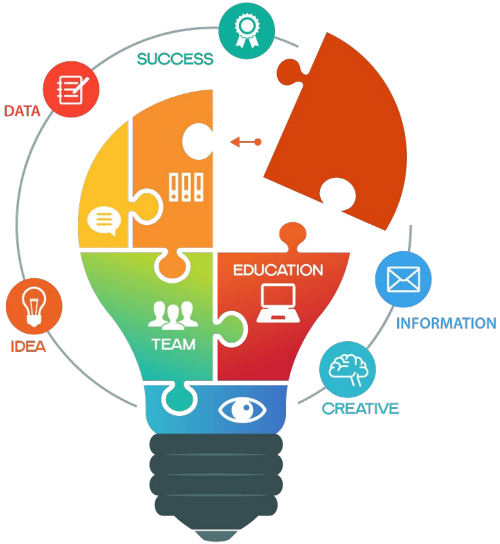
Team: Brown Munde

3D Reconstruction from Accidental Motion



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Objective

We have implemented the following paper : [3D Reconstruction from Accidental Motion]

Our implementation takes the following parameters :

- ➢ **Input :** Sequence of frames of parts of video.
- ➢ **Result :** A 3 Dimensional reconstruction depth map of a reference frame

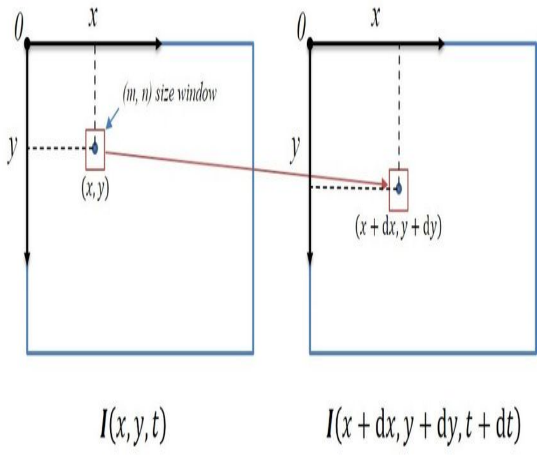
(a) Input image sequence (b) Foreground points of SfM (c) Dense reconstruction

Problem Brief

- We have an image sequence of N_C images and N_P projections (2D points) of corresponding 3D points as seen from every camera , we try to estimate the world coordinates of the real world points using **Bundle Adjustment**.
  - **Bundle Adjustment** : It refers to solving the location of pixels for a given estimated initial pose and location of 3D points.
- Using the estimated camera parameters, the 3D scene is densely reconstructed as a single depth map. A **Conditional Random Field Model** is used to minimize an energy function using plane-sweep approach and mean-field.

Method Overview : Tracking Features

- **KLT** tracking is used to track features between all the frames.
- The next step is to find the **Shi Tomasi Corners.**
- Major difference between **Shi Tomasi Corners and Harris Corners** lie in the change in scoring function : **$R = \min(\lambda_1, \lambda_2)$**
- Corners can be filtered out by the homography matrix between the reference frame(initial frame) and every other frame in the video sequence.
- Corners that are inliers for more than 90 % of camera frames found by estimating homography matrix are chosen.
- Optical flow over all the images of the sequence is considered.

