L0-REGULARIZED HYBRID GRADIENT SPARSITY PRIORS FOR ROBUST SINGLE-IMAGE BLIND DEBLURRING

Ryan Wen Liu[1], Wei Yin[1], Shengwu Xiong[2], Silong Peng[3]

wenliu@whut.edu.cn

[1] School of Navigation, Wuhan University of Technology
[2] School of Computer Science and Technology, Wuhan University of Technology
[3] Institute of Automation, Chinese Academy of Sciences

Problem

Image Formation Process

Blurred image f

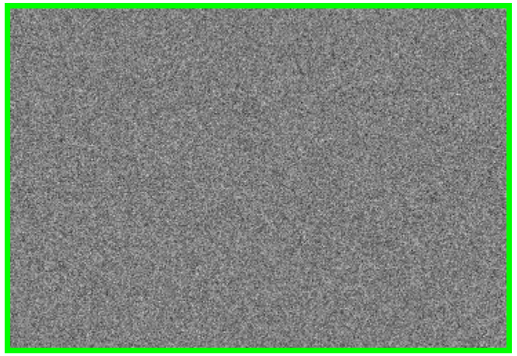
=

Latent image u

$\otimes$

Blur kernel k

+



Camera Noise n

$\otimes$: Convolution Operator

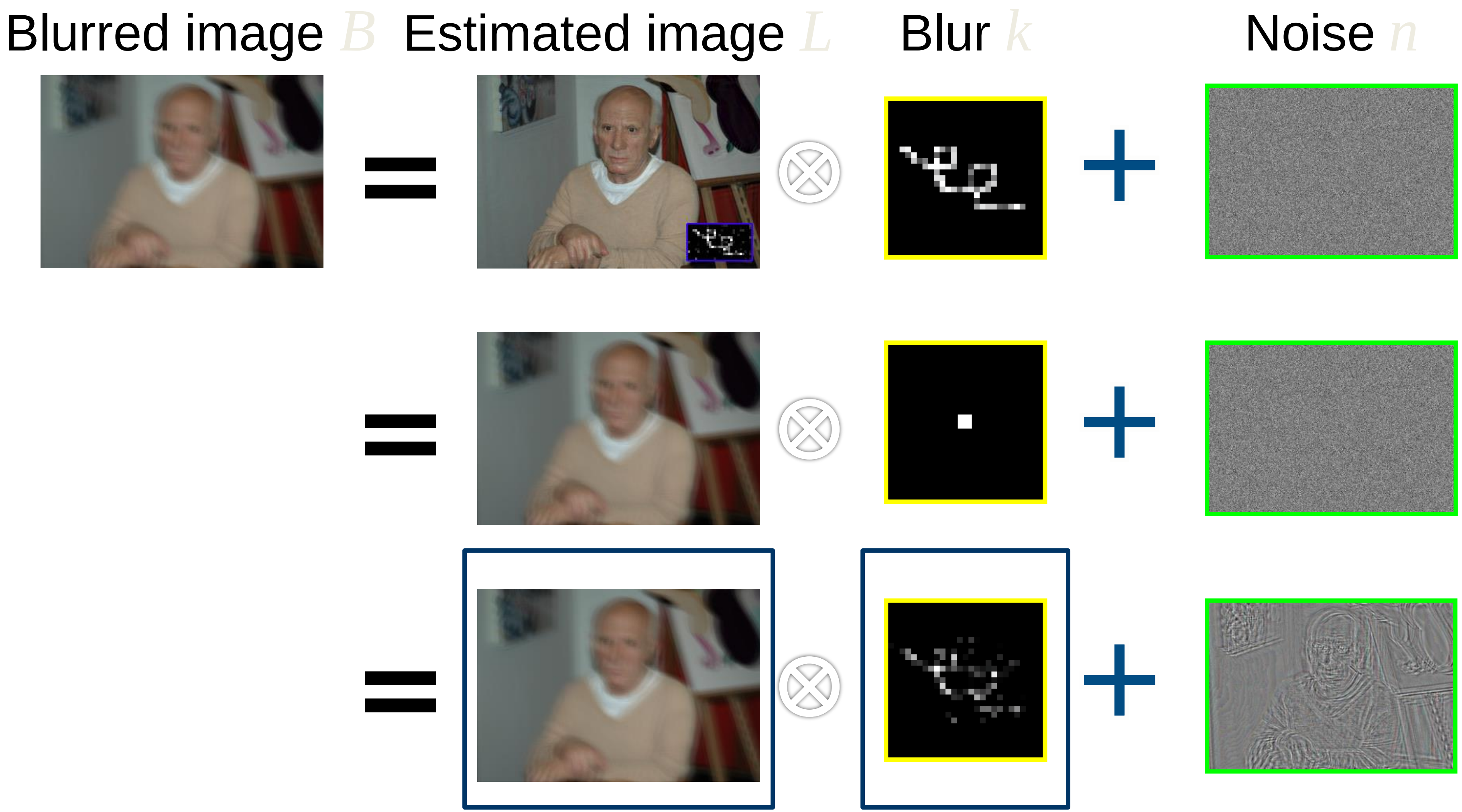
Bind Deblurring Problem

Non-Blind Deblurring

Blind Deblurring

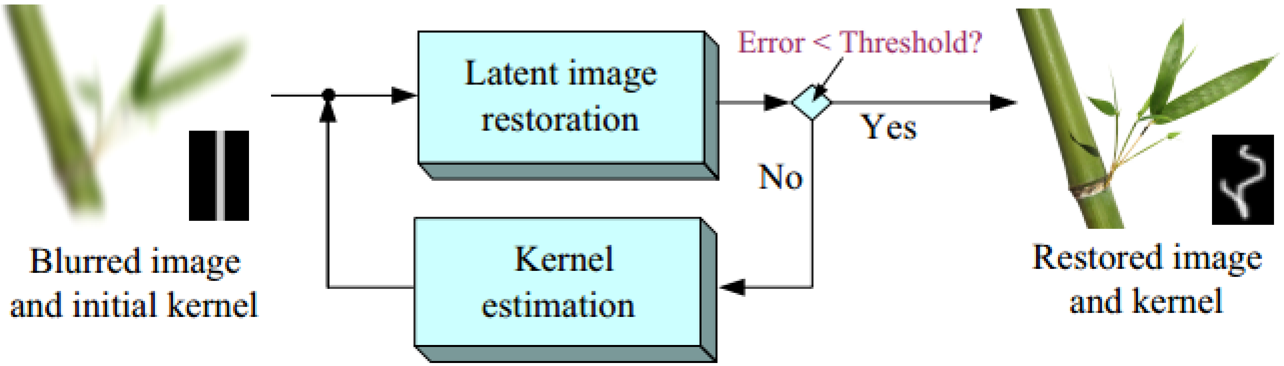
ACM Trans. Graph., 2008.

