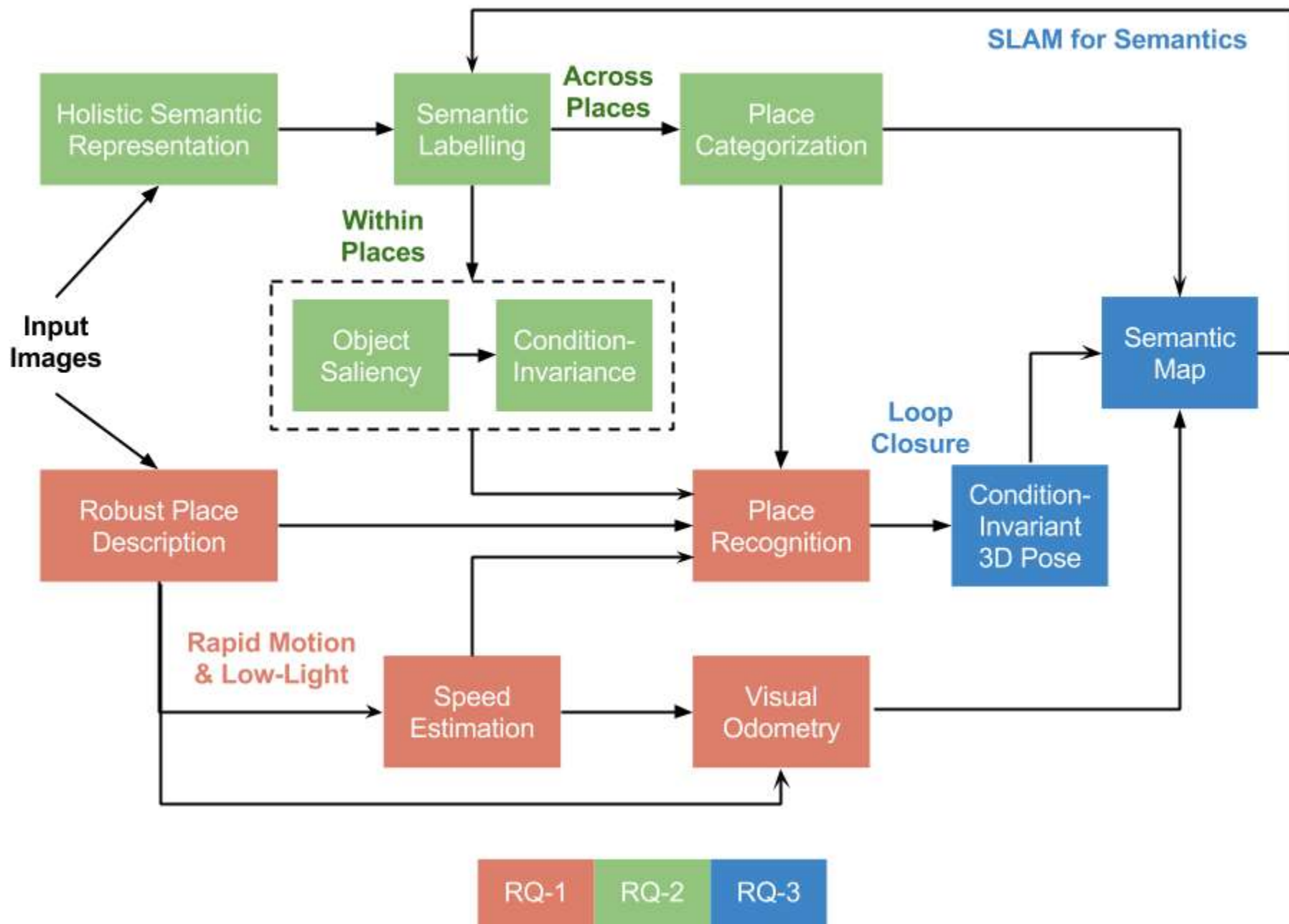
Research Questions

- How can we characterize a visual SLAM system against variations in environment and egomotion, and make it more robust for both visual place recognition and visual odometry?
- How can semantic information related to images add value to a visual SLAM system?
- Can we develop a general purpose 6-DoF semantics-aware SLAM system robust to condition and viewpoint variations.

Research Plan

- Characterizing and Adapting Visual SLAM system
 - Visual Odometry and Place Recognition
 - Adapting to Environment
 - Egomotion Estimation
- Utilizing Semantic Information
 - Holistic Semantic Representation
 - Semantics Across Places
 - Semantics Within Places
- 6-DoF Semantics-Aware Visual SLAM
 - Condition-Invariant 3D Relative Pose Estimation
 - Semantics for SLAM
 - SLAM for Semantics

Research Plan



Characterizing and Adapting Visual SLAM

- Characterizing Viewpoint and Condition Invariance
 - Place Recognition – SeqSLAM
 - Visual Odometry – ORB-SLAM
- Handling Variations within the Environment
 - Transitions in Environment
 - Indoor/Outdoor, Naturally-Lit/Artificially-Lit etc.
 - Environment Segmentation
 - Improve Place Recognition
- Egomotion Estimation in Low Light and Rapid Motion
 - Speed Estimation for Visual Odometry
 - Speed-Normalized Data Sampling for Place Recognition

Utilizing Semantic Information

Holistic Semantic Representation

▫ *Place-Centric*

Semantics (Zhou 2014)

- Environment Type
 - Outdoor
- Categories
 - Harbor -0.44
 - Dock – 0.33
 - Boat Deck – 0.10
- Attributes
 - Open Area
 - Natural Light
 - Far-Away Horizon
 - Man-Made



▫ *Object-Centric* Semantics (Jia 2014)