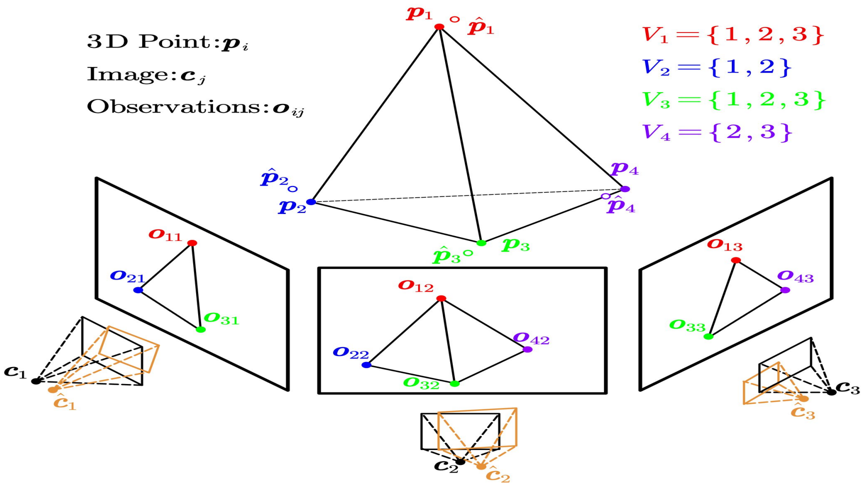


Method Overview : Tracking Features

The point-cloud and the corresponding depth map of the image. The detected features are tracked across all non-reference images. We show here the trajectory of each feature across the set of frames.

Bundle Adjustment Optimization

- L2 norm ($||w||_2$) of 3D points with respect to the pixel values computer by corner pixels tracking is used as the loss function.
- Ceres solver is used to solve the Bundle Adjustment problem.
- The cost function is described as follows:



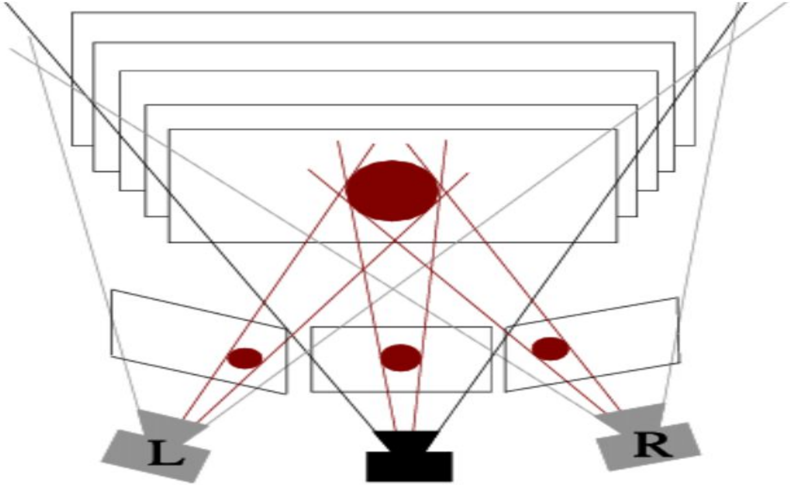
$$F = \sum_{i=1}^{N_c} \sum_{j=1}^{N_p} ||p_{ij} - \pi(R_i P_j + T_i)||^2,$$
$$= \sum_{i=1}^{N_c} \sum_{j=1}^{N_p} \left(\frac{e_{ij}^x + f_{ij}^x w_j}{c_{ij} + d_{ij} w_j}\right)^2 + \left(\frac{e_{ij}^y + f_{ij}^y w_j}{c_{ij} + d_{ij} w_j}\right)^2,$$

where

$$\begin{aligned}
a_{ij}^x &= x_j - \theta_i^z y_j + \theta_i^y, \\
b_{ij}^x &= T_i^x, \\
a_{ij}^y &= y_j - \theta_i^x + \theta_i^z x_j, \\
b_{ij}^y &= T_i^y, \\
c_{ij} &= -\theta_i^y x_j + \theta_i^x y_j + 1, \\
d_{ij} &= T_i^z, \\
e_{ij}^x &= p_{ij}^x c_{ij} - a_{ij}^x, \\
f_{ij}^x &= p_{ij}^x d_{ij} - b_{ij}^x, \\
e_{ij}^y &= p_{ij}^y c_{ij} - a_{ij}^y, \\
f_{ij}^y &= p_{ij}^y d_{ij} - b_{ij}^y.
\end{aligned}$$

Dense Conditional Random Field

- After estimating the sparse 3D structure of the scene along with camera extrinsics, we want to construct a **dense depth map** of the 3D scene using a **conditional random field**.
- We use the **Plane-Sweeping** along with a CRF framework to solve for a dense depth map. The plane-sweeping method generates unary potentials for the CRF model. Using a fully-connected CRF model allows pixel connections with longer range so that the **photo-consistency** measurement can be effectively aggregated from an area to a pixel in it.



