An Adaptive Framework for 3D Data Fusion with Sensors' Error Prior

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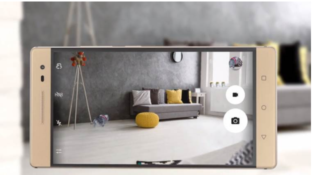
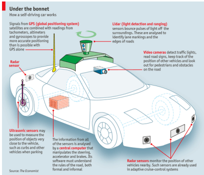
Outline

Requirement of 3D Data of the **Real World**

- **Housework**: sweeping robot
- **Entertainment**: augmented reality
- **Medical Treatment**: 3D model of organs
- **Transportation**: self-driving cars

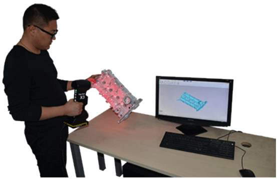


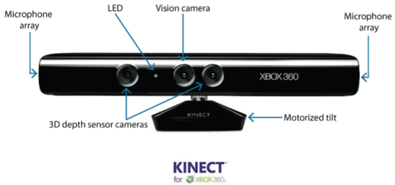


Sensors to Collect 3D Data

Human being's industry level is limited: **trade-off** between

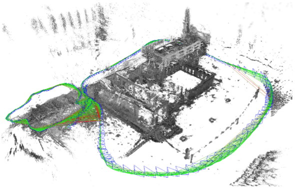
- **Working Condition**
- **Accuracy**
- **Speed**
- **Density**



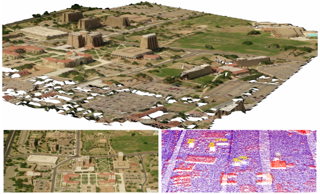


Necessities to Fuse 3D Data

- **Viewpoints**: partial view → comprehensive model
- **Sensor type**: multiple sensors → complex scenes
- **Time**: incremental data input through time



J. Engel, *et al.* LSD-SLAM: Large-scale direct monocular SLAM. In ECCV 2014



R. Cabezas, *et al.* Aerial Reconstructions via Probabilistic Data Fusion. In CVPR 2014

R. A. Newcombe *et al.* DynamicFusion: Reconstruction and Tracking of Non-rigid Scenes in Real-Time. In CVPR 2016

Outline

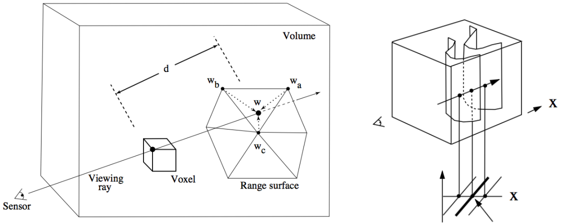
Signed Distance Field

- **Core**: an implicit surface function stored in voxels

$$d_{i,v} = r_z^T(x(v) - x(z))$$

$$D_{i+1,v} = \frac{W_{i,v}D_{i,v} + w_{i,v}d_{i,v}}{W_{i,v} + w_{i,v}}, W_{i+1,v} = W_{i,v} + w_{i,v}$$

- Extract surface at zero-crossing points
- Not explicitly involve error prior



B. Curless and M. Levoy. A Volumetric Method for Building Complex Models from Range Images. In SIGGRAPH, 1996

Inverse Model

- **Core**: model $P(M \mid z)$, infer map from sensor readings

$$\frac{P(M_v \mid z_1, \cdots, z_i)}{P(\bar{M}_v \mid z_1, \cdots, z_i)} = \frac{P(M_v \mid z_i)p(\bar{M}_v)p(M_v \mid z_1, \cdots, z_{i-1})}{p(\bar{M}_v \mid z_i)p(M_v)p(\bar{M}_v \mid z_1, \cdots, z_{i-1})}$$

- **Easy** to implement; efficient
- **Hard** to be reasonable: ad hoc

K. Konolige. Improved Occupancy Grids for Map Building. Autonomous Robots, 4(4):351–367, 1997

Generative Model

- **Core**: model $P(z \mid M)$, measure the generation of sensor readings

$$M_i = \arg\max_m P(z_i \mid m) \mid_{m=M_{i-1}}$$

- **Easy** to involve sensor error model, reasonable
- **Hard** to compute; costly

