UnDeepVO: Monocular Visual Odometry through Unsupervised Deep Learning

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Outline

1. Introduction
2. System Overview
3. Objective Losses
4. Experimental Evaluation
5. Conclusions
6. Contributors

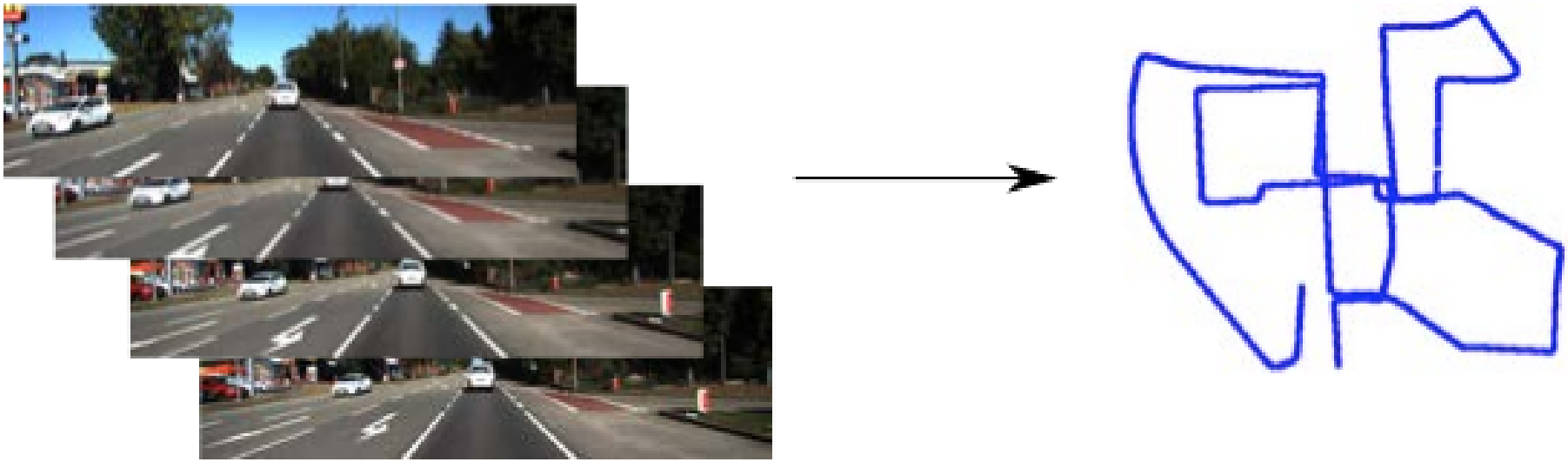
Introduction

UnDeepVO

- A monocular visual odometry system
- Paper by Ruihao Li, Seng Wang, Zhiqiang Long and Dongbing Gu

- Goal
  - Robot localization using only visual information

- Goal
  - Use consecutive monocular images to construct a path of robot movement



Introduction

Research Progress in VO

- Unsupervised Learning
  - CNN for 6-DOF pose regression
  - Video clips
  - Optical flow
  - DeMoN
  - Visual inertial odometry
  - 'Spatial transformer'
  - DeMoN
- Supervised Learning
  - Photometric constraint of stereo imaging
  - Consecutive monocular Imaging

