

Computer Vision Systems Programming VO 3D Vision Applications

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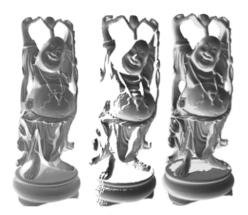
Topics

CV applications utilizing scene geometry (3D data)

► Focus on those based on Kinect



Images by Ryuzo Okada, Shotton et al. 2011, Newcombe et al. 2011



Images from Curless and Levoy 1996



Construction of accurate 3D models from range data

Usually involves combing multiple point clouds

Accomplished in two steps

- ▶ Align range data (map to common coordinate system)
- Merge range data in a way that minimizes errors

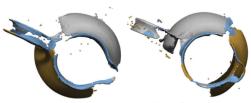
Often followed by surface reconstruction



Range Data Alignment – Iterative Closest Points

Popular method for aligning two point clouds $\{r\}$, $\{s\}$

- lacktriangle Goal is to find parameters $oldsymbol{ heta}$ of some transformation $\mathcal T$
- Usually assuming a rigid transformation



Images from Aiger, Mitra, and Cohen-Or 2008

Range Data Alignment - Iterative Closest Points

Algorithm iterates between

- lacktriangle Finding point correspondences based on distance, $\{(r_n,s_n)\}_n$
- lacksquare Finding the $m{ heta}$ that minimizes $\sum_n \lVert \mathbf{r}_{r_n} \mathcal{T}(\mathbf{s}_{s_n}; m{ heta}) \rVert_2^2$

Converges towards a local minimum

lacktriangle Requires good initial estimate of $oldsymbol{ heta}$

https://www.youtube.com/watch?v=ii2vHBwlmo8



3D Reconstruction Range Data Merging – TSDF Fusion

Truncated signed distance functions (TSDFs)

- ► Similar to distance transforms in 3D (0 = surface)
- But distances are signed, measured along view rays

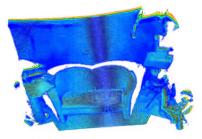
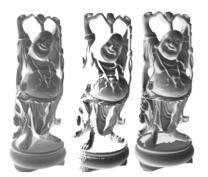


Image from https://www.youtube.com/watch?v=AjjSZufyprU

3D Reconstruction Range Data Merging – TSDF Fusion

Merged data = weighted average over aligned TSDF voxels

▶ Weights based on e.g. object distance, angle



Images from Curless and Levoy 1996



Kinect Fusion

Temporal fusion of Kinect depth maps

Based on the above methods (ICP & TSDF fusion)

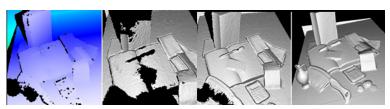
- lackbox But $\{r\}$ is synthesized from merged model
- Suppresses alignment error accumulation



Images from Newcombe et al. 2011

Kinect Fusion

https://www.youtube.com/watch?v=quGhaggn3cQ



Images from microsoft.com

3D Reconstruction Surface Reconstruction

Reconstruction of surface mesh from point cloud

- ▶ Results in a (locally) watertight 3D model
- Allows for further processing (e.g. texturing)

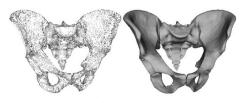
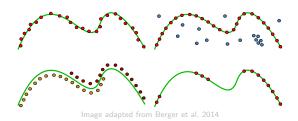


Image from Kazhdan 2005

3D Reconstruction Surface Reconstruction

Correction of point cloud errors

▶ Noise, outliers, alignment errors, missing data



Surface Reconstruction – Poisson Surface Reconstruction

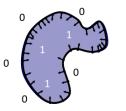


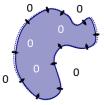
Images from Kazhdan, Bolitho, and Hoppe 2000

Surface Reconstruction - Poisson Surface Reconstruction

Define $\chi(\mathbf{x}) = 1$ if \mathbf{x} inside the object, 0 otherwise

- Surface is at $\chi(\cdot) = 0.5$
- $ightharpoonup
 abla \chi$ equals surface normal near surface, 0 otherwise



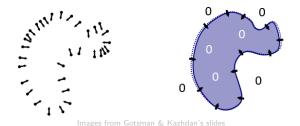


Images from Gotsman & Kazhdan's slides

Surface Reconstruction – Poisson Surface Reconstruction

Regard oriented points $\{(\mathbf{x}, \mathbf{n})\}$ as samples from $\nabla \chi$, $\nabla \chi(\mathbf{x}) = \mathbf{n}$

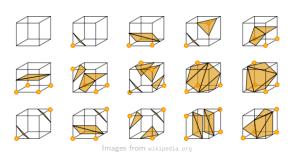
- lacktriangle Points define vector field ${\cal V}$ that corresponds to $abla \chi$
- Sought χ minimizes $\|\nabla \chi \mathcal{V}\|$



Surface Reconstruction – Poisson Surface Reconstruction

Once χ is known, the isosurface $\chi(\cdot) = 0.5$ can be extracted

Using marching cubes, for example



3D Reconstruction Software - Point Cloud Library (PCL)

C++ open-source library for point cloud processing Includes implementations of the above methods



Image from pointclouds.org

3D Reconstruction Software – Point Cloud Library (PCL)

