Image Noise and Filtering (IV)

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Bilateral Texture Filtering [1]

- This is a modification of the original bilateral filter (Tomasi & Manduchi, 1998) , it performs *local patch-based* analysis of texture features and incorporates its results into the range filter kernel.
  - It incorporates texture information (instead of color information) into the range filter kernel.
- The central idea to ensure proper texture/structure separation is based on **patch shift** that captures the texture information from the most representative texture patch clear of prominent structure edges.
  - Texture often contains strong enough contrast to get confused with structure.

Patch Shift

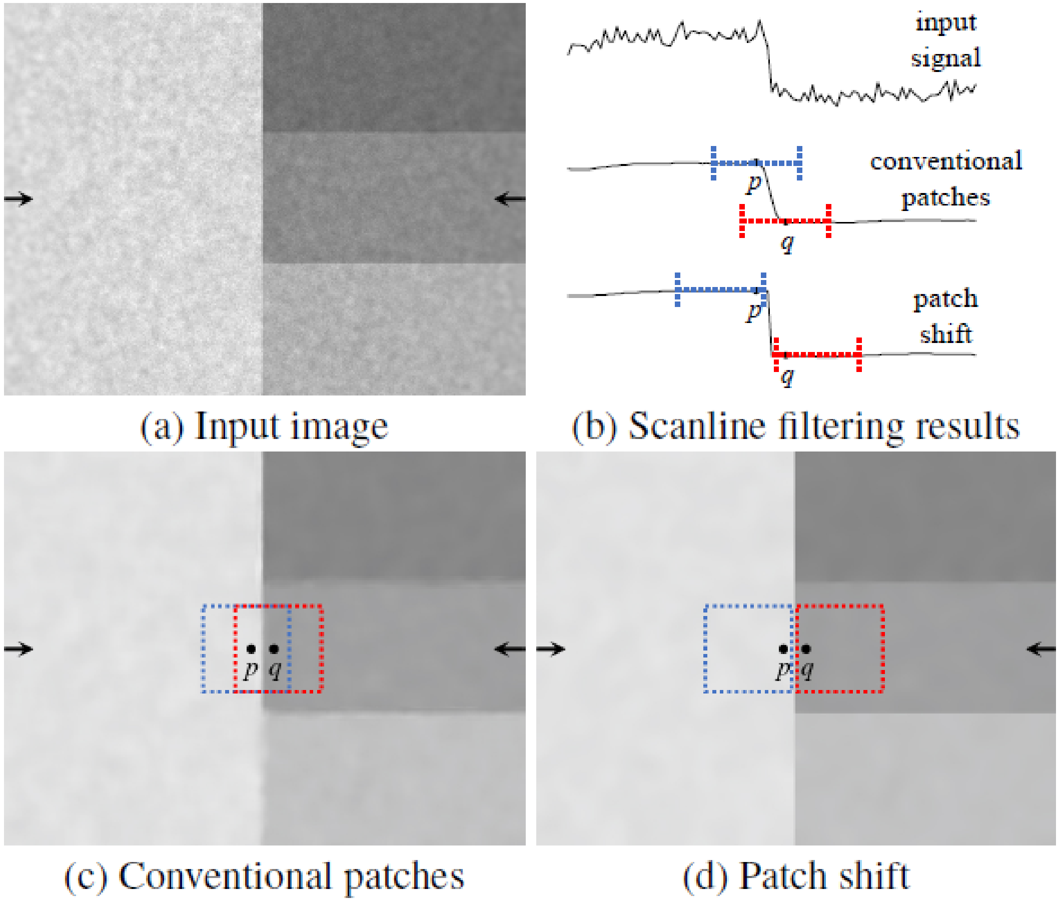
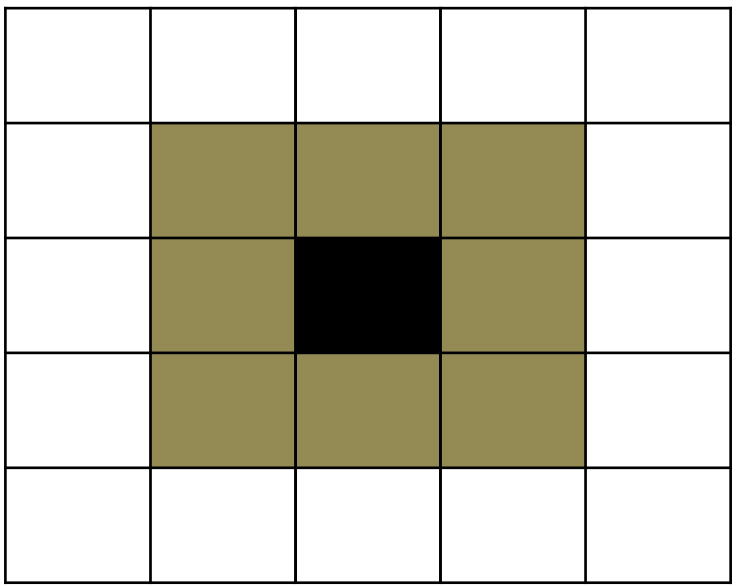
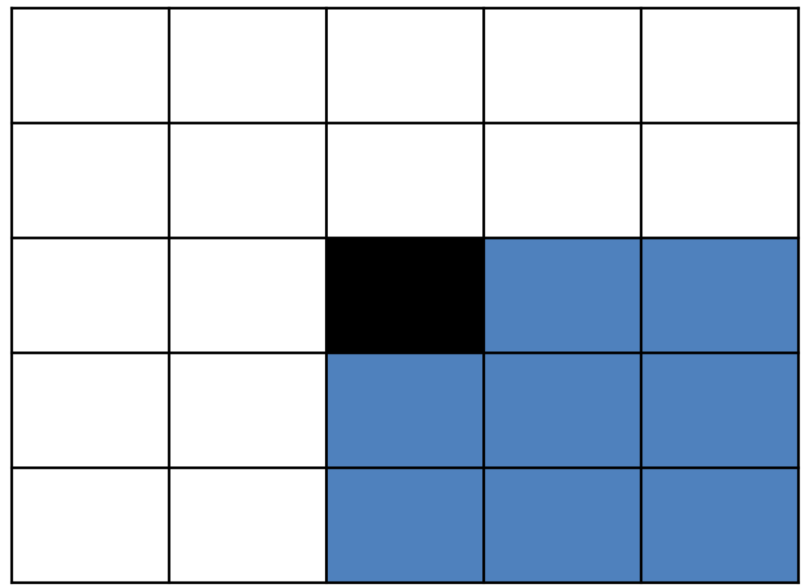


