Computer Vision for Autonomous Systems - Part 2: A VMA Perspective

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https://publish.illinois.edu/visual-modeling-and-analytics/

















Our VMA Vision

Holistic (Computer/Robotic) Vision

Geometric Reconstruction meets Semantic Recognition for 3D holistic vision: Real-time, robust, geometry-centric vision

<u>Where</u>: geometry, location...

Reconstruction

- Real-time camera pose localization
- 3D environment mapping
- **Depth** and **motion** estimation
- Large-scale urban reconstruction

<u>What</u>: semantics, action...

Recognition

- Visual place/scene recognition
- **Object** recognition, localization
- Human re-identification
- Action recognition, tracking

• Multiple sensors

- Modern vehicles
- Moving robots
- Opportunistic scan

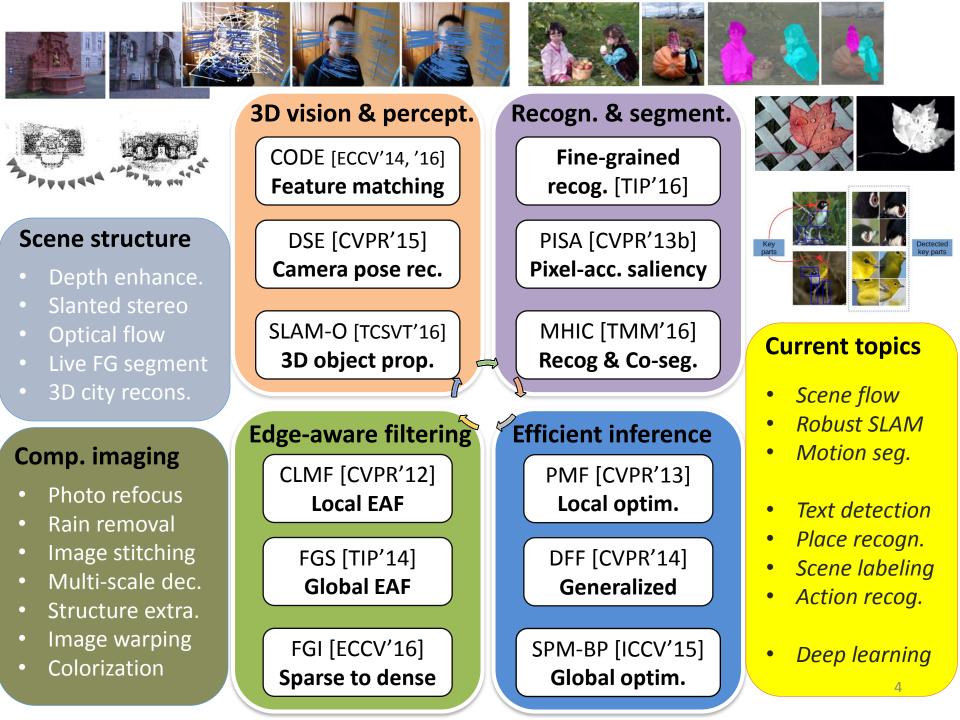