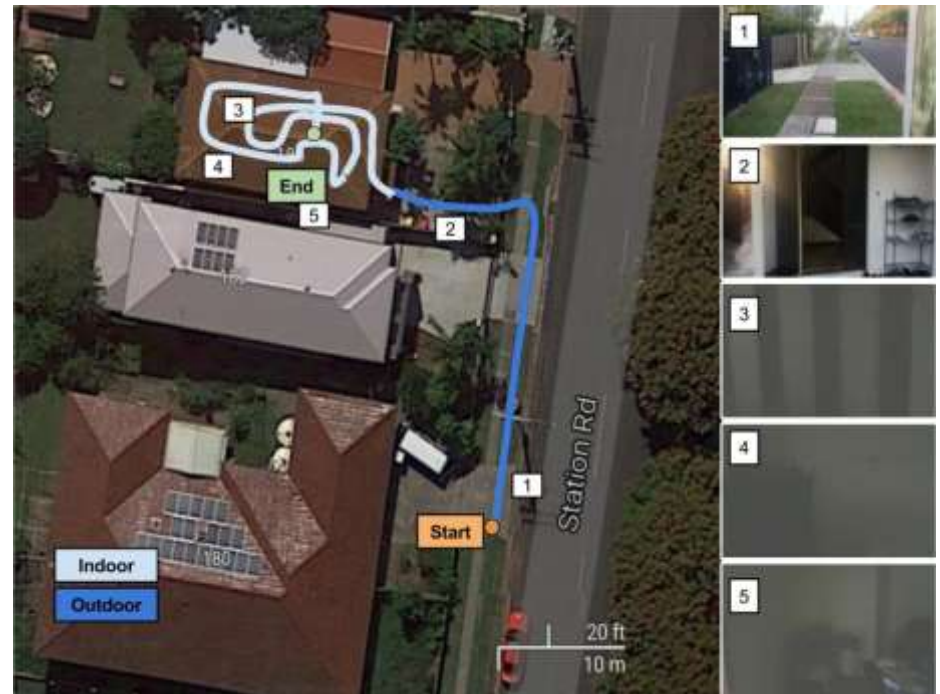
- Vessel – 1.26
- Craft – 1.17
- Vehicle – 0.80
- Ship – 0.76

▫ *Transient Attributes* (Laffront 2014)

- Time of Day
 - Sunrise/Sunset – 0.59
- Weather
 - Sunny/Direct Sun – 0.39
 - Clouds/Overcast – 0.27
- Season
 - Summer – 0.34
 - Winter – 0.07

Semantic Segmentation Across Places

- Semantic Map
 - Segment Environment
 - Office Space - Cubicles, Canteen, Corridor, Restroom etc.
 - Vehicle on Roads - Urban Canyon, Highway, Tunnel etc.
- Place Categorization and Place Recognition
 - Reduce Search Space
 - Coarse Semantic Localization
 - Seamless Transitions Within Environment
 - Indoor/Outdoor, Naturally/Artificially Lit, Bland/Cluttered



Indoor-Outdoor Seamless Localization

Semantic Segmentation *Within* Places

- Object Semantics
 - Deep CNN Object Recognition
 - Learn New Object Classes Online
- Place Semantics
 - Transient Environmental Conditions
 - Condition-Invariant Place Recognition
- Object/Patch Saliency *Within* Place
 - Dynamic Objects
 - Condition-Invariance



Object Oriented Semantic Mapping
(Sunderhauf 2016)

6-DoF Semantics-Aware Visual SLAM

- Condition-Invariant 3D Relative Pose
 - Condition-Invariant Place Description
 - Exploring Bit-Planes Descriptor

- Semantics for SLAM
 - Improved Localization
 - Meaningful Maps
 - Scale to 3D



- SLAM for Semantics
 - Improve Semantic Labelling

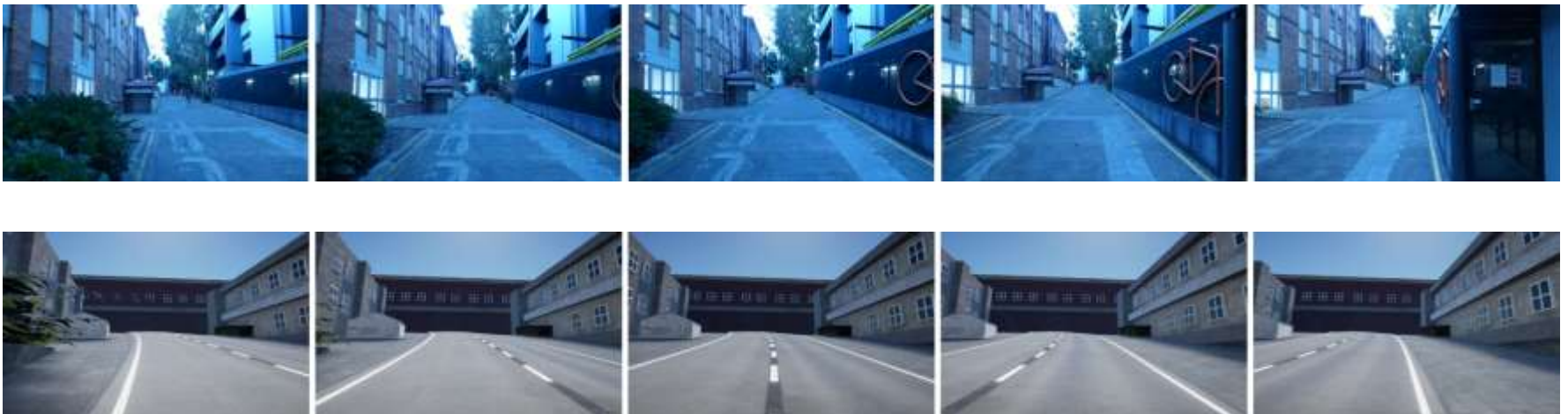
An example of the LBP descriptor evaluated on a 3×3 neighborhood, which results in a 8-channel bit-plane descriptor. Unlike the classic LBP descriptor, the bit-plane descriptor can be employed within a multi-channel LK framework using a sum of squared differences (SSD) cost measure. (Alismail 2016)

