LIDAR DATA ANALYSIS: OBJECT DETECTION VERIFICATION; GRAPH CUTS BASED INTERACTIVE SEGMENTATION

Doria D.

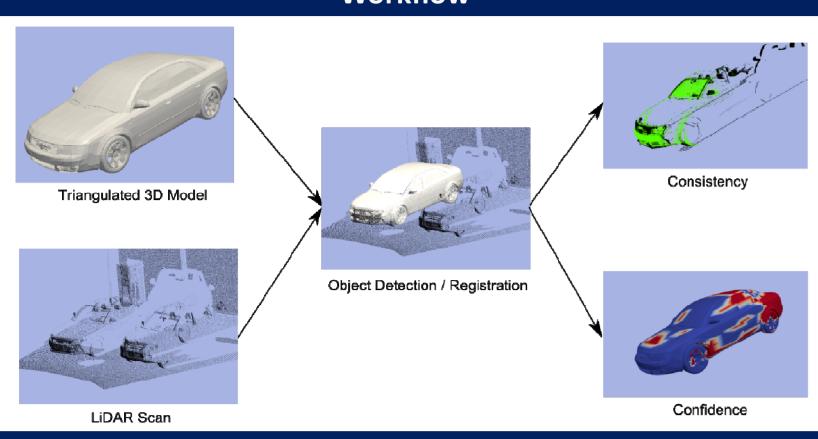
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Object Detection Verification

Abstract

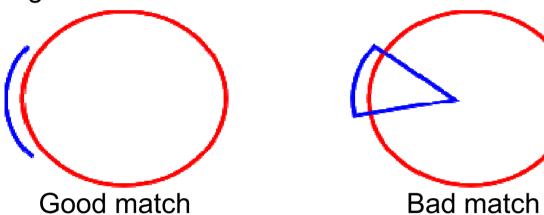
Our work involves analyzing and interpreting data produced by 3D range (LiDAR) scanners. First, we have introduced a dual metric, Consistency and Confidence, for verifying in a physically meaningful way whether a 3D model occupies a hypothesized location in a set of LiDAR scans. Our current work involves interactively segmenting objects in LiDAR data using graph theoretic techniques. Our goal is to allow users to select an entire object in a scan using two mouse clicks.

Workflow



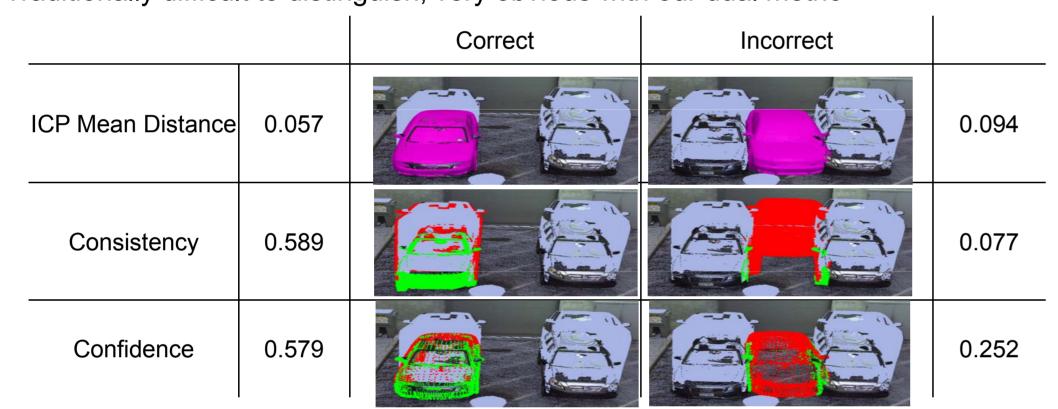
Partial Matches

 Allowing for partial matches forces one to use a cost function which has a similar score in the following cases:



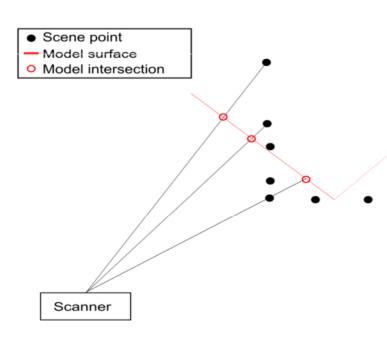
Incorrect Matches

· Traditionally difficult to distinguish; very obvious with our dual metric



The Consistency Measure

"If the model was present, could we have seen this point?"



(consistent) or 0 (inconsistent) to each scan point

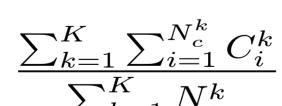
Assign a binary value of 1

Scene

Scan

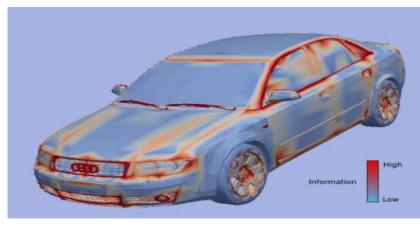
Consistency = $\frac{1}{N_c} \sum_{i=1}^{N_c} C_i$

Multiple Scan Consistency =



The Confidence Measure

- "How much of the model have we observed?"
- If scan is consistent, we can only declare the model *could be* at the hypothesized location, not that it *is* at that location
- Indicates the reliability of the hypothesis