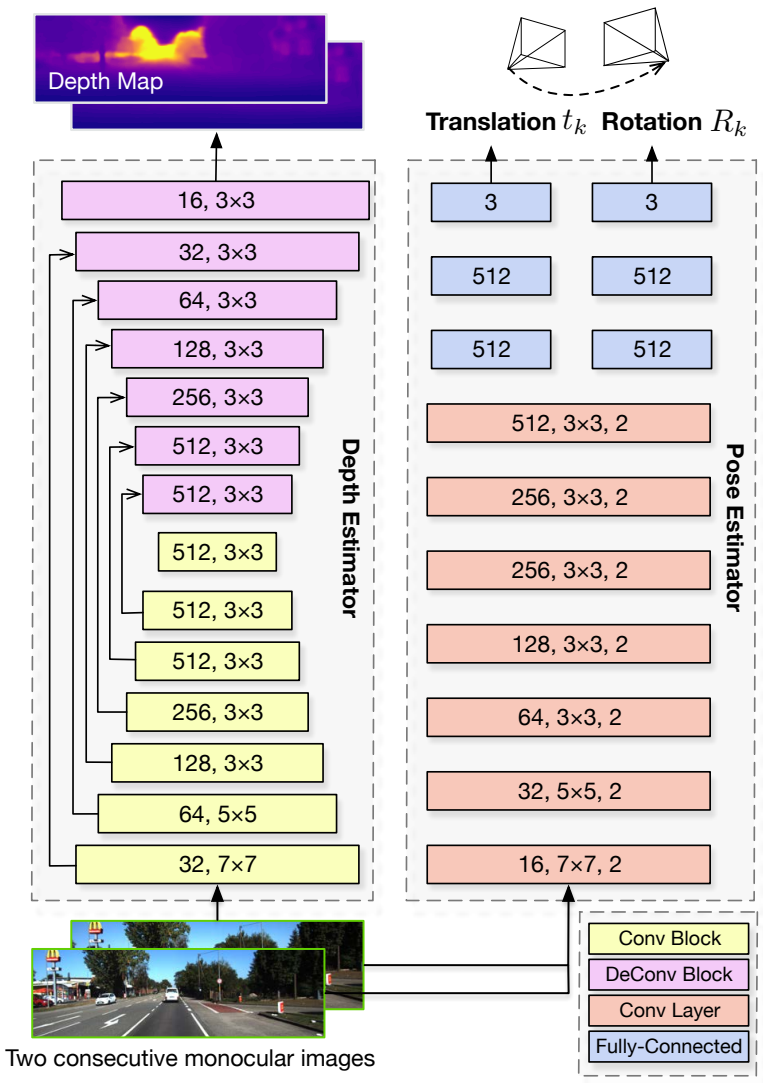
Introduction

UnDeepVO

- Monocular stereo imaging based VO system
- Based on deep learning
- Unsupervised
  - No need for labeled training data
- Pose estimation
- Depth estimation
- Absolute scale retrieval
- Evaluation using KITTI dataset