How: model, solve, compute

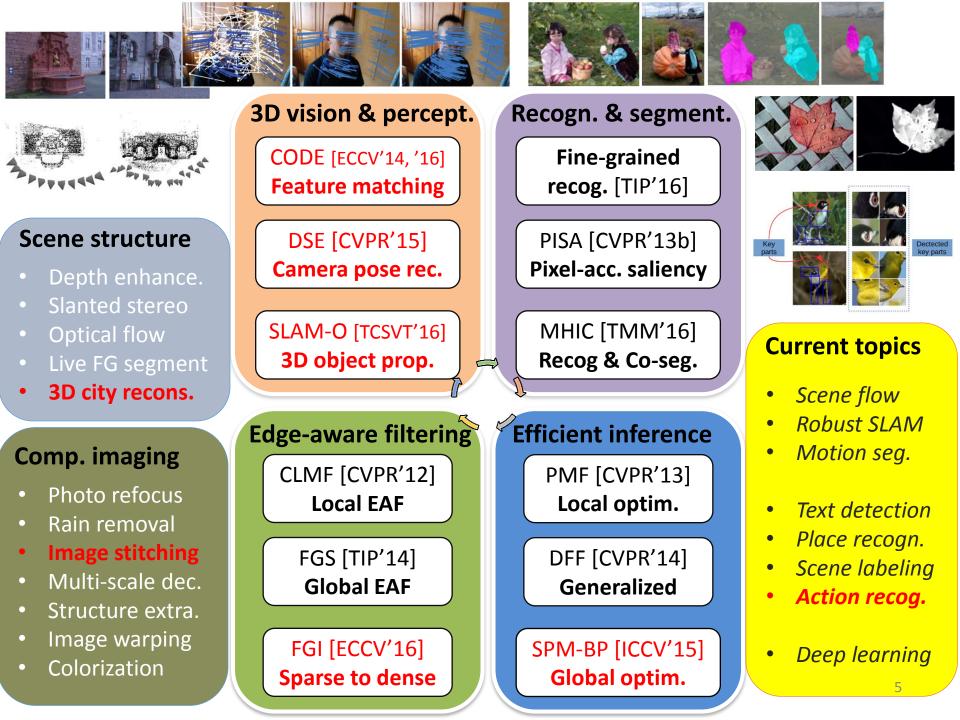
Key techniques

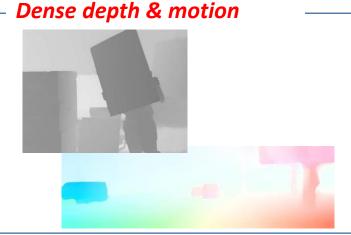
- Geometry-aware filtering
- Fast randomized algorithms
- Efficient inference models
- Deep learning innovation

• Mobile cameras

- Big visual data
- Rich annotations
- Powerful machine





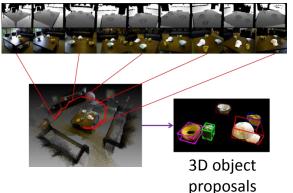


Camera pose localization

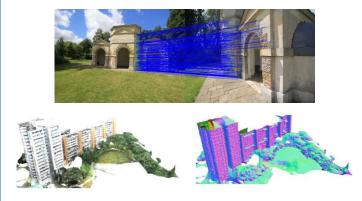




- Localizing 3D object proposals



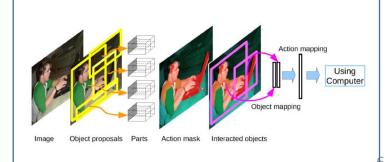
Feature matching and mapping



Stitching & visualization



Action recog. w/ min. labelling



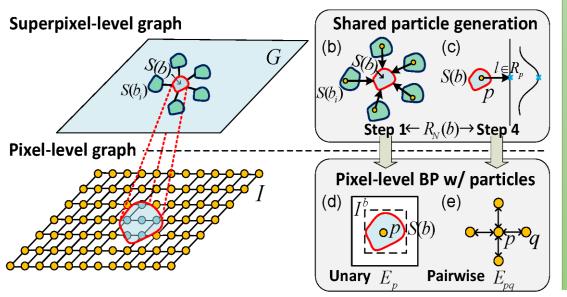
Related VMA Tech

#1 Perceiving Depth & Motion for AS: Matching

A general, efficient discrete optimizer for stereo & flow & etc

$$E = \sum_{p} E_p(l_p; W) + \sum_{p} \sum_{q \in \mathcal{N}_p} E_{pq}(l_p, l_q)$$