S. Thrun. Learning Occupancy Grid Maps with Forward Sensor Models. Autonomous Robots, 15(2):111–127, 2003

Related Work

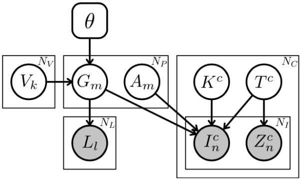
Probabilistic Graphical Model

Multi-Modal Data Fusion

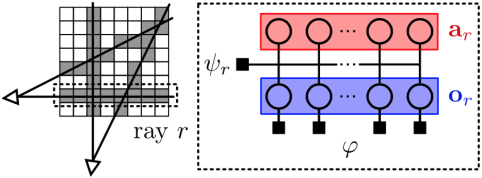
- Fusing data including LiDAR, image with GPS and camera pose
- **Error prior** at the sensor level (≥ 1 sensors) but hard to extend

Probabilistic Volumetric Reconstruction with Ray Potential

- Fusing images with ray potential
- **Error prior** at the sensor level (1 sensor) but not extended



R. Cabezas, *et al.* Aerial Reconstructions via Probabilistic Data Fusion. In CVPR 2014



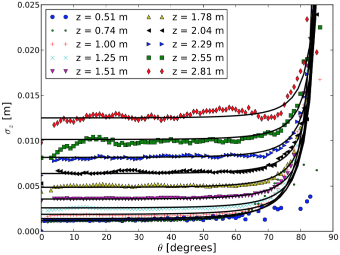
A. O. Ulusoy *et al.* Patches, planes and probabilities: A non-local prior for volumetric 3D reconstruction. In CVPR 2016

Outline

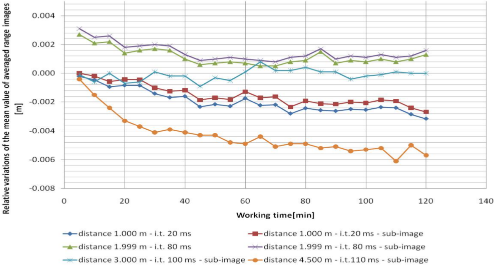
- Explicitly consideration of sensors' **error prior**
- A consistent **error model** for each 3D data point
- An adaptive **generative method** to merge 3D data with proposed **error model**
- Ability to **extract surface** after data fusion

Error Model of Sensors' Reading on Rays

- Model each scanned point z_i along a ray r_i with depth measurement d_i
- Explicitly considering **error prior** σ_i for each data point z_i
- To simplify, σ_i is constrained along r_i



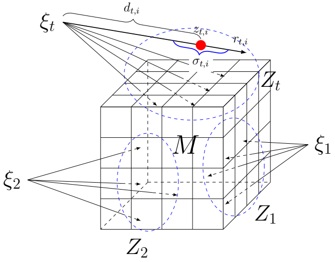
C. V. Nguyen *et al*. Modeling Kinect Sensor Noise for Improved 3D Reconstruction and Tracking. In 3DIMPVT 2012



F. Chiabrando, *et al*. Sensors for 3D imaging: Metric evaluation and calibration of a CCD/CMOS time-of-flight camera. Sensors 9.12 (2009).

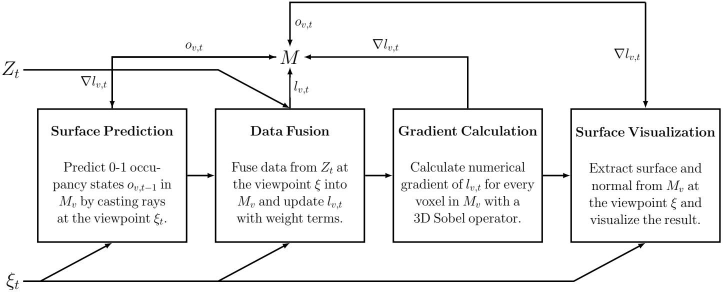
Multiple Sensors

- ξ_t: 3D pose of sensor
- Z_t: the collection of measurements $z_{t,i}$
- $x(z_{t,i})$: transforms $z_{t,i}$ into the coordinate system of M



