Integrating LIDAR into Stereo for Fast and Improved Disparity Computation

Hernán Badino, Daniel Huber, and Takeo Kanade
Robotics Institute, Carnegie Mellon University
Pittsburgh, PA 15213, USA
Stereo/LIDAR Integration

• The appropriate stereo/LIDAR fusion compensates for individual sensor deficiencies
  – Stereo: dense but noisy at large distances
  – LIDAR: sparse but accurate
  – Stereo + LIDAR: dense and accurate

• Stereo can produce large number of false positives leading to phantom objects
  – Problems: lack of texture, depth discontinuities, and repetitive patterns

• Solution: improve stereo estimation before fusion occurs
Stereo Computation

Taxonomy of Stereo Vision Methods: (D. Scharstein and R. Szeliski)

- Matching Cost Computation
  - AD, SD, MI, Census, etc.
- Cost Aggregation
  - Fixed or variable windows, multiple linear paths, tree paths, etc.
- Disparity Comp / Opt.
  - WTA, Dynamic Programming, Belief Propagation, Graph Cut, etc.
- Disparity Refinement
  - Sub-pixel interpolation, occlusion detection, consistency checks, etc.

The Robotics Institute, Carnegie Mellon University
Disparity Space Image

\[ DSI(u, v, d) = L(u, v) - R(u + d, v) \]

The disparity range D defines the depth range of observability
Disparity Space Image
Reduced Disparity Space Image
Reduction of the Disparity Range Space

1. Calculate Spherical Range Image
2. Apply Min/Max filter
3. Predict Min/Max Disparity Images
4. Calculate reduced DSI
Comparison of results with WTA

Left Image

SRI

Reduced DSI

Standard DSI
Stereo Computation

Taxonomy of Stereo Vision Methods: (D. Scharstein and R. Szeliski)

Matching Cost Computation

- AD, SD, MI, Census, etc.

Cost Aggregation

- Fixed or variable windows, multiple linear paths, tree paths, etc.

Disparity Space Image (WxHxD)

Disparity Comp / Opt.

- WTA, Dynamic Programming, Belief Propagation, Graph Cut, etc.

Raw disparity map (WxH)

Disparity Refinement

- Sub-pixel interpolation, occlusion detection, consistency checks, etc.

Final disparity map (WxH)
Disparity Space Image
Disparity Space Image
Dynamic Programming

\[ E(i, j) = \arg \min_k (E(i-1, k) + S(j, k)) + D(i, j) \]
Data Term

\[ E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j) \]

\[ D(i, j) = DSI(i, v, j) \]
Smoothness Term

\[ E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j) \]

\[ S(j, k) = C_S |j - k| \]
\[ E(i, j) = \arg\min_k (E(i - 1, k) + S(j, k)) + D(i, j) \]

\[ S(j, k) = C_S |j - k| \]
Smoothness Term

\[ E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j) \]

\[ S(j, k) = C_s |j - k| \]
Optimal Solution

\[
E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j)
\]
Path Promotion

\[ E(i, j) = \arg\min_k (E(i - 1, k) + S(j, k)) + D(i, j) + P(j, d(i)) \]

\[ P(j, d) = C_P \cdot |j - d| \]
Path Promotion

\[ E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j) + P(j, d(i)) \]

\[ S(j, k) = C_S \cdot |j - k| \]
Path Promotion

\[ E(i, j) = \arg \min_k (E(i-1, k) + S(j, k)) + D(i, j) + P(j, d(i)) \]

\[ S(j, k) = C_S \cdot |j - k| \]

The Robotics Institute, Carnegie Mellon University
Path Promotion

\[ E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j) + P(j, d(i)) \]

\[ S(i, j, k) = C\delta |j - k - d'_{ul}(i)| \]
Path Promotion

\[ E(i, j) = \arg \min_k (E(i - 1, k) + S(j, k)) + D(i, j) + P(j, d(i)) \]
Improvement Achieved
Results
Results
Conclusions

• DSI reduction leads not only to an improved disparity computation but also reduces the computational complexity (20-40%).

• LIDAR ranges can be naturally integrated into the optimization algorithm by promoting paths and path directions in disparity space.

• Early integration of LIDAR range data into the stereo algorithm leads to a substantial improvement of the disparity image.
Thanks for your attention