SIMULTANEOUS COLOR CONSISTENCY AND DEPTH MAP ESTIMATION FOR RADIOMETRICALLY VARYING STEREO IMAGES

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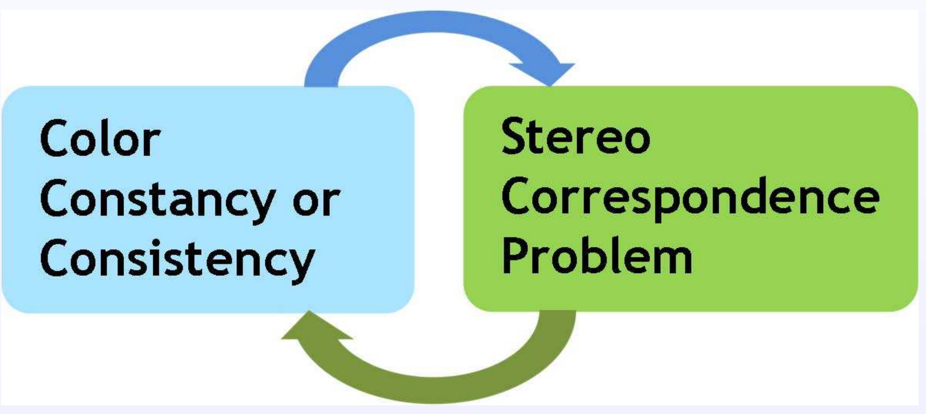
Abstract

We propose a new method that iteratively infers accurate depth maps and color-consistent images for radiometrically varying stereo images. For stereo matching, we utilize the mutual information-based method combined with the SIFT descriptor. Then, we devise a stereo color histogram equalization method to make color-consistent stereo images. Experimental results show that our method produces both accurate depth maps and color-consistent stereo images for severely radiometrically varying stereo images.

Motivation

Color consistency enhances the performance of stereo matching, while accurate correspondences from stereo disparities improve color consistency between stereo images.



Color Model & Transform

We assume that the color value $\mathtt{I}(p)$ of a pixel p is transformed to $I(p)$ by various unknown radiometric factors as follows [1]:

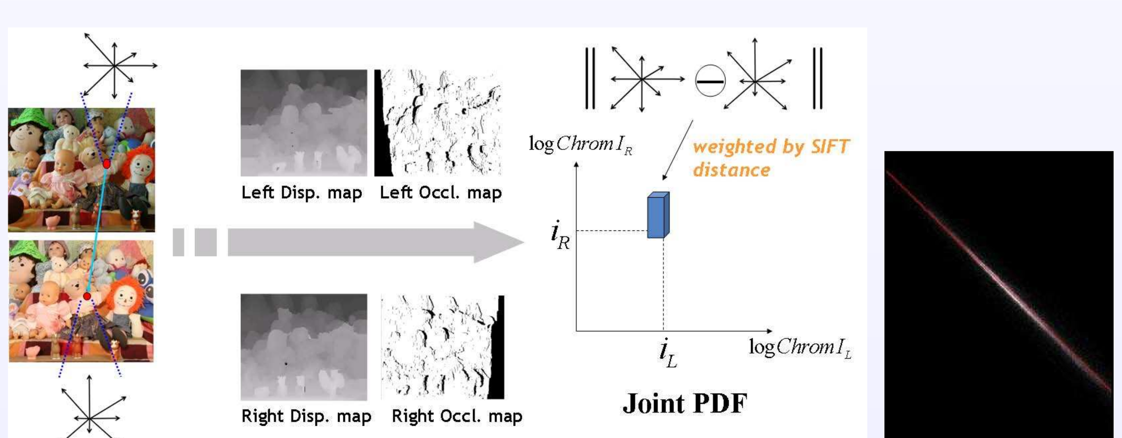
$$\mathtt{I}_k(p) \rightarrow I_k(p) = \rho(p) a_k(\mathtt{I}_k(p))^{\gamma}, \quad (1)$$

where $k \in \{R, G, B\}$. The original nonlinear color value $I_k(p)$ in (1) can be transformed to the linear *log-chromaticity* color value $I'_k(p)$ by proper operations as follows:

$$I'_k(p) \equiv C_k + \gamma L_k(p). \quad (2)$$

Joint Pdf & Linear Function

We compute the joint pdf between the left and right images in the log-chromaticity color spaces, and estimate a linear function from this joint pdf. In order to include the spatial gradient information, the joint probability is weighted by the distance of the SIFT descriptor [2].

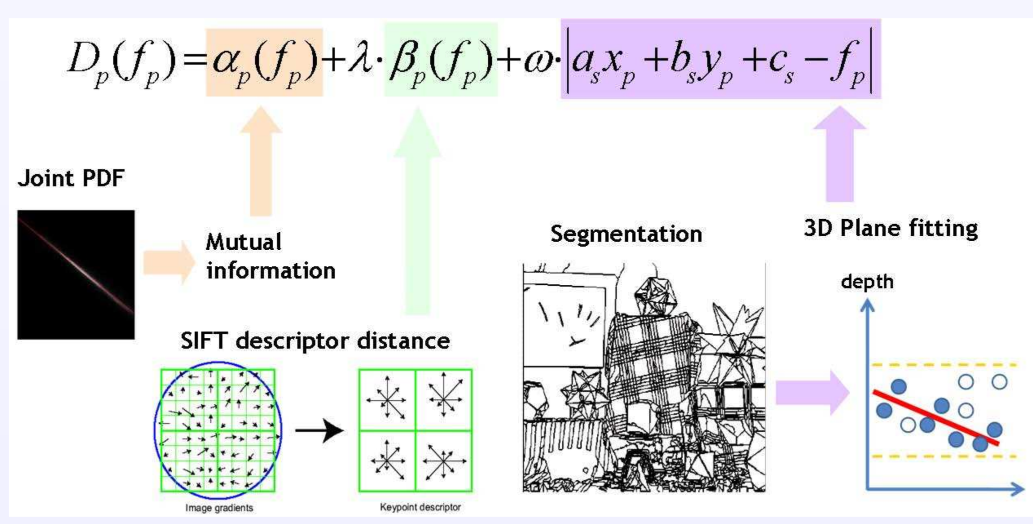


Disparity Map Estimation

In MAP-MRF framework, the disparity map f can be found by minimizing the following energy $E(f)$:

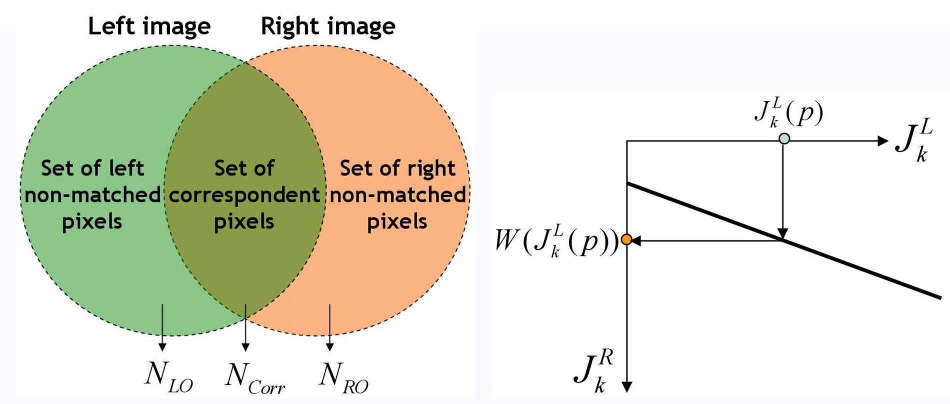
$$E(f) = E_{data}(f) + E_{smooth}(f),$$
$$E_{data}(f) = \sum_p D_p(f_p),$$
$$E_{smooth}(f) = \sum_p \sum_{q \in N(p)} V_{pq}(f_p, f_q), \quad (3)$$

Total energy is minimized using Graph-cuts. For robust and accurate stereo matching [2], we incorporated several cues in our data cost as follows:



SCHE Estimation

CHE (Color Histogram Equalization) [3] uses the invariance of rank ordering under illumination changes.



SCHE (Stereo Color Histogram Equalization) value is defined by

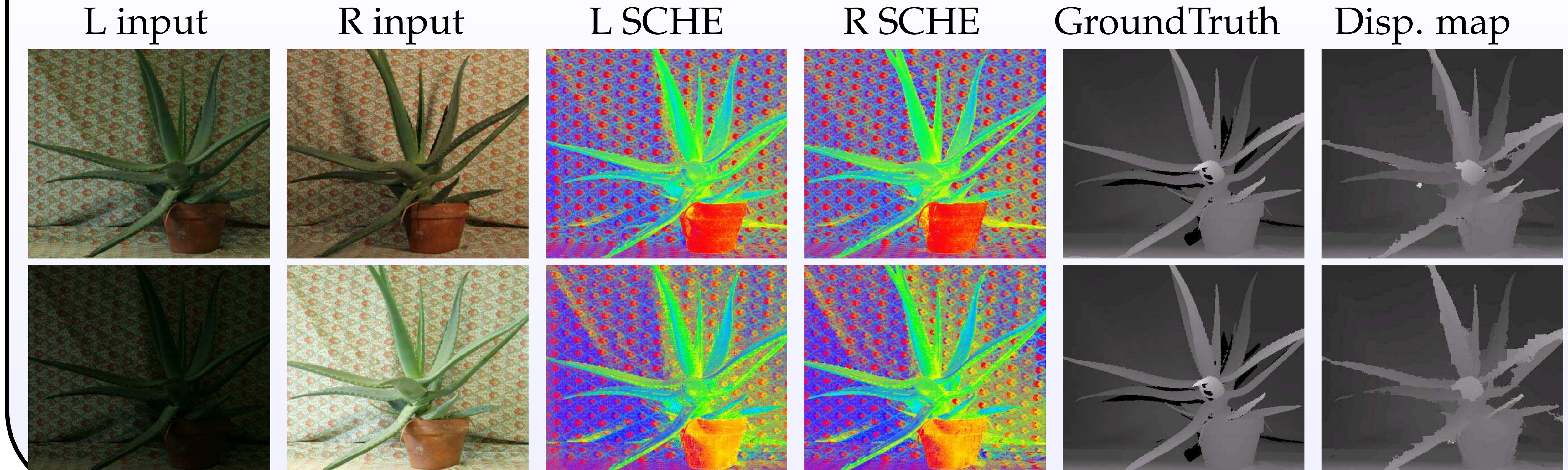
$$S^L_{corr}(p) = \frac{P(J^L_k \leqslant J^L_k(p)) + P(J^R_k \leqslant J^R_k(p+f_p))}{N_{LO} + N_{Corr} + N_{RO}} \quad (4)$$

$$S^L_{nonCorr}(p) = \frac{P(J^L_k \leqslant J^L_k(p)) + P(J^R_k \leqslant W(J^L_k(p))}{N_{LO} + N_{Corr} + N_{RO}}. \quad (5)$$

Experimental Results

To test the performance of our algorithm, we experimented with the Middlebury datasets that have different radiometric variations.

L input | R input | L SCHE | R SCHE | GroundTruth | Disp. map



References

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