# Consistent Filtering of Videos and Dense Light-Fields Without Optic Flow (Supplementary Material)

Submission ID: 1013

### 1. Paramter Analysis

We can interactively control the consistency of resulting outputs by tuning the salient weight parameters  $\beta$ ,  $\varepsilon$  and,  $\mu$ . In this section, we show the effect of each parameter on the output salient weight.

### 1.1. Effect of $\beta$

The parameter  $\beta$  affects the weight globally and is used to scale its intensity. As the value of  $\beta$  is increased, the extent of smoothing mask in the non-salient region increases while the salient region remains unaffected.



Figure 1: Comparison of scaling parameter  $\beta$ , other parameters were set as follows:  $\varepsilon = 0.0$ ,  $\mu = 0.04$ , and  $\sigma = 1.0$ .

### 1.2. Effect of $\boldsymbol{\epsilon}$

The parameter  $\varepsilon$  affects the weight globally as an additive contribution to its intensity. As the value of  $\varepsilon$  is increased, the extent of smoothing mask increases both in the non-salient and the salient regions.

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#### Submission ID: 1013 / Consistent Filtering of Videos and Dense Light-Fields without Optic Flow



Figure 2: Comparison of additive parameter  $\varepsilon$ , other parameters were set as follows:  $\beta = 0.8$ ,  $\mu = 0.04$ , and  $\sigma = 1.0$ .

## **1.3.** Effect of $\mu$

The paramter  $\mu$  is used to identify the regions where the difference betweeen  $C_i$  and  $P_i$  is below a given threshold. It affects the weight locally, thus increasing the threshold leads to increasing the extent of non-salient regions.



Figure 3: Comparison of threshold parameter  $\mu$ , other parameters were set as follows:  $\beta = 1.0$ ,  $\varepsilon = 0.2$ , and  $\sigma = 1.0$ .

## 2. User Study Analysis

In Section 4.2 of the main paper we discuss the qualitative evaluation comparing our algorithm to previous methods using a user study. Overall, our method (Fig. 4a) is able to improve the per-frame processed result for image sequences. However, we perform significantly better in case of light-fields (Fig. 4c).

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Figure 4: Statistics for the rated output quality of each evaluated technique as conducted in our user study (Section 4.2 of the main paper) and according to the type of image sequence (light-field vs. video).

### 3. Optic Flow Extension

Although not required for our consistent filtering, we can extend our optimization approach to also include optic flow using the *smoothness*-warped term defined by Bonneel *et al.* [BTS<sup>\*</sup>15],

$$E(O_i)_{flow} = E(O_i) + \int_{\Omega} \underbrace{w_f ||O_i - warp(O_{i-1})||^2}_{\text{smoothness-warped}} d\Omega$$
(1)

In the above formulation the low-frequency consistent content is taken from the denoised image  $C_i$ , and the warped version of the previous output warp $(O_{i-1})$ . The influence of the *smoothness-warped* term is controlled by a per-pixel optic flow weight  $w_f$ . The weight is a crude measure of the quality of optic flow based on image warping, where  $\gamma$  and  $\kappa$  are scaling parameters.

$$w_f = \gamma exp(-\kappa ||I_i - warp(I_{i-1})||^2)$$
(2)

The objective of the above term is to accommodate potentially accurate optic flow. We believe that such term might further improve the output consistency.

#### References

[BTS\*15] BONNEEL N., TOMPKIN J., SUNKAVALLI K., SUN D., PARIS S., PFISTER H.: Blind Video Temporal Consistency. ACM Trans. Graph. 34, 6 (2015), 196:1–196:9. doi:10.1145/2816795.2818107.3