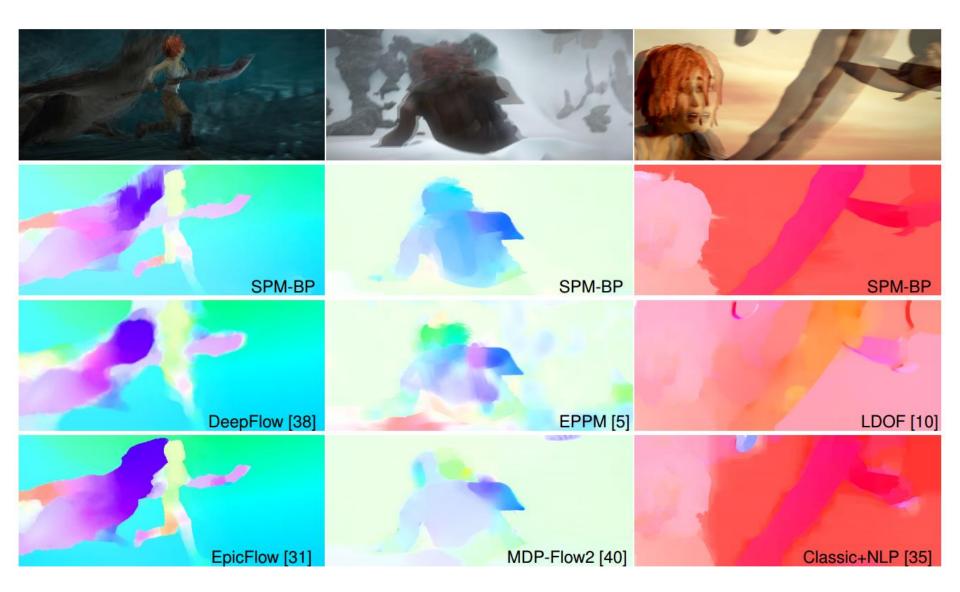
- ✓ General MRF for labeling problems
- ✓ Superior for huge label spaces
- ✓ 50-100x faster than [PMBP]
- ✓ Edge-aware filtering + PM + BP





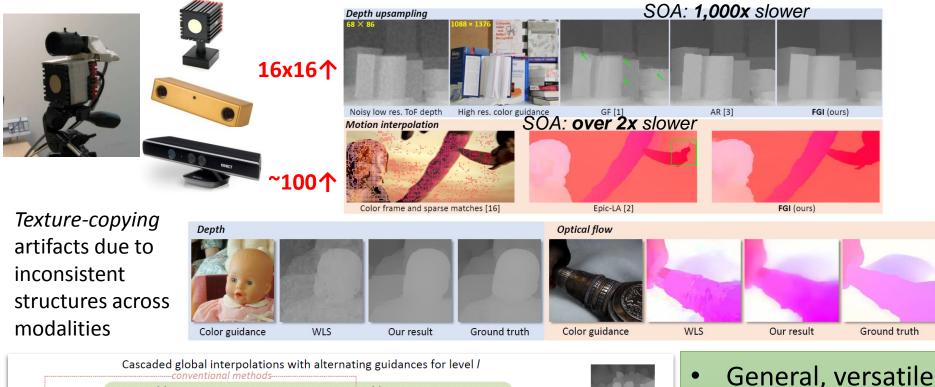


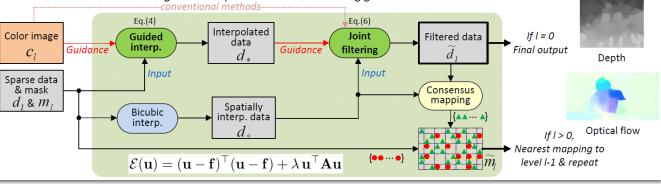
- A simple formulation w/o
 - complex energy terms
 - a separate *initialization*
- Achieved top-tier perform., even when compared to *task-specific* techniques
- Applied on the full pixel grid, w/o coarse-to-fine



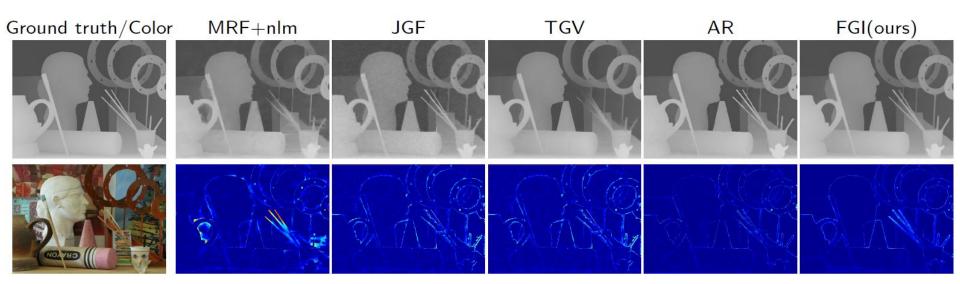
#1 Perceiving Depth & Motion for AS: Interpolation