Work Progress

- Performance Evaluation using High-Fidelity Simulation
 - Place Recognition – SeqSLAM
 - Visual Odometry – ORB-SLAM
- Semantic Segmentation of Environment
 - Transitions in Environment
 - Improve Condition-Invariant Place Recognition
- Egomotion Estimation in Unfavourable Conditions
 - *Hybrid* Visual Odometry
 - Speed-Normalized Data Sampling for Place Recognition

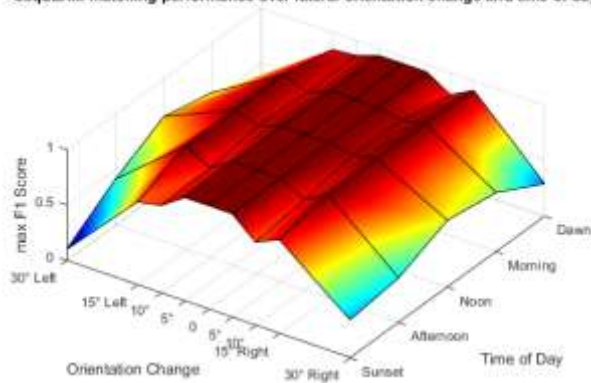
Characterizing Visual SLAM - Progress

- Performance Evaluation Using High-Fidelity Simulation
 - Viewpoint- and Condition-Invariance
 - Place Recognition using SeqSLAM
 - Visual Odometry using ORB-SLAM

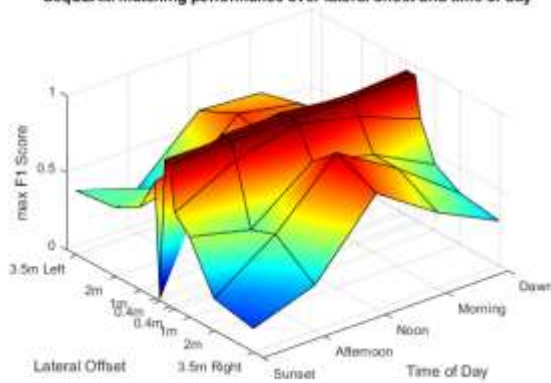




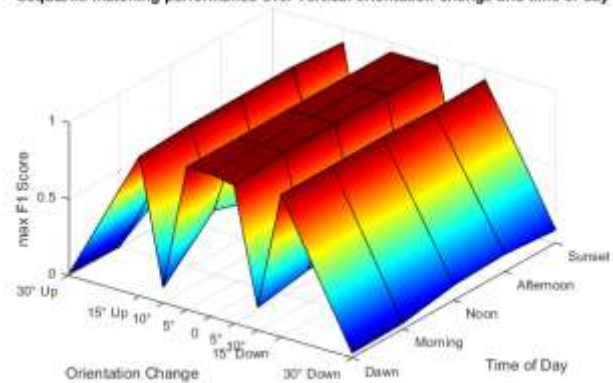
SeqSLAM matching performance over lateral orientation change and time of day



SeqSLAM matching performance over lateral offset and time of day

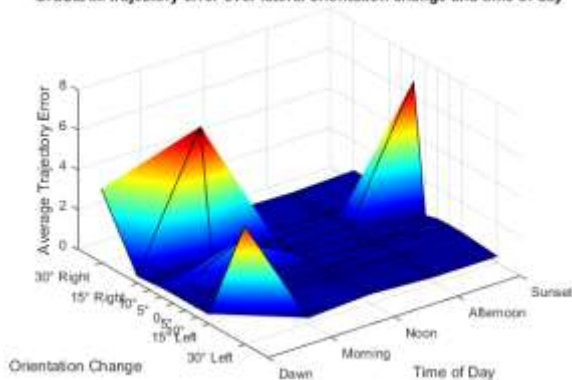


SeqSLAM matching performance over vertical orientation change and time of day

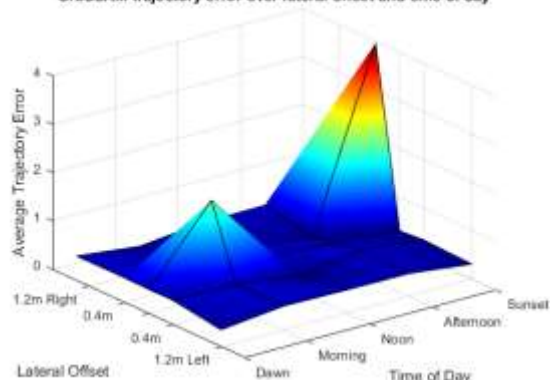


SeqSLAM – Place Recognition

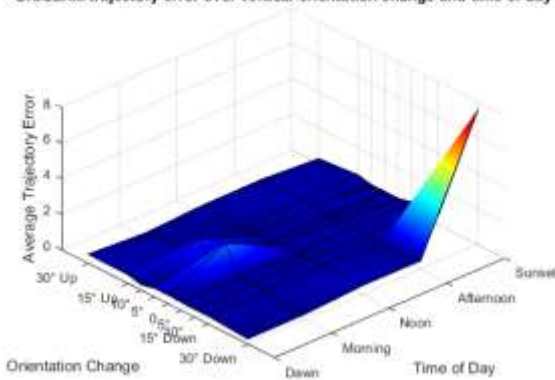
OrbSLAM trajectory error over lateral orientation change and time of day



