Heterogeneous Data Fusion Experiments

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Outline

3D environment perception

Principle of 3D sensing:

$$3D = 2D + 1D$$

Terminology

Sensing techniques:

- passive
- active

Common 3D sensing approaches:

- Stereo camera
- Laser scanner
- Projected light / Time of flight

Morphological matrix:

Table: Morphological matrix

	No camera	*Camera*	*Stereo*
No range		RGB	XYZ-RGB
With range	XYZ	RGB-D	Fused

Need for heterogeneous data fusion

Sensor array for environment understanding

- Depth sensors (Velodyne lidar, Mesa time of flight, etc)
- Several color IR/cameras.

Figure: Robot platform for 2D/3D outdoor perception

NATO robotics field trial in 2014

The custom built robot in the NATO bomb disposal test field

Example data flow

Data flow for sensor processing nodes

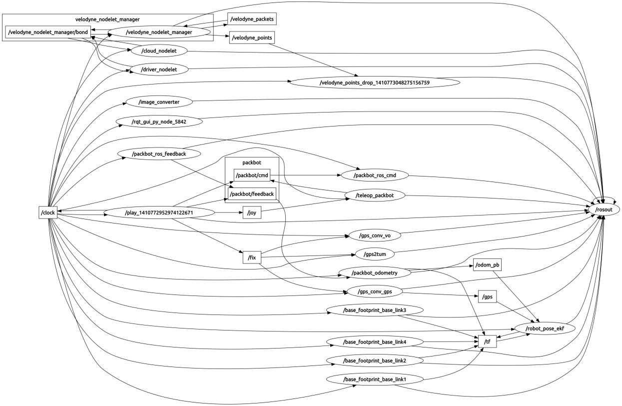
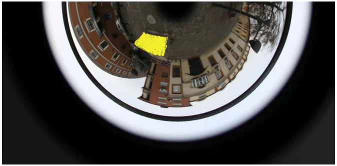


Figure: The interconnected nodes used for communications

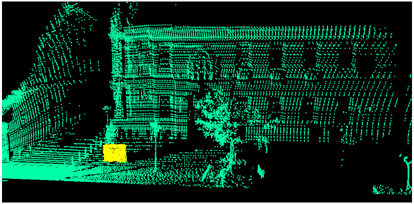
2D/3D fusion challenges

What happens for nonlinear, non-classical camera ?

(a) IR image



(b) Omni camera data



(c) Depth information

2D/3D fusion challenges within robotics

An actual research domain:

- Research centers: WG, DLR, CoTeSYS, etc.
- Workshops, summer schools: BRiCS, ROS, ICCV, etc.

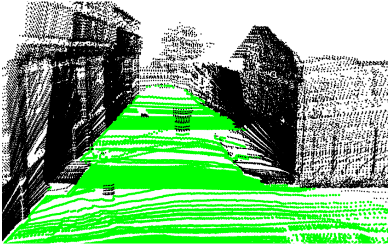


Figure: Outdoor scan example

Outline

3D data acquisition

Several challenges for handling 3D depth data from different sensors

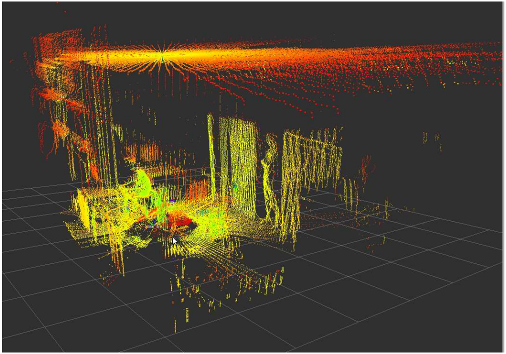


Figure: 3D data acquired from rotating laser base

3D data preprocessing/filtering

Various filters applied at the raw 3D data:

Passthrough - reduce the shadowing and close reflection.

Voxelgrid - ensures a uniform sampling of the data.

Statistical - outliers removal.

Major plane removal

Iterative algorithms

Iterative closest point (ICP) based variant

Figure: ICP based indoor map using Mesa and lidar

Normal distribution transform (NDT) - planes

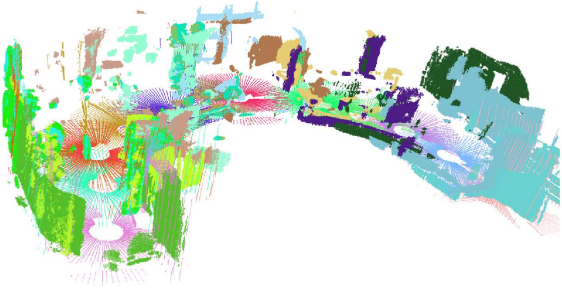


Figure: NDT based 3D registration for Mesa and lidar

Comparison

ICP and NDT comparison using the metric:

$$I(x) = \frac{1}{\sigma^2}\left[\sum_i \begin{pmatrix} -A_i^2 & A_i \\ -A_i & I_3 \end{pmatrix}\right]^{-1} \quad (1)$$

where σ denotes sensor noise, A_i is the skew matrix the i^{th} point, and $I(x)$ denotes the Fisher information matrix.