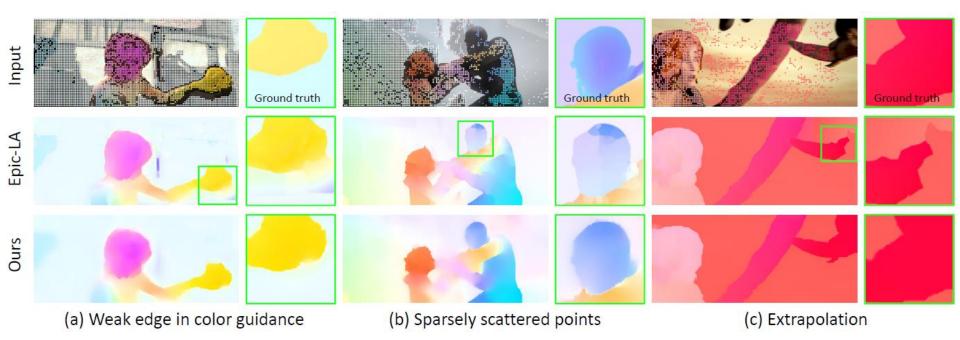
A unifying framework for fast guided (global) interpolation





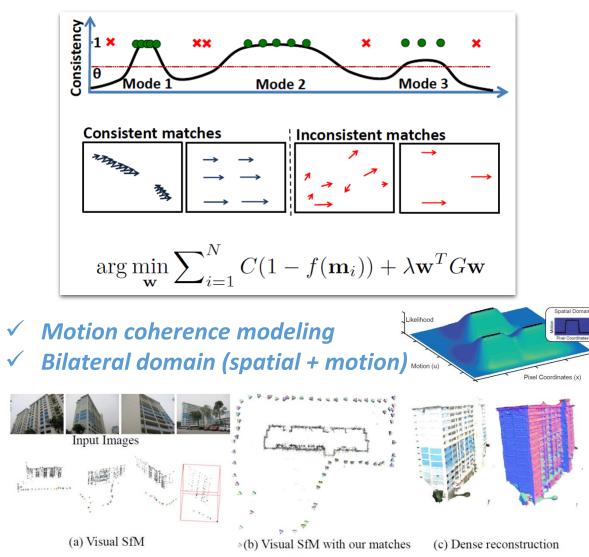
- General, versatile for various tasks
- Simple & effective
- Fast computation
- [FGS] in OpenCV
- * Y. Li et al., "Fast Guided Global Interpolation for Depth and Motion," ECCV 2016 (spotlight)
 * D. Min et al., "Fast Global Image Smoothing Based on Weighted Least Squares," TIP 2014

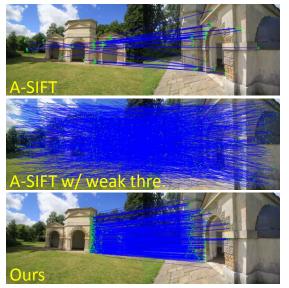




#2 Wide-Baseline Matching & 3D Mapping for AS

A reliable feature matcher for pose and 3D reconstruction





- Providing a number of
 matches, while having
 almost *no* outliers
- w/ RANSAC to handle repetitive structures
- Highly reliable 2-view pose for SfM, mapping
- * W.-Y. Lin et al., "RepMatch: Robust Feature Matching and Pose for Reconstructing Modern Cities," ECCV 2016 12 * W.-Y. Lin et al., "Bilateral functions for global motion modeling," ECCV 2014



A set of multi-view images [42]



Visual SfM [3], [43], [44], [45], [46]



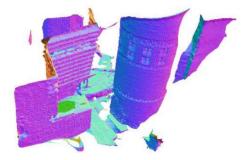
Agisoft [47]: A commercial 3D reconstruction software



Visual SfM using feature matches returned by A-SIFT w CODE









Our ADSC lab reconstructed w/ only color images ¹³

#3 Structure-First Camera Pose Estimation for AS

A unified **pose estimation** approach to **man-made scenes**

 $\frac{d_i'}{d_i} = \lambda_i, \ \frac{d_j'}{d_i} = \lambda_j$

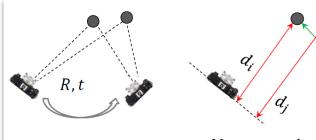
All directions (single plane)