OrbSLAM trajectory error over lateral offset and time of day



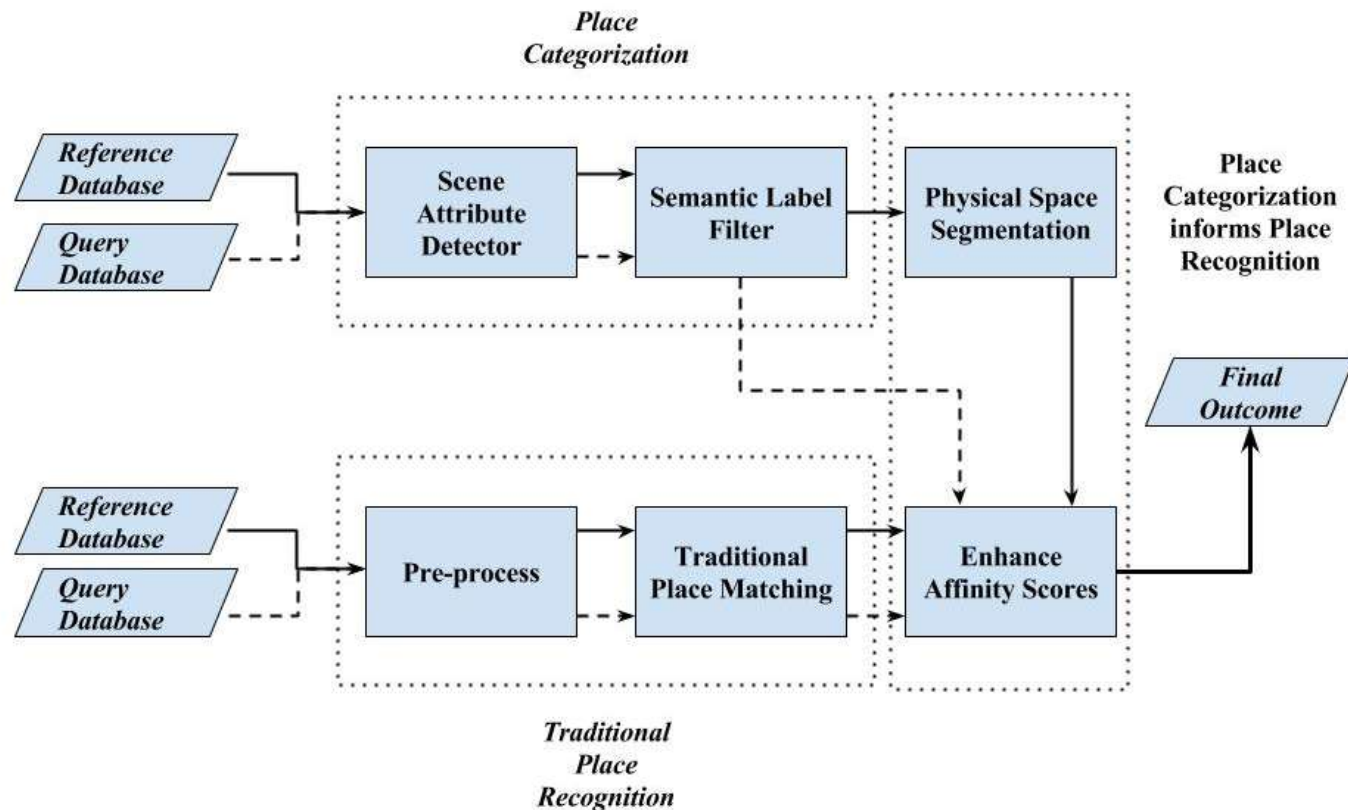
OrbSLAM trajectory error over vertical orientation change and time of day