Unary Potential Calculations

- We first sample different depth values in the acceptable depth range of the 3D scene. To calculate the unary potentials we compute a homography between the reference image and every other image. The homography matrix between the reference image and jth camera frame at these different depths D is computed as follows:

$$H_j^{ref}(D) = D * K * {}^{C}_{W}R_{ref} * {}^{C}_{W}R_j^{-1} * K^{-1}$$

$$H_j^{ref}(D)[:,2] = K * {}^{C}_{W}R_{ref} * (C_j - C_{ref})$$

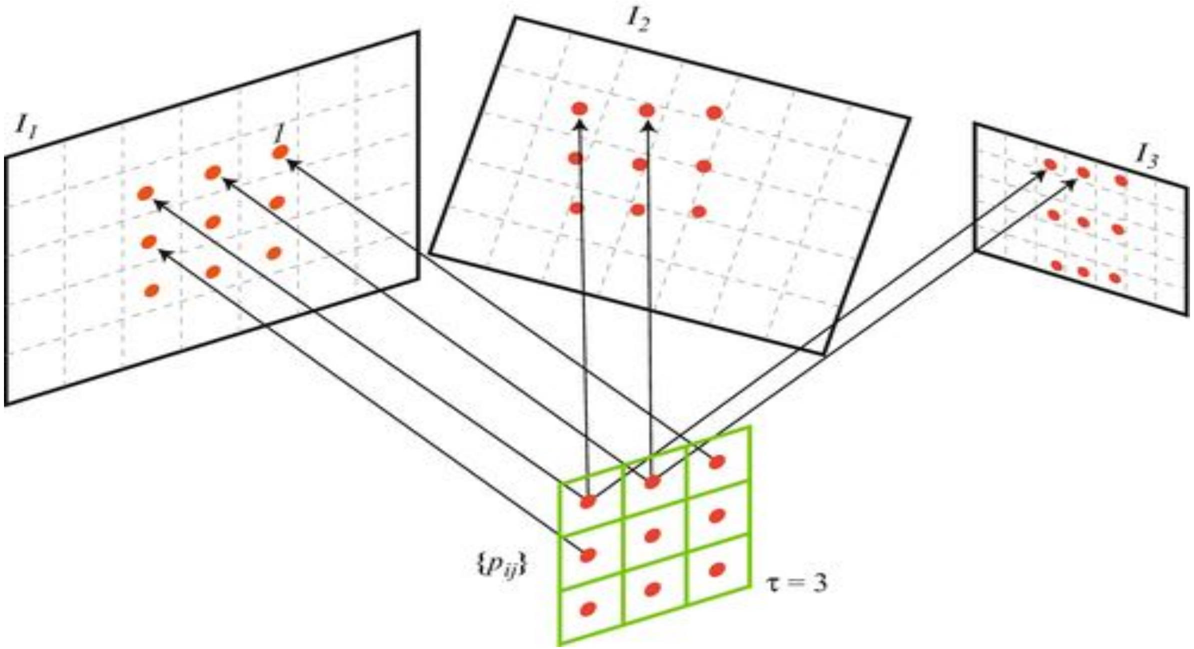
Here d, W Rj , K, and C are the depth, rotation matrix, camera intrinsic matrix, and camera centers respectively.

- Ep is the photo-consistency term defined as an L1 Loss between small patches in the reference image and the warped image from another viewpoint. It can be expressed as:

$$E_p(D) = \sum_j \sum_i \left| p_{i,ref} - H_j^{ref}(D) * p_{i,j} \right|$$

pi,ref and pi,j are the gray-scale patches of the reference camera and j th camera respectively.

Unary Potential Calculations



Pair-wise Potential Calculations

- ❖ The pairwise potential is a Gaussian kernel in arbitrary feature space.
- ❖ It has a spatial term such that the depth within a small neighbourhood is consistent.
- ❖ It has an intensity term such that pixels within an area with similar colours have consistent depth, since they are likely to belong to the same object.

$$E_s(D) = \sum_{i \in \mathcal{I}, j \in \mathcal{I}, i \neq j} C(i, j, I, L, D) \qquad C(i,j,I,L,D) = \rho_c(D(i), D(j)) \times \exp\Big(- \underbrace{\frac{||I(i) - I(j)||^2}{\theta_c}}_{\text{Intensity term}} - \underbrace{\frac{||L(i) - L(j)||^2}{\theta_p}}_{\text{Spatial term}} \Big)$$

Here ρc (.) is the truncated linear function defined as **ρc = min(t, |D(i) − D(j)|)** with some threshold t. The pairwise term has a spatial term such that depth within a small neighborhood is consistent as well as a intensity term such that pixels within an area with similar colors have consistent depth, since they are more likely to belong to the same object.