Table: Evaluation of the registration on public dataset.

	t_x	t_y	t_z
NDT	1.60 ± 1.85	1.32 ± 1.85	2.1 ± 3.29
ICP	2.13 ± 2.17	1.42 ± 2.28	1.82 ± 3.17
CombinedNDT	1.32 ± 1.48	1.22 ± 1.86	1.71 ± 2.15

Evaluation using ground truth

NDT based registration using both Mesa and lidar results

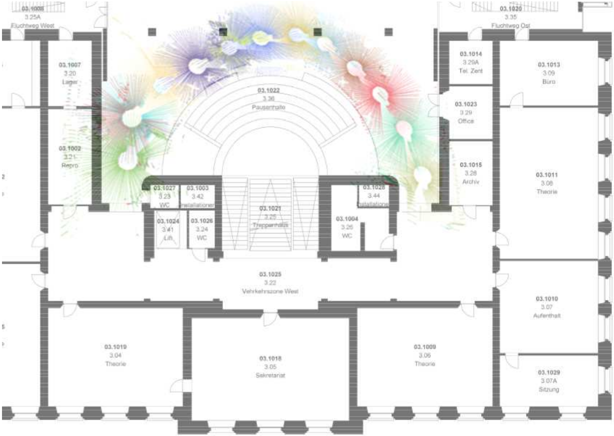
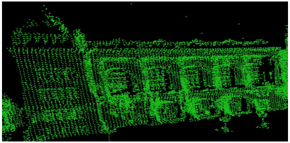


Figure: NDT based 3D registration - comparison

Outline

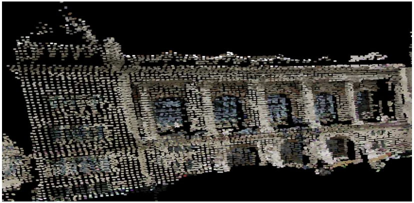
1. Introduction
2. Depth data fusion
   - Datasets
   - 3D registration algorithms
3. 2D/3D Fusion
   - The main problem with 2D/3D registration

Register central camera and depth data



(a) Depth image

(b) Omni camera data



(c) Fused information

Levente Tamas, Robert Frohlich, and Zoltan Kato. Relative Pose Estimation and Fusion of Omnidirectional and Lidar Cameras. In Proceedings of the ECCV Workshop on Computer Vision for Road Scene Understanding and Autonomous Driving, Lecture Notes in Computer Science, Zurich, Switzerland, September 2014.

Problem formulation

Registration without point correspondences! Use the projection equation:

$$\mathbf{x} = \mathbf{P}\mathbf{X} \tag{2}$$

for which an arbitrary nonlinear function can applieds

$$\omega(\mathbf{x}) = \omega(\mathbf{P}\mathbf{X}), \tag{3}$$

and the integral equation of becomes

$$\int_D \omega(\mathbf{x})\mathbf{dx} = \int_{\mathbf{PF}} \omega(\mathbf{z})\mathbf{dz}. \tag{4}$$

Thus, an arbitrary number of equations can be generated.

Levente Tamas and Zoltan Kato. Targetless Calibration of a Lidar - Perspective Camera Pair. In Proceedings of ICCV Workshop on Big Data in 3D Computer Vision (ICCV-BigData3DCV), Sydney, Australia, pages 668-675, December 2013. IEEE.

Fused results

Fusing heterogeneous input data

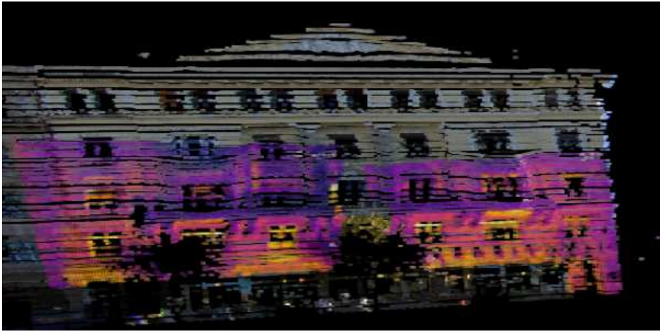


Figure: Fusing omni, ir over the same depth data

Thank you!

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References I

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Mathematical Techniques in Multisensor Data Fusion.
Artech House, 2004.

RANSAC background

1. Select the scene control points:
   - Randomly select a couple of points s_1 and s_2 in the set $\mathscr{S}$ and compute the distance $d_{\mathscr{M}} = \|s_1 - s_2\|$.
2. Select the model control points:
   - Select in the $\mathscr{M}$ a couple of points (m_1, m_2) with the constraint $d_{\mathscr{M}} \approx d_{\mathscr{S}}$
3. Estimate the model parameters
   - Find the transformation parameters R and T
   - Apply the transformation to the set $\mathscr{S} : \mathscr{S} = g(R, T)\mathscr{S}$
4. Verify the model
   - Count the number of inliers of points in the set $\mathscr{S}$
   - If the max iter is not exceeded, go back to the first step
   - select the hypothesis with the largest number of inliers. The solution to the least squares problem $(R, T)^*$ is returned.
   - if the found number of inliers is less than the minimum threshold, then no result is returned.