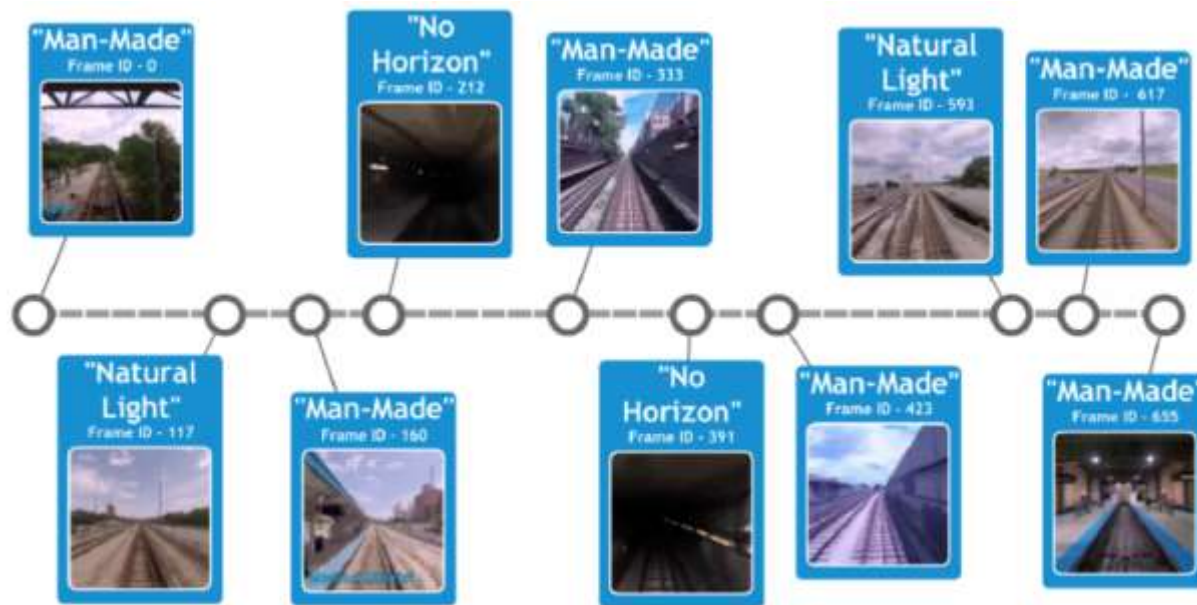


ORB-SLAM – Visual Odometry

Adapting to Environment

- Semantic Segmentation of Environment
- Improving Place Recognition





Semantic Labels
for Segmented
Environment

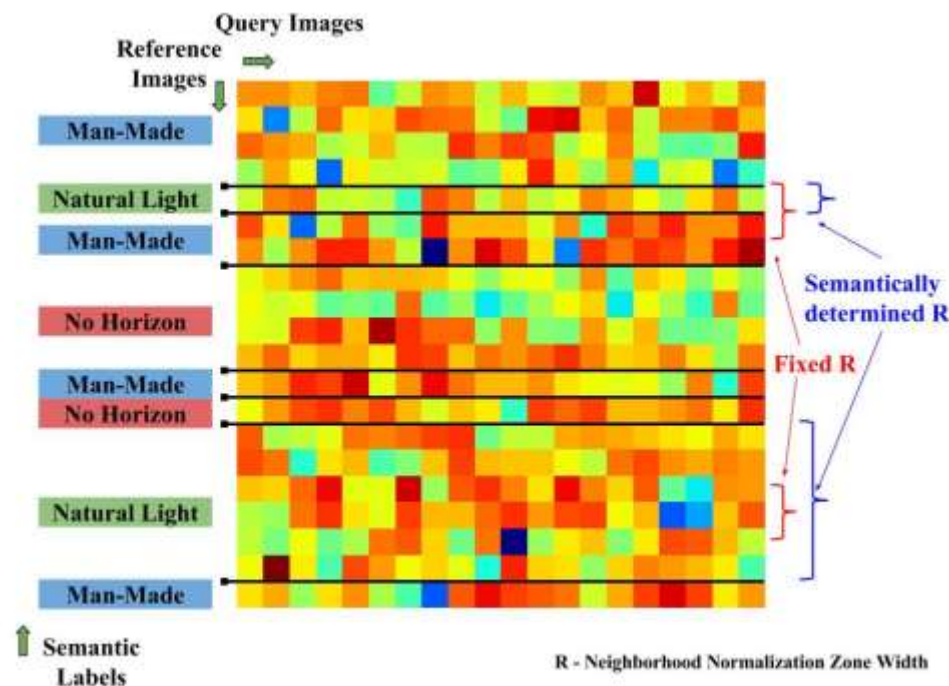


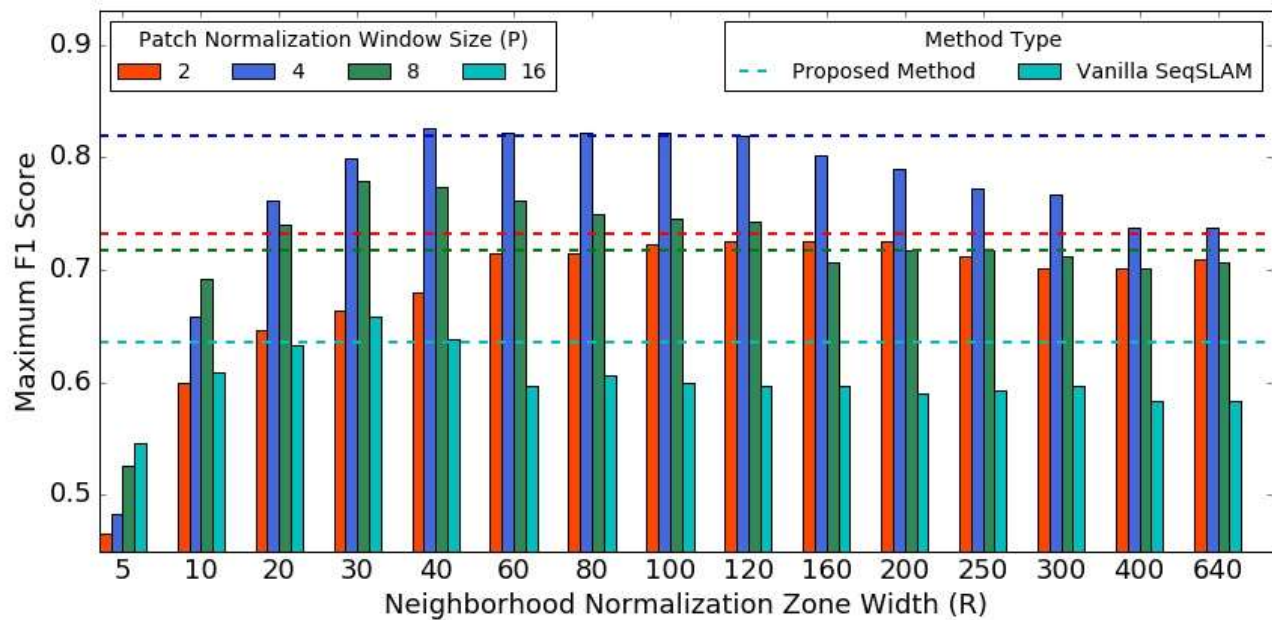
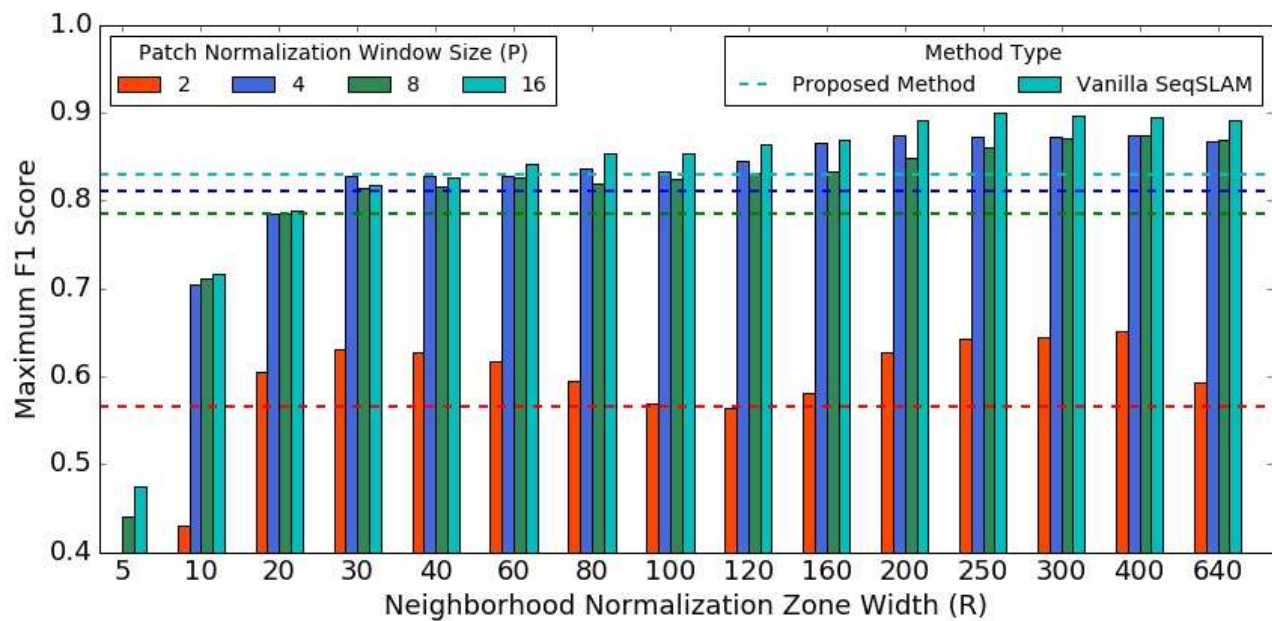
Extreme
Variations in
Appearance
Within
Environment



