

Free your Camera: 3D Indoor Scene **Understanding from Arbitrary Camera Motion**



A. Furlan¹, S. Miller², D. G. Sorrenti¹, L. Fei-Fei², S. Savarese²

¹Computer Science Department – University of Milano - Bicocca ²Computer Science Department – Stanford University

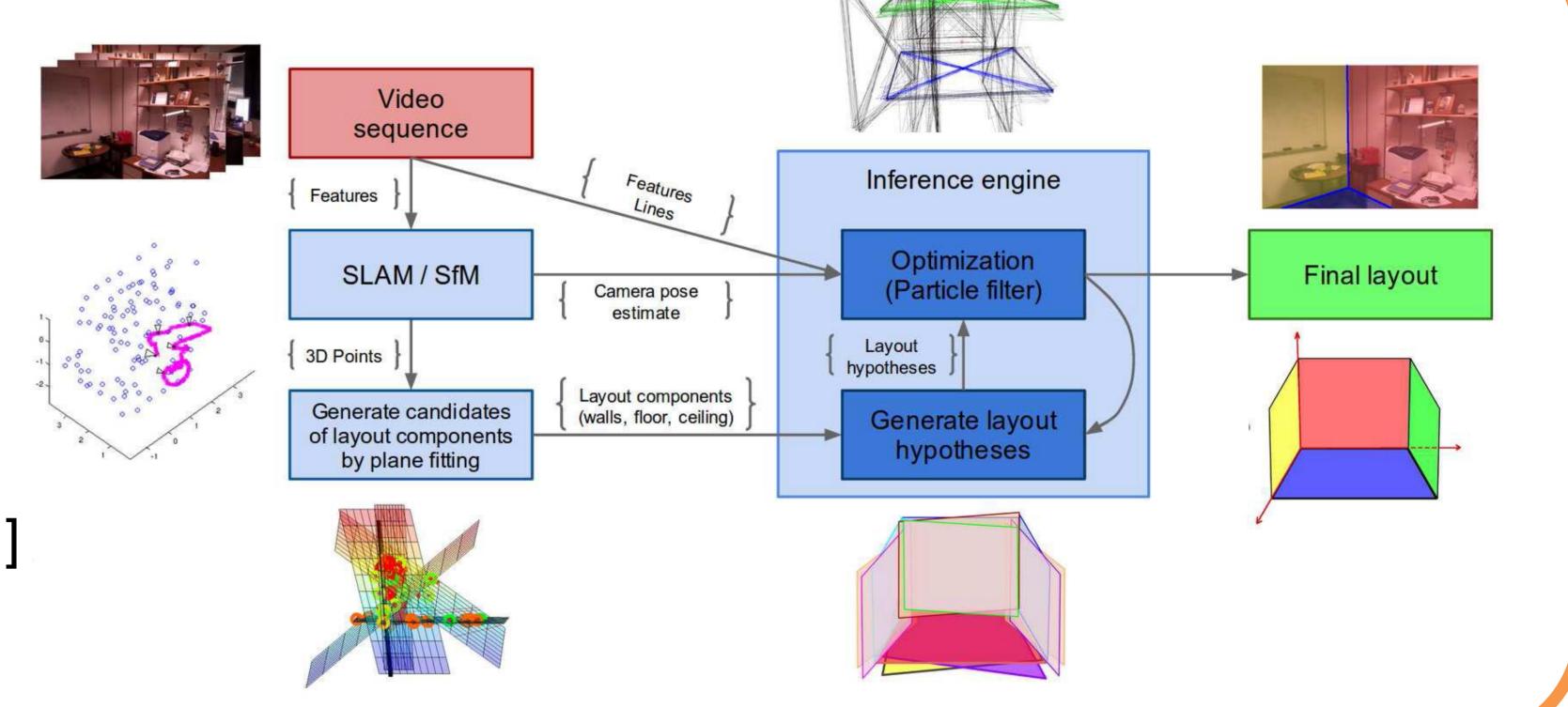
{furlan, sorrenti}@disco.unimib.it

{sdmiller, feifeili, ssilvio}@stanford.edu

Overview

Problem statement

•3D Indoor semantic layout estimation Full 6DoF freely moving observer No hard Manhattan assumptions Near real-time performances





