Stereo Matching

Involves determining disparities indicating difference in locations of corresponding pixels in left (I_L) and right (I_R) images.

Application:

3D scene reconstruction, using disparity and depth inverse relation and known camera geometry.

Corridor I_L

Corridor I_R

Disparity Groundtruth

Bayesian-MRF model for Stereo Matching

Disparity Markov Random Field (MRF) model: With disparity d and observation I = (I_L, I_R).

Posterior distribution p(d|I):

\[ p(d|I) \propto \Phi(I|d) \Psi(d) \]

Likelihood term \( \Phi(I|d) \): measures observation agrees with the disparity.

Prior term \( \Psi(d) \): encodes interaction between the neighbouring disparities.

Interaction: First-order differences (blue arrows in the figure).

Approximate inference: Belief Propagation, Mean Field or Graph-cuts.

Limitation:

• Using first-order differences involves an inherent fronto-parallel assumption.

• Fronto-parallel assumption: Supposes that the scene under consideration can be approximated by patches of constant disparities.

• This biases the results towards staircase solutions.

Possible Solution:

Post-processing the disparities using plane-fitting on segmented regions.

Limitation: Cannot handle curved surfaces.

Related Work

Solution Proposed by Li and Zucker CVPR 2006

Explicitly takes into account both disparities/depth and scene-structure in terms of surface normals in an MRF-based framework.

Geometric consistency: An additional geometric constraint to ensure both disparity/depth and normals are consistent with the surface.

Limitations:

• Requires knowledge of the internal camera parameters.

• Precomputes the local surface normals.

Proposed Solution

Cooperatively estimate both disparity and normal using:

Disparity-MRF, \( d \): incorporates differential geometric constraints.

Normal Conditional Random Field (CRF), \( n \): assumes a piecewise smooth scene surface.

Alternating Maximization:

Iteratively maximizes the posterior probability alternately in \( d \) and \( n \).

\[ d^{(k+1)} = \arg \max p(d|n^{(k)}, I) \]

\[ n^{(k+1)} = \arg \max p(n|d^{(k+1)}, I) \]

Application: 3D scene reconstruction, using disparity and depth in-verse relation.

Stereo Matching: Involves determining disparities indicating difference in locations of corresponding pixels in left (I_L) and right (I_R) images.

Percentage for bad pixels

Distribution of disparity \( d \) conditional to the normal field \( n \) and the observation \( I \):

\[ p(d|n, I) \propto \Phi(I|d, n) \Psi(n, d) \]

Data term \( \Phi(I|d, n) \):

\[ \Phi(I|d, n) = \exp \left( - \sum \lambda \min \left( |I(x) - I(x')|, 27 \right) \right) \]

\( \phi(I_L, I_R, d) \): Cost at location \( x \) based on weighted window matching metric.

\( \psi(d, n) \):

\[ \psi(d, n) = \prod_{x,y} \psi(d_x, d_y, n) \]

\( \psi(d_x, d_y, n) \) incorporates a general surface model:

\[ \exp \left( -|d_x - d_y| - \frac{\partial d_x}{\partial u} \Delta u - \frac{\partial d_y}{\partial v} \Delta v \right) - \frac{\partial d_x}{\partial v} \Delta u - \frac{\partial d_y}{\partial u} \Delta v \]

With \( x = (u, v), n_x = (n_{x_1}, n_{y_1}, n_{z_1}) \)

Normal-DRF model

Normal Field \( n \) conditioned on disparity \( d \) and observation \( I \) expressed as a Gaussian distribution:

\[ p(n|d, I) \propto \prod_{x,y} \exp \left( - \frac{1}{2} \| n_x - w_2(d(x), I) \|_2^2 \right) \]

Error between \( \hat{y} \) and the plane described by \( n_x \):

\[ w_2(x, d(I)) = \exp \left( - \frac{\| \hat{y} - d(x) \| + \| \hat{y} \| }{\| \hat{y} \| } \right) \]

\( \hat{y} \): angle between \( n_x \) and the vector \( \hat{y} \), from \( x = (x, d) \) to \( y = (y, d) \)

Alternating Maximization

Initialization:

Normal map values are set to \( (0, 0, 1) \). Disparity map is obtained using standard Mean Field.

Alternation:

Update normal field by optimizing the proposed normal model using Iterated Conditional Mode (ICM).

Update disparity field by:

• Computing the first order disparity derivatives using \( \hat{y} \) and \( \hat{y} \) updating disparity estimations into \( d \) with Mean Field applied to the proposed disparity model.

Results

Estimated Disparity and Normals

Error Plots

Contributions

• Estimation of surface consistent disparity solutions.

• Embedding of the surface properties in the model rather than refining the results using post-processing.

• Uses a separate random field to estimate the normals based on the disparity and vice-versa.

• Does not involve precomputing normals.

• Alternating maximization procedure results in mutual improvement of both disparities and normals.

• The two conditional models allow for more dependence or independence according to the information to be incorporated.