- Performance Changes

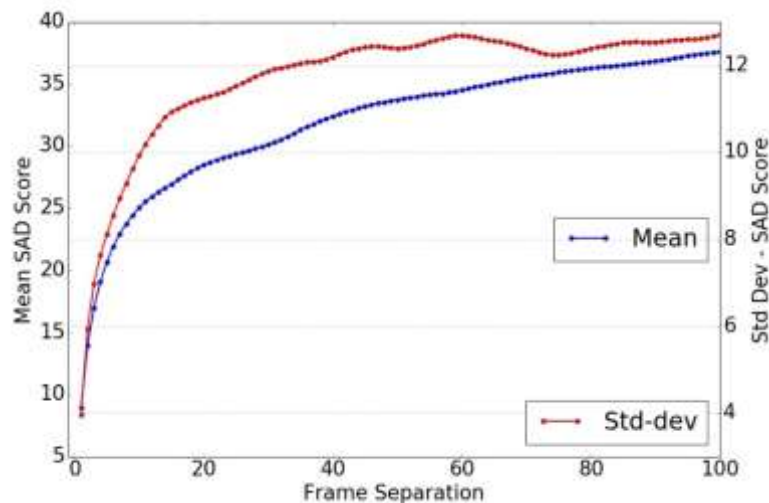
- More pronounced with extreme variations within environment
- Global Conditions
 - If similar – Global minima generally works
 - If different – Depends on Query Image
- Semantics later replaced by segmentation based on image matching score



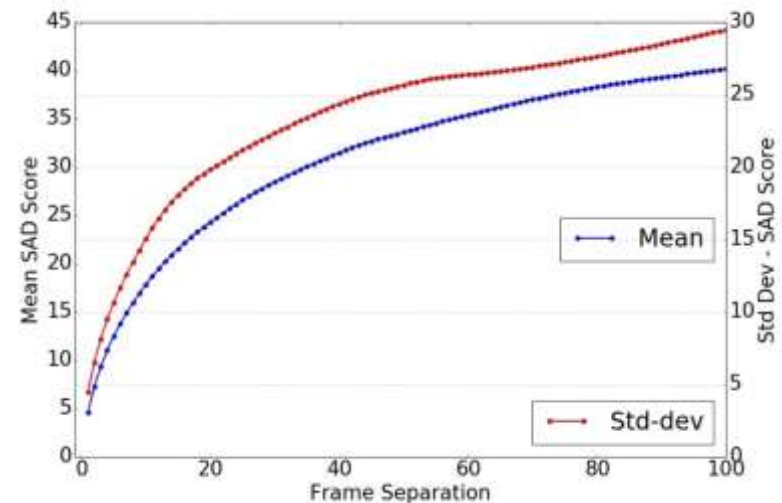


Egomotion for Unfavourable Conditions

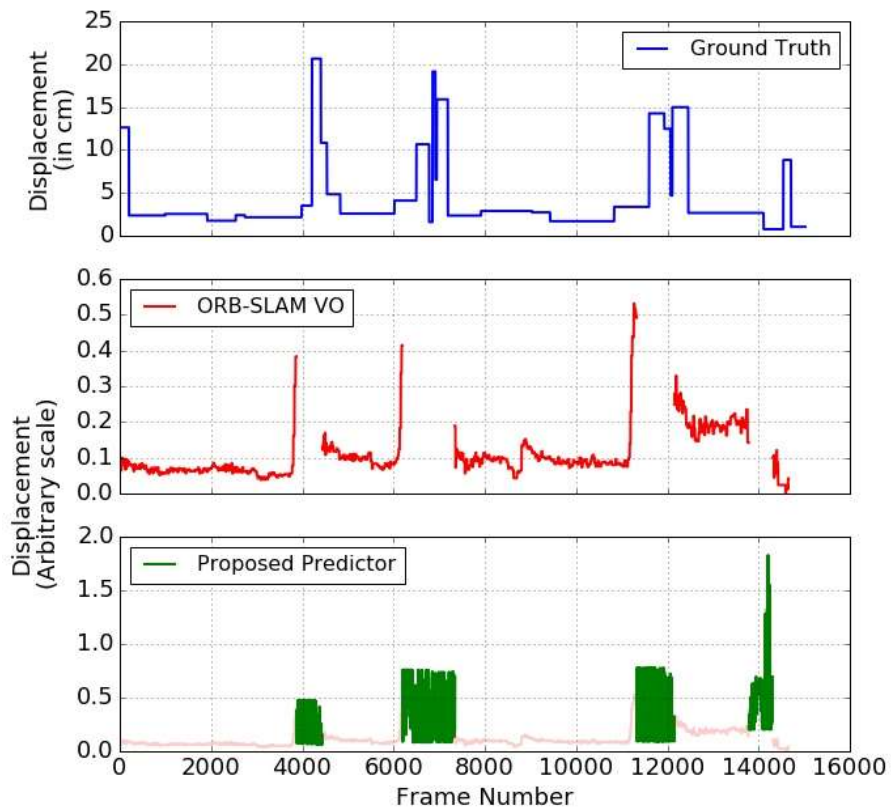
- Speed Estimation
 - Low Light and Rapid Motion
 - Approximate Linear Relationship between Appearance and Geometry (Lukas and Kanade 1981)
 - Image Matching Score vs Frame Separation