Figure 2: *Patch shift. Conventionally, texture feature is computed in a patch centered at each pixel, in which case the patches for two adjacent pixels should have a large overlap, reducing the feature discriminability. In contrast, patch shift finds a nearby patch that stays clear of a prominent structure edge. (b) Filtering of the scanline marked by arrows. (c) Filtered by [Karacan et al. 2013]. (d) Filtered with patch shift. The results in (b) show that our approach preserves structure edges, unlike the conventional approach.*

Patch Shift

- Assuming a $k \times k$ box representing a patch, each pixel $\mathbf{p}$ has a total of k^2 patches in I and contains $\mathbf{p}$.





Bilateral Texture Filter

- The bilateral filter of Tomasi and Manduchi (1998)

$$BF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right) G_{\sigma_r}\left(\| I_{\mathbf{p}} - I_{\mathbf{q}} \|\right) I_{\mathbf{q}}$$

- The bilateral texture filter

$$BTF[I]_{\mathbf{p}} = \frac{1}{W_{\mathbf{p}}} \sum_{\mathbf{q} \in S} G_{\sigma_s}\left(\| \mathbf{p} - \mathbf{q} \|\right) G_{\sigma_r}\left(\| T_{\mathbf{p}} - T_{\mathbf{q}} \|\right) I_{\mathbf{q}}$$

T: the guidance image based on local texture measure

Salient Structure Measure

- Assuming a $k \times k$ box representing a patch, each pixel $\boldsymbol{p}$ has a total of k^2 patches in the input image that contains $\boldsymbol{p}$.
- Let us *assume* for the moment that texture signal has **smaller amplitude** than the neighboring structure edge.
- We define texture as **fine-scale spatial oscillations** of signals.
- To measure the likelihood of containing **structure edge** for a patch Ω_q via its ***tonal range*** $\Delta(\Omega_q)$:

$$\Delta(\Omega_q) = I_{\max}(\Omega_q) - I_{\min}(\Omega_q)$$

where $I_{\max}(\Omega q)$ and $I_{\min}(\Omega q)$ denote the maximum and the minimum image intensities in patch Ω_q, respectively.