Pair-wise Potential Calculations

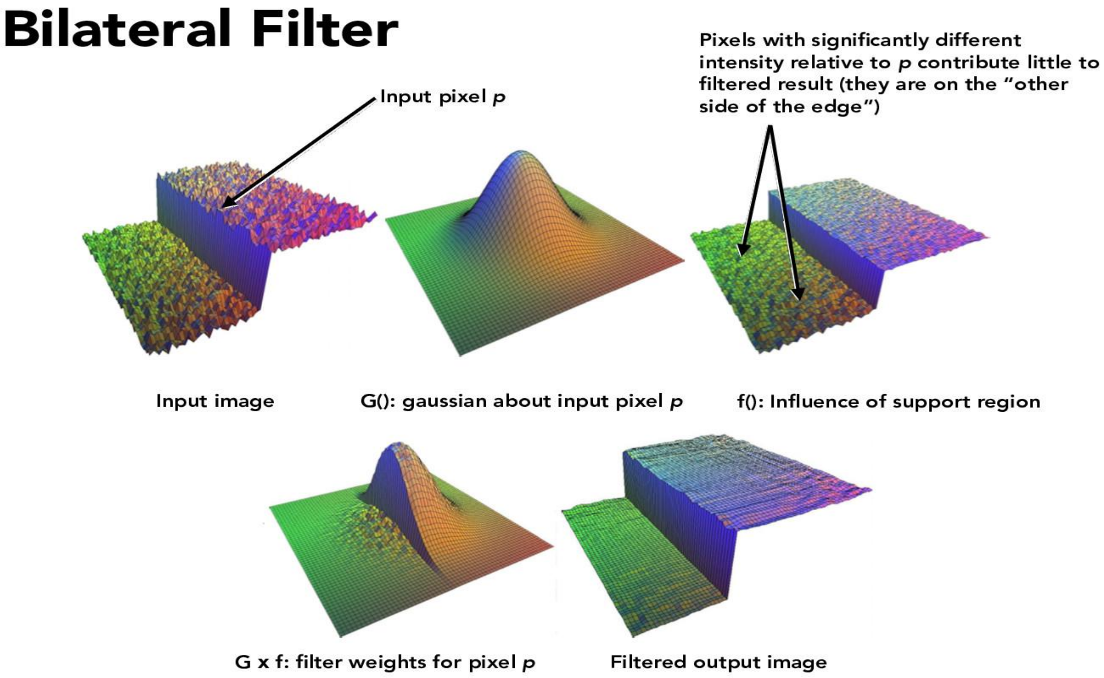
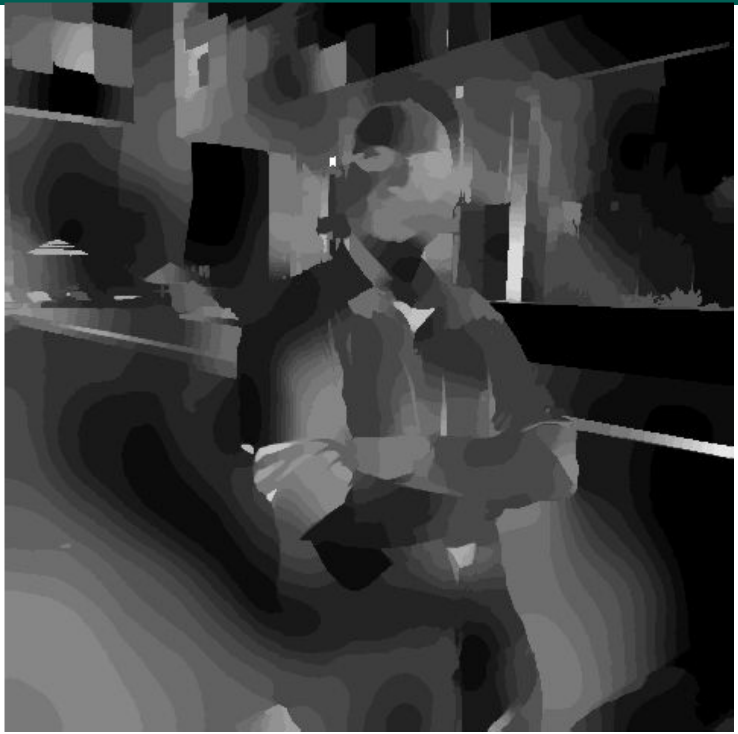