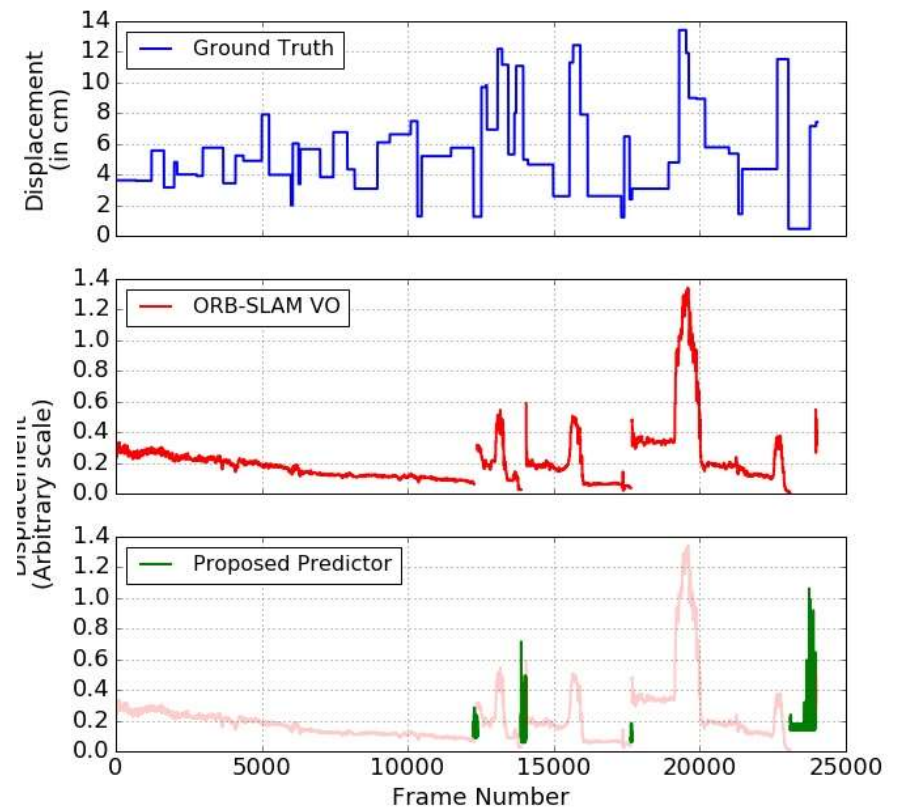
Campus Indoor-Outdoor Dataset



Home Indoor-Outdoor Dataset



Night Traverse

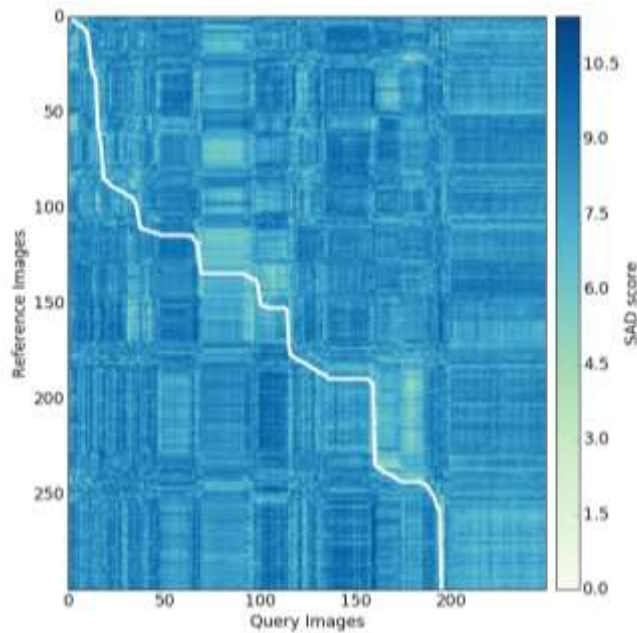


Day Traverse

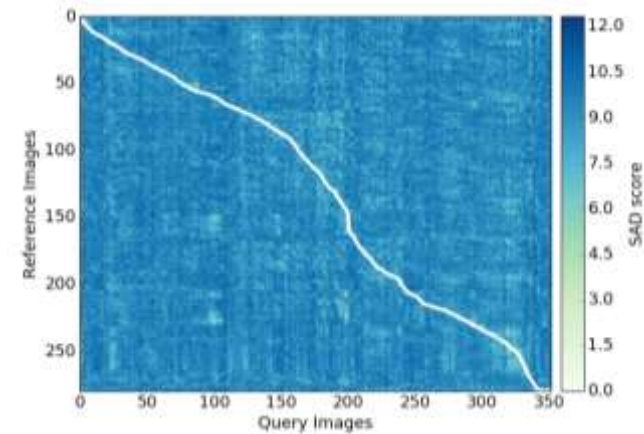
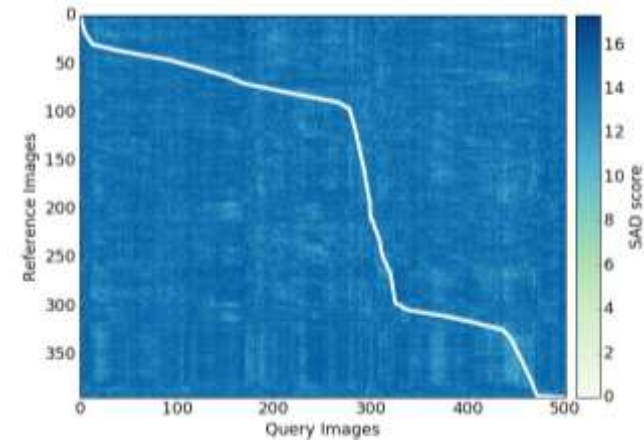
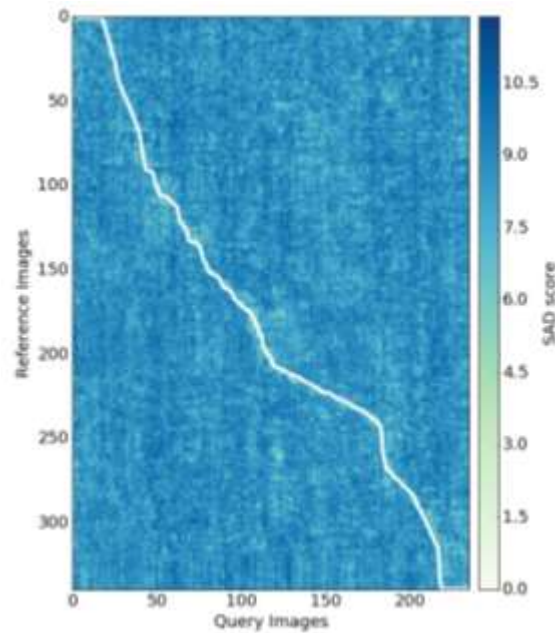
Kelvin Grove On-Foot Dataset featuring Low Light Environment and Rapid Motion