The Guidance Image

- 1) Given an input image I, we first apply $k \times k$ box kernel to compute the average image B.
- 2) For each pixel $\mathbf{p}$, we compute the tonal range $\Delta(\Omega_q)$. We then obtain **the guidance image** T via patch shift on each pixel. That is, we find the patch Ω_q whose $\Delta(\Omega_q)$ is *the minimum among k^2 candidates*, then copy $B_{\mathbf{q}}$ to $T_{\mathbf{p}}$.
- 3) Finally we obtain the output image J by applying joint bilateral filter on I, using T as the guidance image.

Modification of the Guidance Image (I)

- The tonal range suggests that patch shift *may not* work properly if the tonal range within **a pure texture region is *as large as* the nearby structure edge**.
- Modified Relative Total Variation (*mRTV*)

$$mRTV(\Omega_q) = \Delta(\Omega_q) \frac{\max_{\mathbf{r} \in \Omega_q} \left| (\partial I)_{\mathbf{r}} \right|}{\sum_{\mathbf{r} \in \Omega_q} \left| (\partial I)_r \right| + \varepsilon} \qquad (4)$$

- The *mRTV* value is relatively **large** in a **structure** patch containing only a few edges, and relatively ***small*** in a ***texture*** patch having frequent oscillations.

Modification of the Guidance Image (II)

- The *mRTV* values in **a smooth or flat image region** tend to be very small and thus may become sensitive to image noise.
  - Small nosiy peaks can be mistaken for edges
- When copying $B_{\mathbf{q}}$ to $T_{\mathbf{p}}$, if the two *mRTV* values of $\Omega_{\mathbf{p}}$ and $\Omega_{\mathbf{q}}$ are similar, $B_{\mathbf{p}}$ is preferred over $B_{\mathbf{q}}$ as the value of $T_{\mathbf{p}}$; if and only if $mRTV(\Omega_{\mathbf{q}})$ is *considerably smaller* than $mRTV(\Omega_{\mathbf{p}})$, $B_{\mathbf{q}}$ is used for $T_{\mathbf{p}}$.

$$T_p^{'} = \alpha_p T_p + (1 - \alpha_p) B_p \qquad (5)$$

$$\alpha_p = 2\left(\frac{1}{1 + \exp(-\sigma_\alpha (mRTV(\Omega_p) - mRTV(\Omega_q)))} - 0.5 \right) \qquad (6)$$

Bilateral Texture Filtering

Algorithm 1 Bilateral texture filtering

Input: image I
Output: texture filtered image J

> **for** $iter = 1 : n_{itr}$ **do**
> $\quad B \leftarrow$ Uniform blurring of I
> $\quad$ mRTV $\leftarrow$ Compute Eq. (4) for each pixel p
> $\quad$ **for all** $p \in I$ **do**
> $\quad\quad$ Find $q \in \Omega_p$ with minimum mRTV_q $\quad \triangleright$ *patch shift*
> $\quad\quad$ $G_p \leftarrow B_q$
> $\quad$ **end for**
> $\quad$ $\alpha \leftarrow$ Compute Eq. (6) for each pixel p
> $\quad$ $G' \leftarrow \alpha G + (1 - \alpha) B$ $\quad \triangleright$ *Eq. (5)*
> $\quad$ $J \leftarrow$ joint bilateral filtering of I using G' as guidance
> $\quad$ $I \leftarrow J$ $\quad \triangleright$ *input for the next iteration*
> **end for**

Experimental Results (I)

Input Images

Bilateral Texture Filtered Images

Experimental Results (II)

Input Images

Bilateral Texture Filtered Images

References

- [1] H. Cho, H. Lee, H. Kang, and S. Lee, ” Bilateral texture filtering,” ACM Transactions on Graphics, 33(4):1-8, 2014.

Thank You!

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