Example: align two point clouds using ICP

```
typedef pcl::PointXYZ Pt; // a point
typedef pcl::PointCloud<Pt>::Ptr Pc; // a point cloud

// assume we have two clouds r, s (above notation)
pcl::IterativeClosestPoint<Pt, Pt> icp;
icp.setInputSource(s);
icp.setInputTarget(r);
icp.align(r, theta); // theta = initial estimate
theta = icp.getFinalTransformation(); // final estimate
```

Application Fields - Cultural Heritage

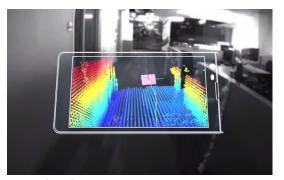
Preservation of physical artifacts



Image from Levoy et al. 2000

Application Fields - Virtual and Augmented Reality

Project Tango



mage from https://www.youtube.com/watch?v=Qe10ExwzCqk

Person Detection

3D data enables reliable person detection

- Robust motion detection
- ► Distinctive, invariant features



Person Detection Motion Detection

Reliable motion detection via background subtraction

- Measurements represent object distances
- Not affected by illumination, clothing, shadows



Person Detection

Scene geometry allows for distinctive, invariant features

▶ Object size, extent, volume, shape, ...

More on object detection later



Person Detection Applications – Breaking Assistance

https://www.youtube.com/watch?v=oU4XQvx010k









Image from Ryuzo Okada, Toyota

Person Detection

Applications – Interactive Art Installations



Image from ortlos.com

Person Detection Applications – Fall Detection (fearless)

Fall detection system developed at CVL

- Uses data from a single Kinect sensor
- Detects falls by tracking the height of persons



Person Detection

Applications – Entertainment (Kinect Player Pose Estimation)

https://www.youtube.com/watch?v=p2qlHoxPioM



Let's take a look at how this works

Assuming we have already detected the person

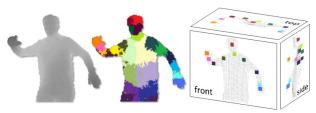


Image from Shotton et al. 2011



Estimate body part of each pixel independently

Perform clustering to obtain joint position proposals

Fit skeleton model to joint proposals

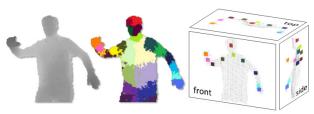


Image from Shotton et al. 2011



Pixel Classification

For each pixel \mathbf{x} with depth $d(\mathbf{x})$ compute $\Pr(w|\mathbf{x})$

- ▶ With w representing the body part, $w \in \{0, ..., 30\}$
- ▶ Note that this is a discriminative model



Image from Shotton et al. 2011

Pixel Classification

Classification using simple depth offset features f_{θ} ,

$$f_{\theta=(\mathbf{u},\mathbf{v})}(\mathbf{x}) = d\left(\mathbf{x} + \frac{\mathbf{u}}{d(\mathbf{x})}\right) - d\left(\mathbf{x} + \frac{\mathbf{v}}{d(\mathbf{x})}\right)$$



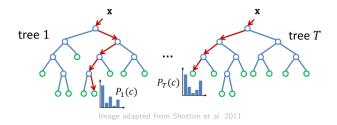
Image adapted from Shotton et al. 2011

Pixel Classification

One such feature is weak

But a strong classifier can be built by combining them

Implemented using a random forest



Pixel Classification - Random Forests

Random forest consists of T randomized decision trees

Each tree t consist of split and leaf nodes

Each split node consists of a feature $f_{m{ heta}}$ and a threshold au

- lacktriangle f x branches down based on $f_{m{ heta}_k} > au_k$
- ▶ Until a leaf node is reached, which stores $\Pr_t(w|\mathbf{x})$

Tree trained from training samples (\mathbf{x}, w)

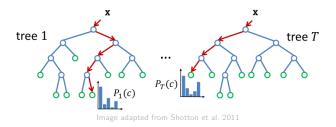
- ► Samples differ between trees
- \bullet θ_k, τ_k selected from random subset



Pixel Classification - Random Forests

All trees contribute to the result, $P(w|\mathbf{x}) = 1/T \sum_{t=1}^{T} \Pr_t(w|\mathbf{x})$

► This training & inference strategy is called **bagging**



Kinect Player Pose Estimation Joint Proposals

Project classified pixels to 3D

Perform clustering for each label w using mean-shift

https://www.youtube.com/watch?v=kmaQAsotT9s

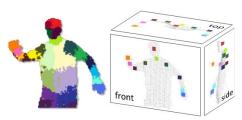


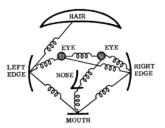
Image adapted from Shotton et al. 2011

Kinect Player Pose Estimation Skeleton Fitting

Results in n_w joint position proposals per body part w

Goal is to find best joint configuration

Can be accomplished using a constellation model, for example



mage from Fischler and Elschlager 1973



Skeleton data is available from Kinect SDK

▶ http://www.microsoft.com/en-us/kinectforwindows/

Random forests make for powerful classification/regression models

Implementations readily available

- ► Matlab (TreeBagger)
- OpenCV (cvRTrees)
- scikit-learn (RandomForestClassifier)



Summary

Knowledge of scene geometry enables powerful CV applications

We have covered a selection

- 3D reconstruction for virtual reality
- Person detection for breaking assistance
- Human pose estimation for gaming

3D Vision Lecture

Interested in 3D vision?

► There is an own VO (183.129) and UE (183.130)

Bibliography I

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