A certain amount of information, I_i, is associated with every model point, related to how locally distinctive the point is

Each scan point collects information from the scene

$$O_i \leftarrow \min \left(I_i, O_i + I_i e^{rac{-d_{ij}^2}{2\sigma^2}}
ight)$$
 $ext{Confidence} = \sum_{i=1}^{N_m} O_i$

• The computation of the confidence over ${\bf K}$ multiple scans is computed as if all scene points came from a single scan

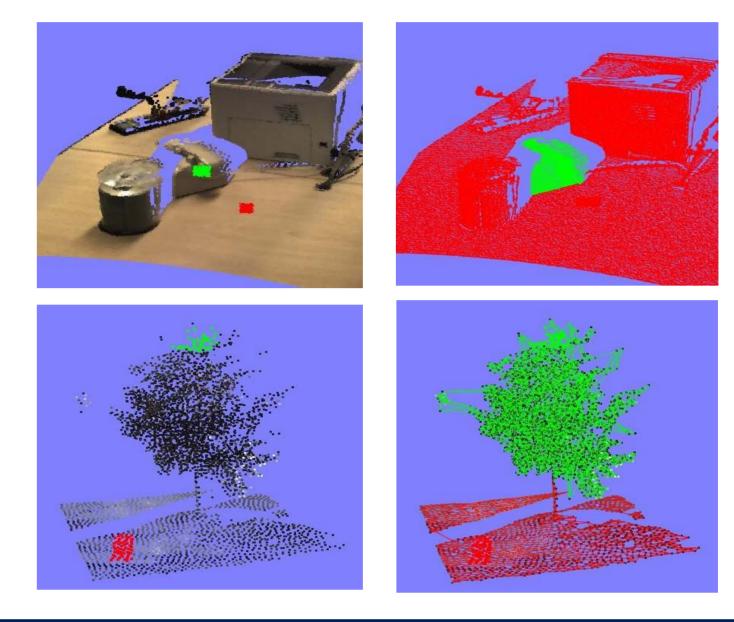
Graph Cuts Based Interactive Segmentation

Building the Graph

- We use a Riemannian graph on the scan points
- Building the Riemannian graph on large scans is very slow (depends on the EMST which depends on the Delaunay tetrahedralization)
- We are experimenting with simpler graphs (connected KNN graphs, etc)

Weighting the Graph

- We incorporate all of the information we have about the points into the edge weight function
- Normal distance (D_N) the angle between the normals of adjacent points
- Color distance (D_C) the Euclidean distance in RGB space between the color of adjacent points
- Euclidean distance (D_E) the distance between the coordinates of adjacent points
- Many objects can be segmented using only one of these distances:



Optimizing the Weight Function

 We want to weight these three distances appropriately according to what kind of object we are segmenting

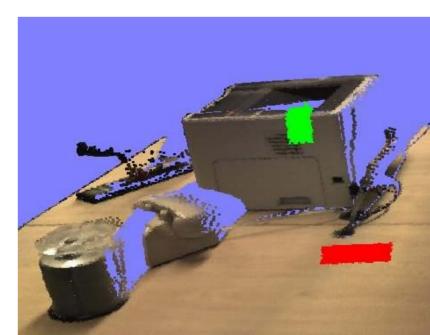
$$W = W_N D_N + W_C D_C + W_E D_E$$

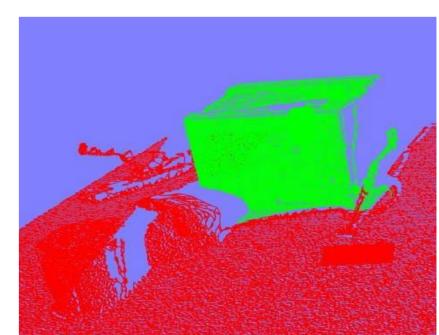
- Automatic
 - No need for a training database
 - No user parameter estimates required
- Gradient descent optimization on the cut weight

Current/Future Work

Compactness

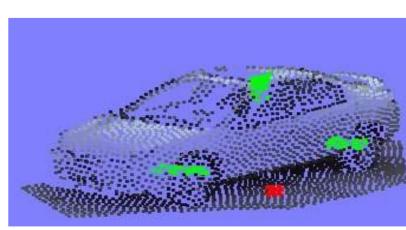
- We are looking for a definition of "compactness" of a segmentation
- Many researchers have added "boundary smoothness" terms to the graph cut optimization function in images
- This is not directly applicable, but we hope to address cases like this:

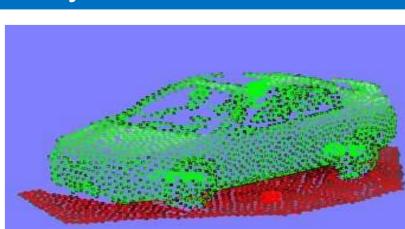




- The segmentation should group the wires with the background
- The segmentation with the wires in the foreground leads to a much less "constrained" object
- By defining and analyzing the "shape" of the 3D cut, we hope to correct these cases.

Complex Objects





- Some difficult object require more than one foreground or background stroke
- The goal is to select any object with a single stroke, just as humans recognize the collection of points as a single object

Contact



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