Figure credit: Durand and Dorsey, "Fast Bilateral Filtering for the Display of High-Dynamic-Range Images", SIGGRAPH 2002

Results

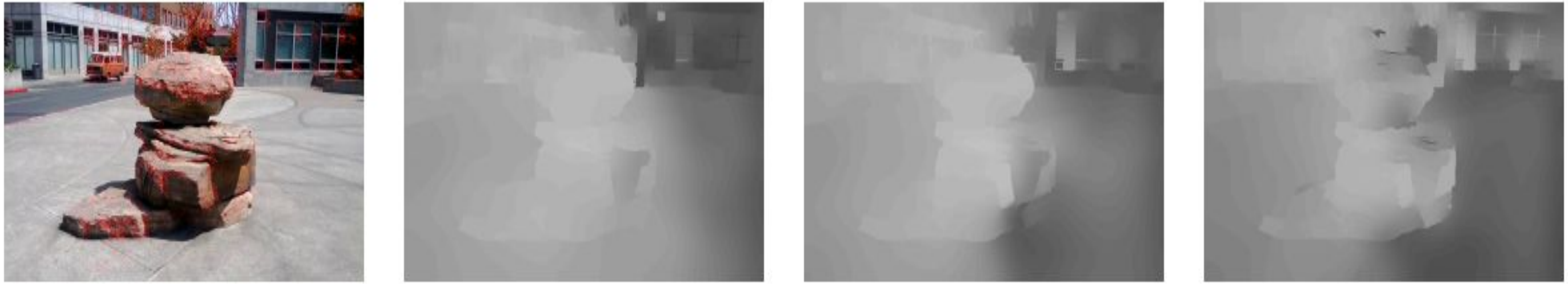
Optical Flow



Dense Map

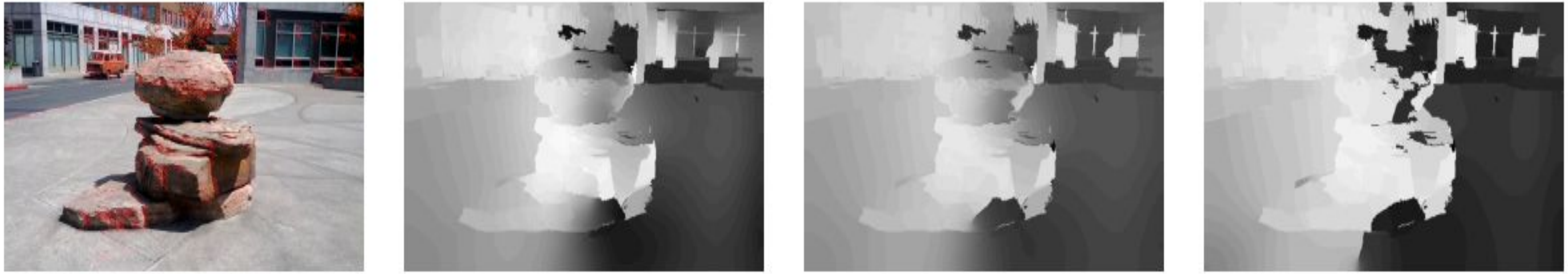
Experiments

Experiment 1 : Number of Images



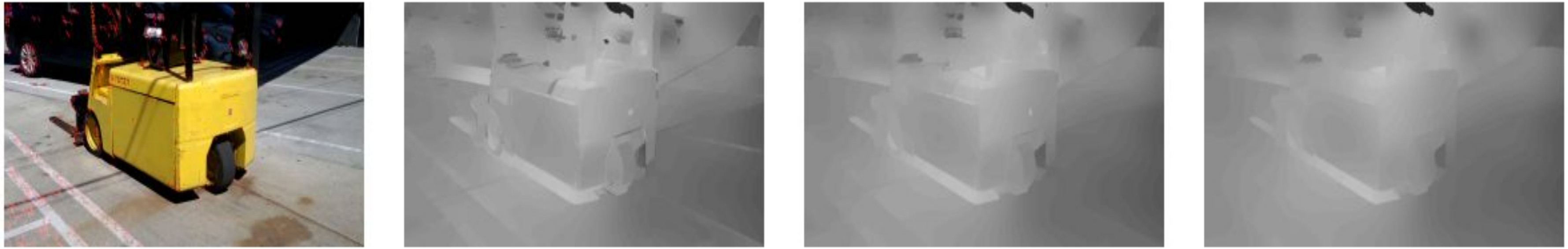
(a) Optical flow (b) 30 frames (c) 50 frames (d) 100 frames

Experiment 2 : Weight for CRF



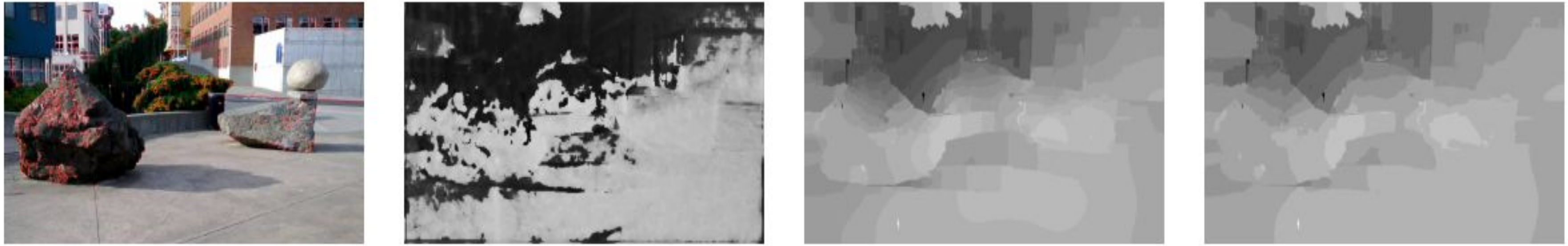