Key Challenge: Ill-Posedness

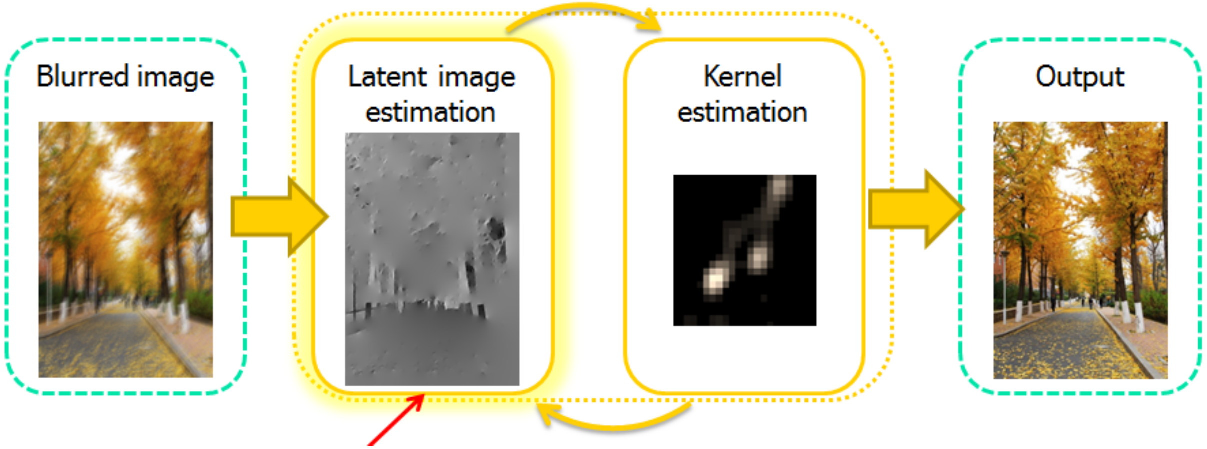


Related Work – Deblurring Framework

□ One-Step Blind Deblurring



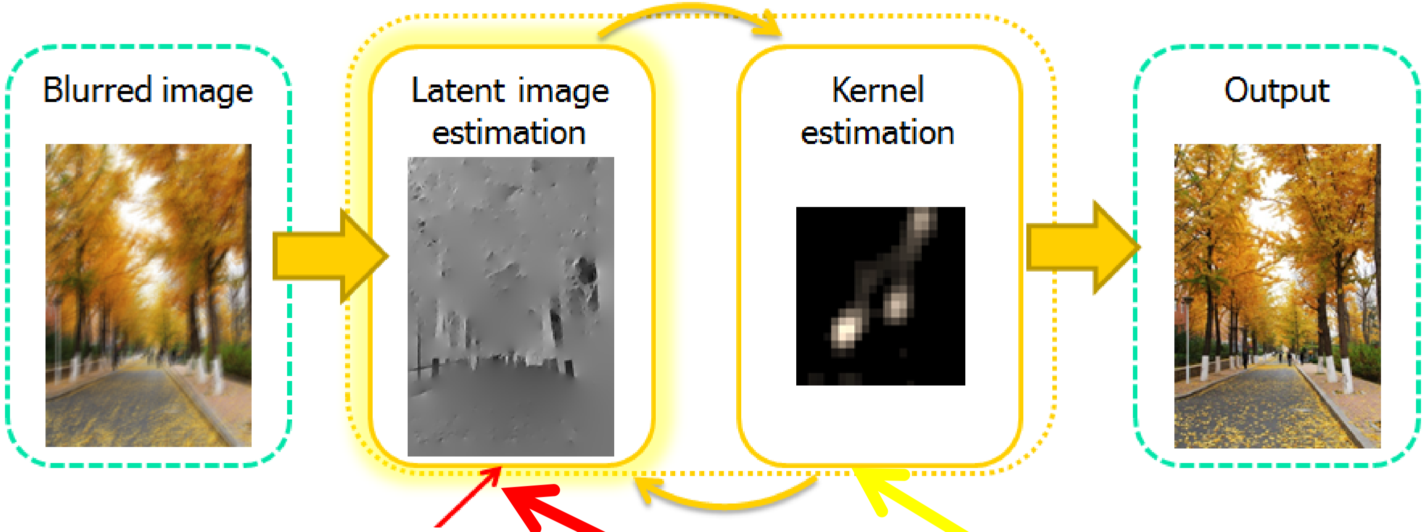
□ Two-Step Blind Deblurring



Step 1: **Blur Kernel Estimation;** **Step 2:** **Non-Blind Deconvolution**

Robust Blur Kernel Estimation

Image degradation model : $B = L * k + \epsilon$



$$\min_{k,\nabla L} \left\{ \frac{1}{2} \|\nabla L * k - \nabla B\|_2^2 + \lambda \Phi \left(\nabla L, \Delta L \right) + \gamma \|k\|_2^2 \right\}$$

Robust Blur Kernel Estimation

Numerical Optimization Algorithm

k-Estimation

$$k_{t+1} = \min_k \left\{ \frac{1}{2} \|\nabla L_t * k - \nabla B\|_2^2 + \gamma \|k\|_2^2 \right\}$$

∇L-Estimation

$$\nabla L_{t+1} = \min_{\nabla L} \left\{ \frac{1}{2} \|\nabla L * k_{t+1} - \nabla B\|_2^2 + \lambda \Phi \left(\nabla L, \Delta L \right) \right\}$$