Translation direction

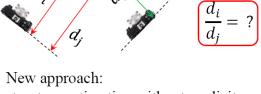
30 Translation direction

60

60



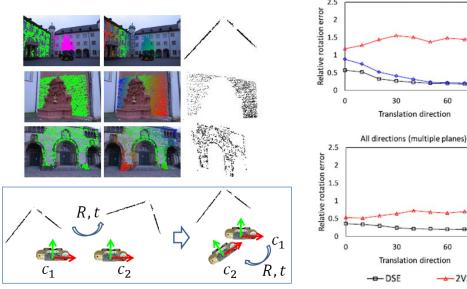
Standard approach: relative pose + triangulation



structure estimation without explicit camera pose computation

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- Using homography estimation
- Euclidean rigidity constraint







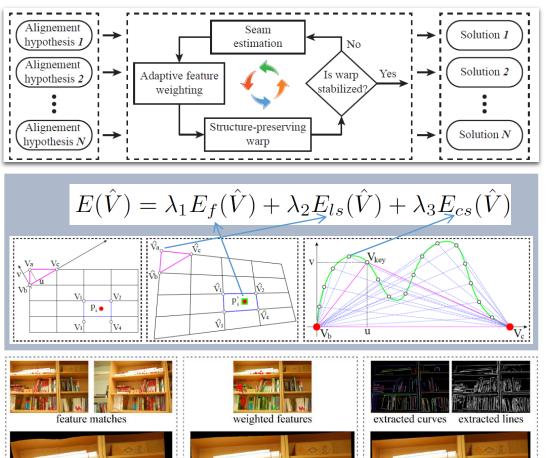


- Reversing the std. pipeline
- No model selection regardless of #planes
- Significant outperformance in stability & accuracy
- Esp. for *sideway* motions

* N. Jiang et al., "Direct structure estimation for 3D reconstruction," CVPR 2015

#4 Large Parallax Stitching & Visualization for AS

A high-quality image **stitching** method to handle **large parallax**



with weighted features

content-preserving warp (CPW)



- Coupled local alignment and seam estimation
- #alignment hypotheses significantly reduced
- Curve structure constraint
- State-of-the-art quality for challenging scenes

* K. Lin et al., "SEAGULL: Seam-guided local alignment for large parallax image stitching," ECCV 2016

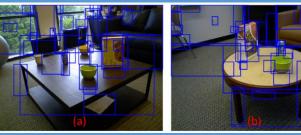
Structure-preserving warp





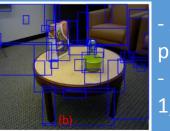
#5 Localizing 3D Object Proposals for AS

An online method for **3D object proposals** using **RGB-D videos**

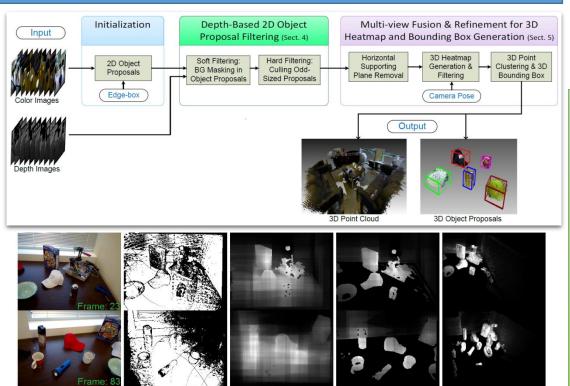


(b) Matched pixels

(a) Color image

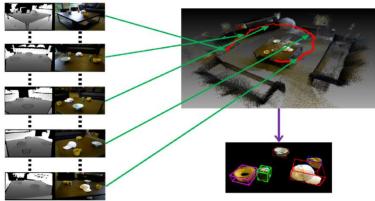


- Allow any 2D object prop., e.g. Edge-box - No good bbox out of 1,000 for yellow bowl



(c) Weighted 2D

heatmap H_{2D}



- RGB-D video for 3D object proposals w/o detectors
- High precision, much more accurate than state-of-art
- Class-independent for *new* data collection on the fly
- Good for improved SLAM, navigation, object search