- Image Matching Using
 - Patch-Normalized Images with SAD Score
 - Bit-Plane Descriptor with SSD Score
- Polynomial fitting - SAD score and Frame Separation
- Challenges
 - Depends on Environment
 - Is 1-D
- State-of-the-art VO failure reasons
 - Less features in low-light for ORB-SLAM
 - Mainly rapid motion for LSD-SLAM
- Possible Uses
 - Hybrid approach with state-of-the-art
 - Adapting parameters with change in speed

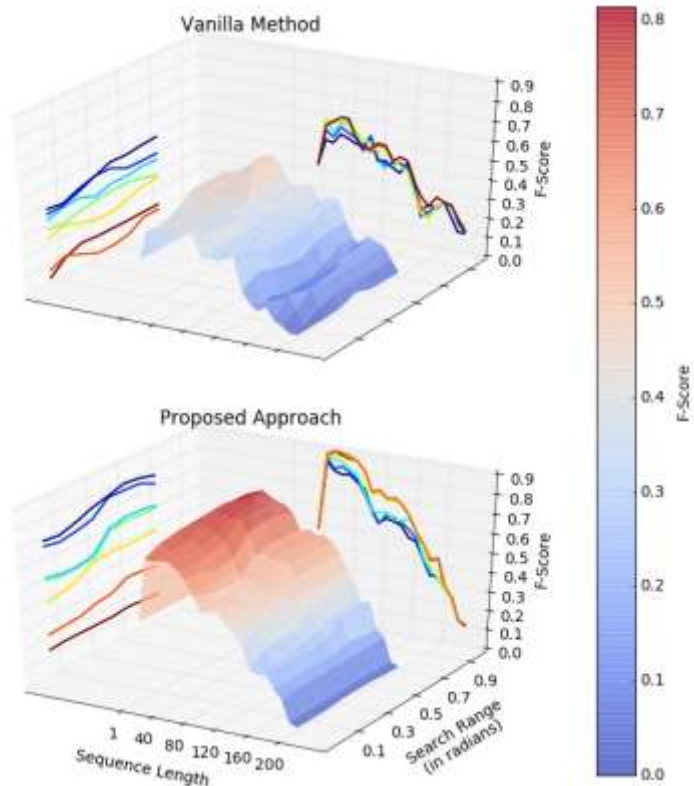
- Improving Place Recognition
 - Speed-Normalized Data Sampling
 - Ground Truth Trajectory Comparison



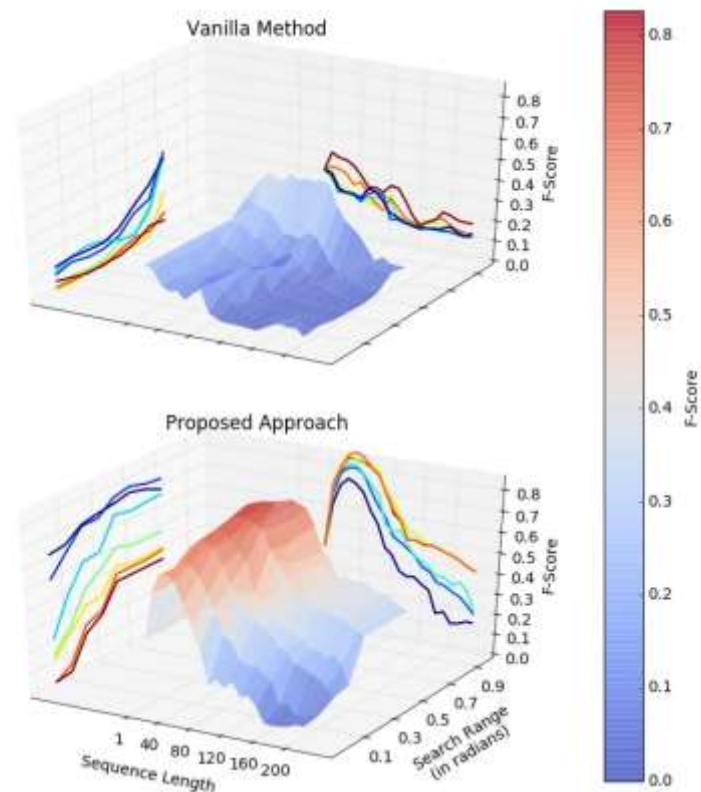
Vehicle Moving in Heavy
Traffic Conditions



Varying Pedestrian
Motion on Footpath



Vehicle Moving in Heavy Traffic Conditions



Varying Pedestrian Motion on Footpath





Thank You!