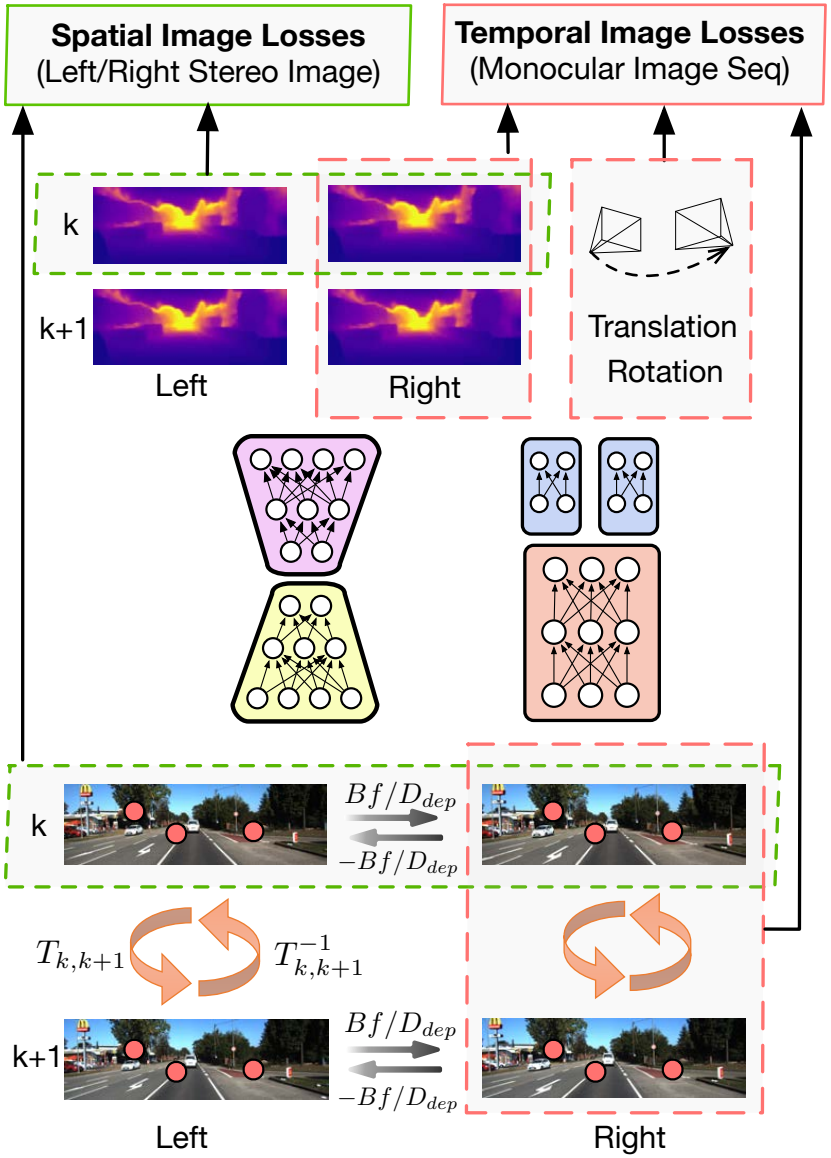
System Overview

Architecture



System Overview

Training Scheme



Objective Losses

Spatial Losses

The spatial losses are based on the fact that, given the structure of stereo cameras, for a pixel $p_l(u_l, v_l)$ on the left image and $p_r(u_r, v_r)$ on the left image:

$$u_l = u_r \quad \text{and} \quad v_l = v_r + D_p$$

- Photometric Consistency Loss (Image reconstruction)

$$L_{pho} = \lambda_s L^{SSIM}(I, I') + (1 - \lambda_s) L^{l_1}(I, I')$$

- Disparity Consistency Loss (Depth)

$$L_{dis} = L^{l_1}(D_{dis}, D'_{dis})$$

- Pose Consistency Loss (Camera orientation)

$$L_{pos} = \lambda_p L^{l_1}(t_l, t_r) + \lambda_o L^{l_1}(R_l, R_r)$$

Objective Losses

Temporal Losses

This is based on the reconstruction of pixels on time k and $(k+1)$ as

$$p_{k+1} = KT_{k,k+1}D_{dep}K^{-1}p_k$$

- Photometric Consistency Loss (Image reconstruction)

$$L_{pho} = \lambda_s L^{SSIM}(I, I') + (1 - \lambda_s)L^{l_1}(I, I')$$

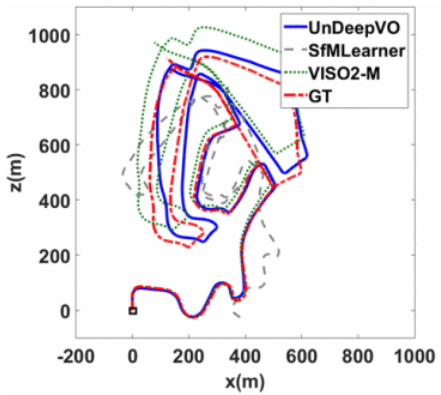
- 3D Geometric Registration Loss (Adding depth with $P(x, y, z)$)

$$L_{geo} = L^{l_1}(P, P')$$

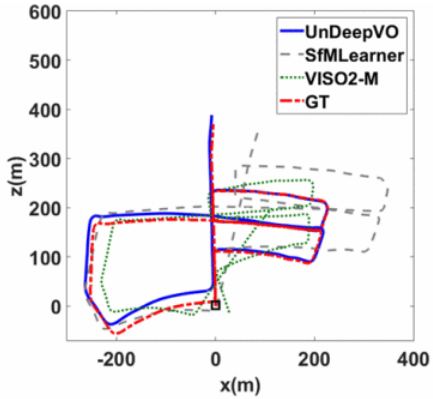
Evaluation

Trajectory

- KITTI Odometry Dataset
- Comparison between UnDeepVO, SfMLearner VISO2-M and ORB-SLAM-M
- UnDeepVO qualitatively closest to the ground truth for all sequences