17 * R. Pahwa et al., "Locating 3D Object Proposals: A Depth-Based Online Approach," TCSVT 2016 (minor revision)

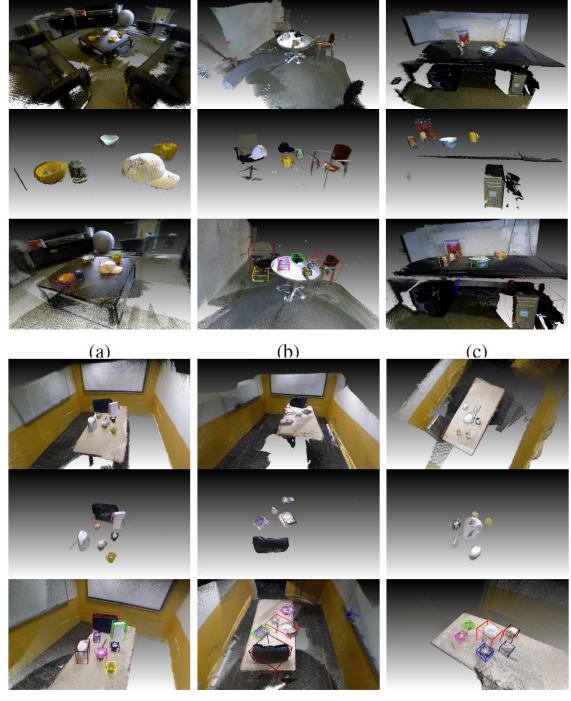
(e) Global heatmap H_{3D}

projected onto image plane

(d) Heatmap after plane

removal \tilde{H}_{2D}

UW-RGBD dataset



Point cloud

Top-ranked filtered points

Resulting 3D object proposals

Point cloud

Top-ranked filtered points

Resulting 3D object proposals

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Our dataset

(d)

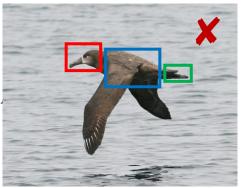
(e)

(f)

#6 DNN Recognition w/ Minimum Annotation Efforts

Red-bellied Woodpecker vs. Red-headed Woodpecker [Zhang et al. TIP'16]





- Without human-annotated bounding-boxes for parts
- 78.92% on CUB 200-2011 datasets of 200 bird species



[Zhang et al. TIP'16-2]

- Without requiring human bounding-boxes
- On a single-image
- 83.23% on PASCAL VOC
 2012 of 10 action classes

https://publish.illinois.edu/visual-modeling-and-analytics/research/



Visual Modeling and Analytics of Dynamic Environments for the Mass

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Research

This project will focus on addressing the following fundamental challenges key to a multitude of visual data analytics applications: 1) raw visual data cleaning; 2) visual data registration and fusion; and 3) visual data analytics and management. The existing efforts, either from the academia or the industry, are not capable of robustly and efficiently modeling, analyzing, and fusing continuous or discrete visual data captured by individuals or big companies.

Grounded on the recent novel and exciting developments described in this project, we plan to extend, generalize, and optimize them to address the aforementioned key challenges of visual modeling and analytics for the masses using the following research directions:

- Localization recovering the geometric locations of the user, the camera viewpoint, or the objects in the environment around the user;
- Registration aligning and modeling dynamically captured images and measurements of the scene over different time and viewpoints together;
- Inference estimating and analyzing the semantic information of the scene from the registered visual information and recovered geometric information.

We aim at achieving both high robustness and accuracy for the above tasks at unprecedented processing speeds on commodity computing devices and mobile cameras, often producing more than one or two orders of magnitude of speedup over the existing state-of-the-art solutions.

We have been working on the following clusters of research topics, and now are actively innovating in a broader scope.

- Edge-aware filtering and joint filtering
- Dense stereo, optical flow and view synthesis
- Dense correspondences across scenes
- Motion coherence and wide-baseline matching
- <u>Structure from motion, 3D</u> reconstruction
- <u>Computational photography, image</u> <u>enhancement</u>
- <u>Efficient inference for continuous MRFs</u>
- Fast guided global interpolation
- <u>Saliency, recognition, cosegmentation</u>
 - Hash techniques 20

Thanks