(a) Optical flow (b) w = 0.5 (c) w = 1.0 (d) $\theta_c = 2.5$

Experiment 3 : Intensity STD for potential



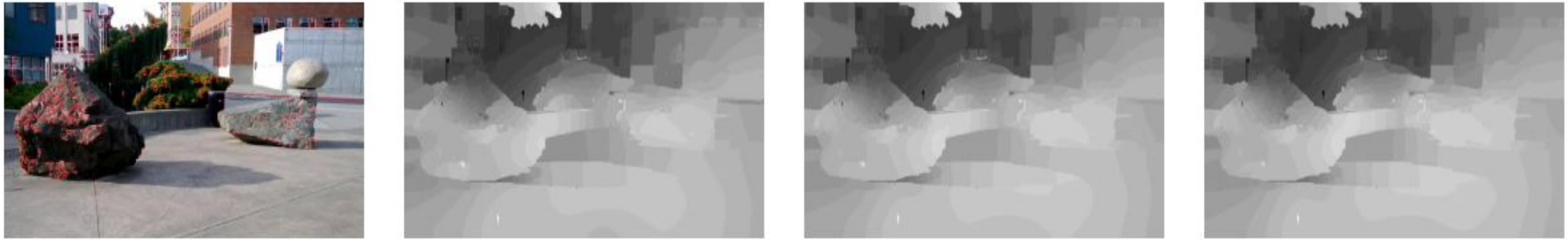
(a) Optical flow (b) $\theta_c = 10$ (c) $\theta_c = 20$ (d) $\theta_c = 35$

Experiment 4 : Max Penalty for CRF



(a) Optical flow (b) t = 0.1 (c) t = 0.25 (d) t = 0.35

Experiment 5 : Patch Radius for Unary



(a) Optical flow (b) patch radius = 1 (c) patch radius = 2 (d) patch radius = 3

Thank You