Experiments

Tested on the Michigan Indoor Corridor dataset [1] Introduction of a new challenging dataset

Proposed approach

Sparse 3D reconstruction

Estimate camera pose and a sparse map with: •Fast Monocular V-SLAM – All frames in real-time Slow VisualSfM – Few frames to preserve real-time

Layout definition

Made of layout components (walls, ground, floor) Walls are orthogonal to the ground plane Arbitrary number of walls, not mutually orthogonal

Experiments

- Michigan Indoor Corridor dataset [1]
 - Indoor video sequences from a mobile robot
 - Object-free corridor scenes
- Proposed dataset
 - Indoor video sequences from hand-held smartphone
 - Various cluttered scenes
 - Offices, corridors, large rooms
 - Complex layouts (not box-room, not Manhattan)
- Results

Layout estimation

Iterative RanSaC plane fitting Large number of inaccurate layout components Initialize layout hypotheses as random combinations of layout components Local perturbation and optimization of hypotheses Each hypothesis is a particle in a particle filter

Scoring hypotheses

 $P_{t} = \prod P_{f}^{i} P_{o}^{i}(\theta_{i}) P_{r}^{i}(e_{r}^{i}) \prod P_{m}^{ij}(\phi_{ij}) P_{s}^{ij}(d_{ij}^{-1})^{p_{ij}} (P_{w}^{ij})^{a_{ij}}$

Terms in the score function enforce fitness (P_f), orthogonality to ground (P_0), reprojection error (P_r), wall-to-wall orientation (P_m), simplicity (P_s), wall-to-wall

- Our method significantly outperforms [1], [2] and [3] in both classification accuracy and execution time
- Table below:
 - Left Results on the Michigan Indoor Corridor dataset [1] (excluding and including ceiling)
 - Right Results on the proposed dataset (classification accuracy and computation time)



Method	Excl. ceil	Incl. ceil
[1]	90.58	82.17
[2]	82.62	83.30
[2]+MRF	81.44	82.13
[3]	84.70	84.33
Our + VSLAM	86.92	87.01

Method	Clas. acc.	Avg. fps
Baseline	70.64	
[2]	59.29	0.17
[3]	73.59	0.03
Our + VSLAM	86.24	21.63
Our + VSfM	75.94	16.90

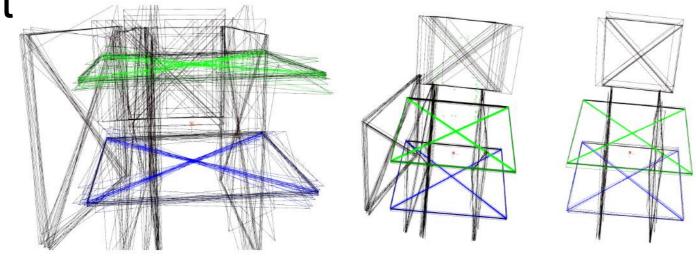
intersection (P_w).

Advantages:

- No hard Manhattan assumptions
- No *a priori* knowledge of the observer motions w.r.t. the scene Near-real-time performances (~20fps)

Particle filter implementation allows recovering from noisy and wrong initialization exploiting multimodal posterior, re-

sampling and particle clust



[1] Grace Tsai, Changhai Xu, Jingen Liu, and Benjamin Kuipers. Real-time indoor scene understanding using bayesian filtering with motion cues. In ICCV, 2011.

[2] Varsha Hedau, Derek Hoiem, and David Forsyth. Recovering the spatial layout of cluttered rooms. In ICCV, 2009. [3] Derek Hoiem, Alexei A. Efros, and Martial Hebert. Recovering surface layout from an image. IJCV, 75(1), 2007.

Conclusions

- Real-time oriented approach for indoor scene understanding
- Probabilistic framework to generate, evaluate and optimize layout hypotheses
- Extensive experimental evaluation, that demonstrates that our formulation outperforms state-of-the-art methods in both classification accuracy and computation time
- Dataset available: <u>http://www.ira.disco.unimib.it/free_your_camera</u> http://vision.stanford.edu/3Dlayout/

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