Volumetric Map

- **Prediction**: $o_v \in \{0, 1\}$, is surface (occupied)?
- **Probability**: $l_v \in (-\infty, \infty)$, log-odds of the probability



Pipeline

- **Surface prediction**: predict surface o_v
- **Data fusion**: update volumetric probability map l_v providing Z and ξ
- **Gradient computation**: compute gradient ∇l_v around surfaces
- **Surface visualization**: determine surface and normal

How M Generates z

- Voxels $\boldsymbol{c}$ in M along ray r potentially generates z:

$$P(z \mid M) = \sum_j P(z, c_j \mid M) = \sum_j P(z \mid c_j, M) P(c_j \mid M)$$

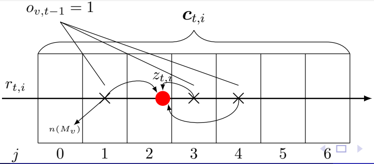
- How a voxel c generates z with error prior σ_z:

$$P(z \mid c_j, M) = \mathcal{N}(x(c_j); x(z), \sigma_z)$$

- Whether a voxel c is hit or miss

$$P(c_j \mid M) = P_{hit}(c_j \mid M) \prod_{k<j} (1 - P_{hit}(c_k \mid M))$$

$$P_{hit}(c_j \mid M) = o_j \cos(n(c_j), r)$$



From Joint Distribution to Voxel-wise

- $P(z \mid M) = P(z \mid M_v, M_{-v}) \rightarrow$ joint to separate
- $P(z \mid \boldsymbol{M_v}, M_{-v})$: probability that M generates z when M_v is occupied
- $P(z \mid \boldsymbol{\bar{M}_v}, M_{-v})$: probability that M generates z when M_v is free
- Enumerate M_v state **at current** and M_{-v} state **at the previous timestamp.**

From a Bunch of Points Z to Separate Points z

- Independency assumptions: z a independently sampled by the sensors
- $P(Z \mid M_v, M_{-v}) = \prod P(z \mid M_v, M_{-v})$

Voxel-wise Updating: Bayesian Rules

- Bayesian rule:

$$P(M_v \mid M_{-v}, Z_{1:T}) = \frac{P(Z_T \mid M_v, M_{-v}) P(M_v \mid M_{-v}, Z_{1:T-1})}{P(Z_t \mid M_{-v}, Z_{1:T-1})}$$

- Dual form with division operation to eliminate denominators:

$$\frac{P(M_v \mid M_{-v}, Z_{1:T})}{P(\bar{M}_v \mid M_{-v}, Z_{1:T})} = \frac{P(Z_T \mid M_v, M_{-v})}{P(Z_T \mid \bar{M}_v, M_{-v})} \frac{P(M_v \mid M_{-v}, Z_{1:T-1})}{P(\bar{M}_v \mid M_{-v}, Z_{1:T-1})}$$

- Log form:

$$l_{v,T} = \log \frac{P(Z_T \mid M_v, M_{-v})}{P(Z_T \mid \bar{M}_v, M_{-v})} + l_{v,T-1} = \sum \log \frac{P(z_{T,i} \mid M_v, M_{-v})}{P(z_{T,i} \mid \bar{M}_v, M_{-v})} + l_{v,T-1}$$

- **Interpretation**: the contribution of generating all points in Z is positive or negative if M_v is occupied (given M_{-v})

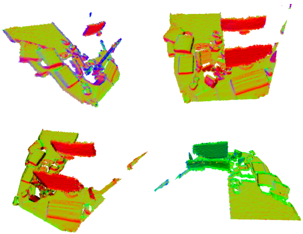
Surface Extraction

- The 1st local maximum $P(M_v \mid M_{-v}, Z_{1:T})$ along a ray
- $r^T \nabla P(M_v \mid M_{-v}, Z_{1:T}) = 0$
- Numerical gradient: 3D Sobel descriptor on each voxel
- Generalization of SDF:

$$r^T \nabla \log \mathcal{N}(x; z, \sigma) = \frac{\boldsymbol{r}^T (z - x)}{\sigma^2}$$