Algorithm 1 Robust Blur Kernel Estimation

```
Input: Blurred image B, τ = 1.618, γ = 5 × 10^{-2}, η_1 = η_2 = 10^{-3}, and M_max = 15.
Initialize: k_0 = uniform, ∇L_0 = ∇B and t = 0.
while (not converged and t ≤ T_max) do
  // Step 1 : Blur Kernel Estimation k_{t+1}
    Update k_{t+1} according to (3).
  // Step 2 : Image Gradient Estimation ∇L_{t+1}
    ∇L_{t,0} ← ∇L_t.
    for s = 0 to S_max do
        Update ∇L_{t,s+1} according to (7).
        Update Y_{s+1} and Z_{s+1} according to (8) and (9).
        ξ_{s+1} = ξ_s − τβ_1 (Y_{s+1} − ∇L_{t,s+1}).
        φ_{s+1} = φ_s − τβ_2 (Z_{s+1} − ΔL_{t,s+1}).
    end for
    ∇L_{t+1} ← ∇L_{t,S_max}.
end while
Output: blur kernel k.
```

Non-Blind Deblurring

TV-regularized Variational Model for Non-Blind Deconvolution

$$\min_{L} \left\{ \|L * k - B\|_1 + \mu \|\nabla L\|_1 \right\}$$

Experiments

Experiments on Synthetical Blurred Images

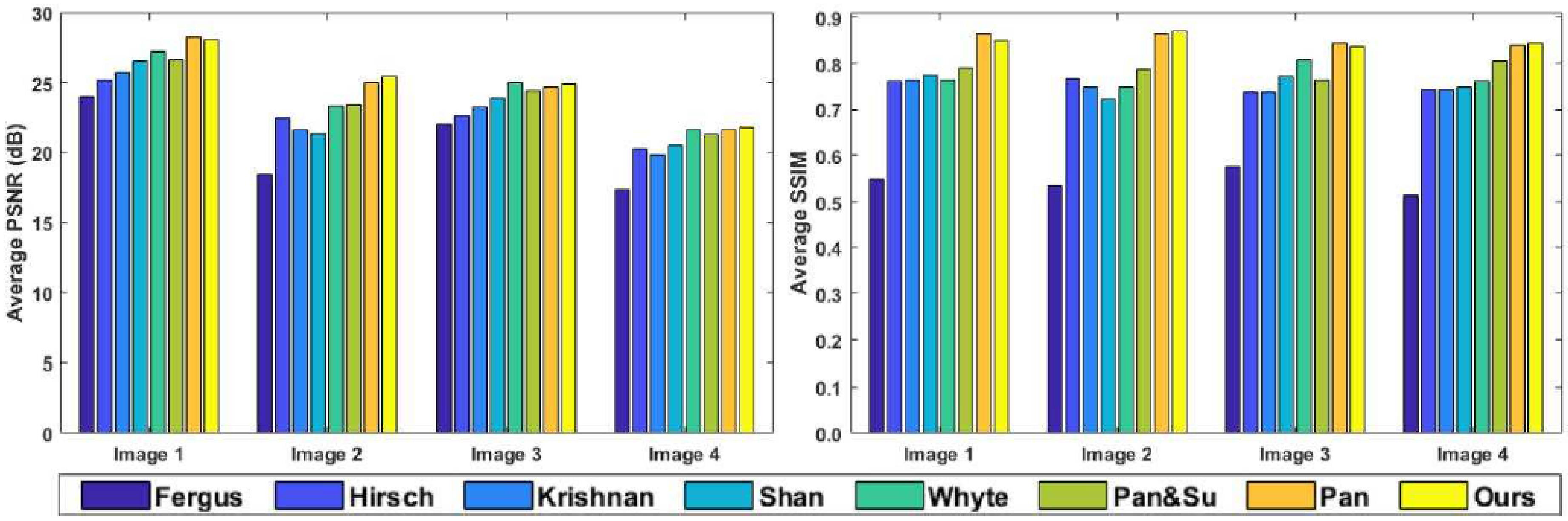


Fig. 1. Quantitative evaluation (left: PSNR, right: SSIM) on the benchmark dataset by [25] for different deblurring methods, i.e., Fergus [22], Hirsch [23], Krishnan [8], Shan [17], Whyte [24], Pan&Su [11], Pan [9] and our method.