(a) 02



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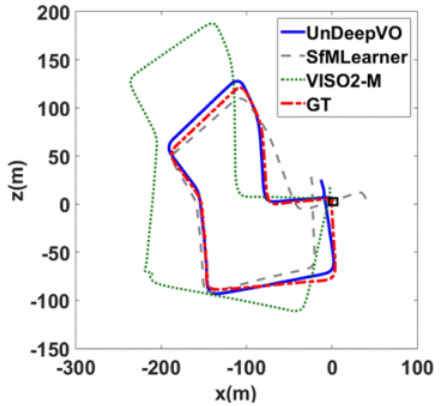
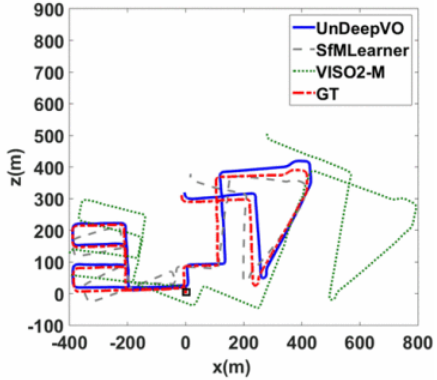


(c) 07

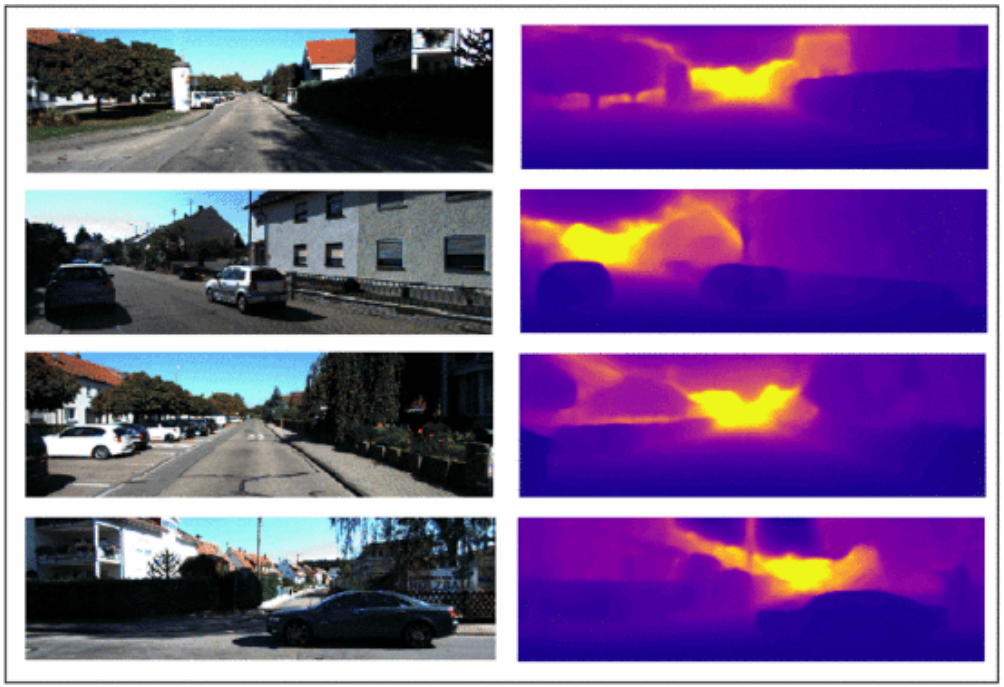


(d) 08

Evaluation

Depth

- UnDeepVO also produces a scaled depth map
- Depth of objects estimated accurately
- Model outperforms some competitors but not all
  - Only part of KITTI dataset used
  - Lower image resolution
  - Temporal image sequence loss might have introduced noise



Conclusions

- First unsupervised Visual Odometry model
  - Trained with unlabeled stereo images
  - Uses stereo image pairs to recover the scale
    - Scale can not be recovered from monocular images
- Performs inference on monocular images
- Pose and dense estimations for recovering the trajectory
  - One CNN for depth estimation
  - Another CNN for pose estimation
- Outperforms previous methods in almost all cases
- Plans to extend to a full SLAM system

Contributors

- Bolaños Tlahui
  - Objective Losses
- Kilkkilä Miikka
  - Probably not participating?
- Kurki Lauri
  - Evaluation
- Rehn Aki
  - Organization, introduction, conclusions
- Zaka Ayesha
  - UnDeep VO Key Contributions
- Zhao Zhao
  - System Overview