Normal Estimation

- Interpolation of ∇P is not proper
- $\nabla (r^T \nabla P)$ as an approximation



Outline

TUM: J. Sturm, *et al.* A benchmark for the evaluation of rgb-d slam systems. In IROS, 2012

- Depth images from a moving Kinect
- Error prior from C. V. Nguyen *et al.* Modeling Kinect Sensor Noise for Improved 3D Reconstruction and Tracking. In 3DIMPVT 2012
- Compared against Signed Distance Function (SDF)

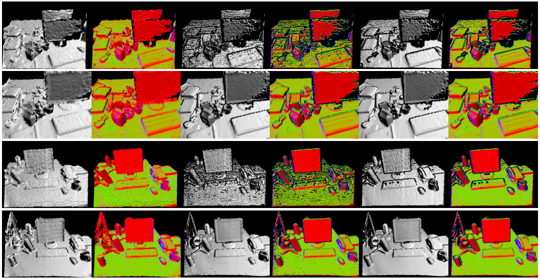


Figure: Surface and normal map extracted from M during the fusion of data from multiple viewpoints.

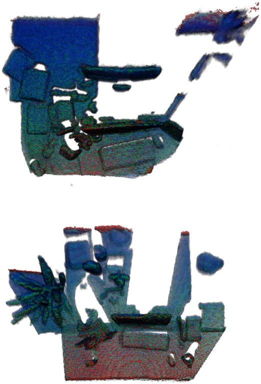
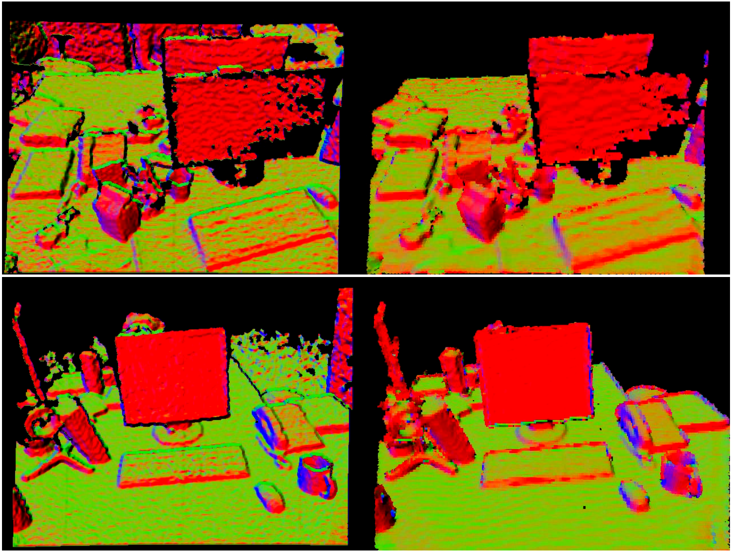


Figure: Probability color map generated by Volume Rendering

Experiments
TUM



Experiments

KITTI: A. Geiger, *et al.* Are we ready for autonomous driving? the kitti vision benchmark suite. In CVPR 2012

- Aligned depth images from a LiDAR and a stereo camera pair
- Only 1 frame: the scene is too large for GPU
- Error prior from J. Engel, *et al*. Semi-dense Visual Odometry for a Monocular Camera, In ICCV 2013
- Compared against SDF

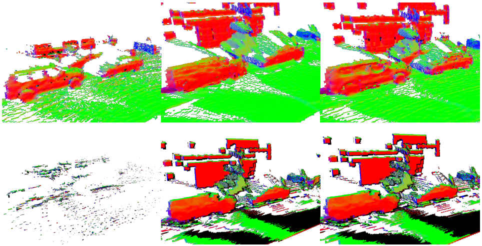


Figure: Normal map extracted from M with LiDAR data only, stereo camera data only, and both.

Figure: Probability color map generated by Volume Rendering.

Conclusions and Future Work

Conclusions

- Emphasizes **error prior** per data point
- **Adaptive, generative, incremental** framework
- Surface extraction

Future Work

- Improve surface quality
- Use memory-saving data structure to integrate more data
- Take unknown pose ξ into consideration

Thank you!