Experiments

Fig. 2. Comparison with state-of-the-art deblurring methods on a synthetic image of size 800×800. Our estimated (*uniform*) blur kernel of size 145×145 is visually illustrated in the bottom-left panel.

Experiments

Experiments on Realistic Images

(a) Input (b) Krishnan (c) Pan&Su (d) Pan (e) Ours

Fig. 3. Blind deblurring of three realistic natural images with large-scale blur kernels. The sizes of the estimated blur kernels from top to bottom are 135×135, 101×101 and 95×95, respectively. (The images are best viewed in full-screen mode.)

Experiments

Experiments on Realistic Images

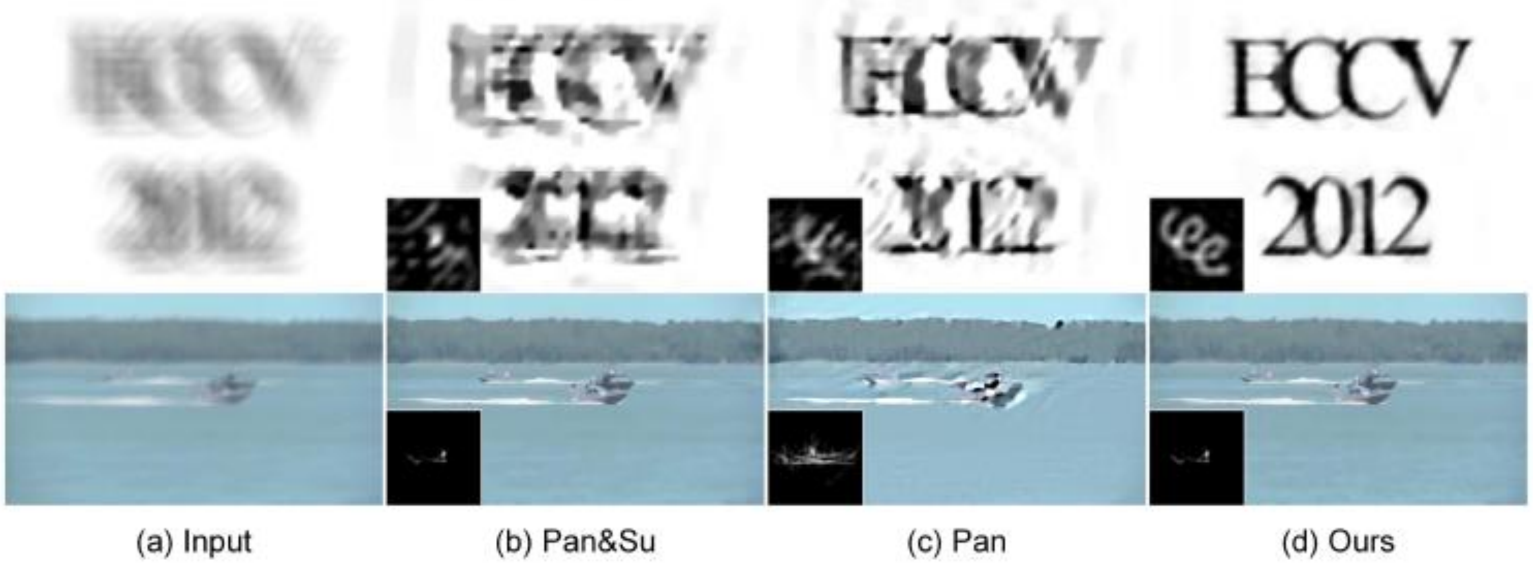


Fig. 4. Blind deblurring of two different realistic images. The sizes of the estimated blur kernels from top to bottom are 23×23 and 95×95, respectively.

Conclusion

- Introduce the L0-regularized hybrid gradient sparsity priors for robustly estimate blur kernels, The hybrid sparsity priors were able to preserve the gradient sparsity and salient edges, assisting in stabilizing the blur kernel estimation.
- The outlier-suppressing TVL1 model was proposed to guarantee high-quality non-blind image deblurring.

Future Work

- **Non-uniform image Deblurring** (Pixels are blurred differently)

Thank you for your attention!