Discriminative Blur Detection Features

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Image Blurriness

• Commonly occurred photo degradation
• Visual effect by photographers
• Important to analyze
Image Blur Detection

• Problem Definition
  – Finding blur pixels for a given input image

• Potential application
  – Image segmentation,
  – Object detection,
  – Image quality assessment,
  – ...

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Previous Works

• De-convolution based approach
Previous Works

• Deconvolution based approach

• Explicit blur detection
  – Frequency based: Liu 2008, Chakrabarti 2010
  – Matting based: Dai 2008, Dai 2009
Our Blur Features

- Image Gradient Distribution
- Spectra in Frequency Domain
- Local Filters
Our Blur Features

- Image Gradient Distribution

Properties:
1. Peakedness
2. Heavy-tailedness
Our Blur Features

- **Image Gradient Distribution**
  - Previous $L^{0.8}$ norm
Our Blur Features

• Image Gradient Distribution
  – Peakedness Measure
    • Definition: Kurtosis
      \[ K(a) = \frac{E[a^4]}{E^2[a^2]} - 3 \]

• Proposition 1: Given the local blur model and kurtosis measure, it is guaranteed to have \( K(B_x) \leq K(I_x) \) and \( K(B_y) \leq K(I_y) \).
Our Blur Features

• Image Gradient Distribution
  – Peakedness Measure
  • Kurtosis feature

\[ f_1 = \min(\ln(K(B_x) + 3), \ln(K(B_y) + 3)) \]
Our Blur Features

• Image Gradient Distribution
  – Peakedness Measure
  • Kurtosis feature

Figure. An illustration of kurtosis for different patches. The kurtosis feature value $f_1$ is given in Eq. (7). Unblurred patches yield larger values than blurred ones.
Our Blur Features

• **Image Gradient Distribution**
  – Heavy-Tailedness Measure

• Fit a Gaussian mixture model with two components to gradient magnitude $\nabla B$

\[
\nabla B \sim \pi_1 G(\nabla B | \mu_1, \sigma_1) + \pi_2 G(\nabla B | \mu_2, \sigma_2)
\]
Our Blur Features

• Image Gradient Distribution
  – Heavy-Tailedness Measure
    • Fit a Gaussian mixture model with two components to gradient magnitude $\nabla B$
      $$\nabla B \sim \pi_1 G(\nabla B|\mu_1, \sigma_1) + \pi_2 G(\nabla B|\mu_2, \sigma_2)$$
    • The heavy-tailedness feature is the larger variance
      $$f_2 = \sigma_1$$
Our Blur Features

• Spectra in Frequency Domain
  – Average power spectrum $J(\omega)$
    \[ J(\omega) = \frac{1}{n} \sum_{\theta} J(\omega, \theta) \sim \frac{A}{\omega^\alpha} \]

  • It intuitively represents the strength of change
  • Blur attenuates high frequency components.
  • The power spectrum fall off faster for blur region
Our Blur Features

• Spectra in Frequency Domain
  – Average power spectrum $J(\omega)$
    \[
    J(\omega) = \frac{1}{n} \sum_{\theta} J(\omega, \theta) \sim \frac{A}{\omega^\alpha}
    \]
  – Proposition 2: Given a natural image patch $x$ and its Gaussian or box blurred version $y$ by PSF $k$, the fall-off speed of the average power spectrum on $y$ is several orders faster than that of $x$. It is expressed as
    \[
    \lim_{\omega \to \infty} \omega^2 J_y(\omega) = 0
    \]
Our Blur Features

• Spectra in Frequency Domain
  – Spectrum feature:
    \[ f_2 = \sum_{\omega} \log(J(\omega)) \]
  – Proposition 3: Given a natural image patch \( x \), which is blurred by a PSF to form patch \( y \), the cumulated average power spectrum for the blurred patch is smaller than that for the sharp patch, i.e.,
    \[ \sum_{\omega} \log(J_y(\omega)) \leq \sum_{\omega} \log(J_x(\omega)) \]
Our Blur Features

• Spectra in Frequency Domain
Our Blur Features

• Local Filters
  – Data driven approach based on our labeled dataset
  – Linear discriminative analysis
    \[
    \max_W \frac{\text{tr}(W^T S_b W)}{\text{tr}(W^T S_w W)}
    \]
  – Learned feature
    \[
    f_3^n = \{ w_1^T B, \ldots, w_n^T B \}
    \]
Our Blur Features

• Local Filters

Figure. Our learned local linear filters. (a) Top 11 learned features. (b) Spectra of DFT for the learned linear filters. (c) and (d) Spectra for blurred and unblurred patches respectively.
Visualizing Features in 3D

(a) Input.  (b) Features in 3 dimensions.
Feature Covariance

Figure. Feature covariance. Features of kurtosis, heavy-tailedness, spectrum area, the 1st local filter, and the 2nd local filter are indexed from 1 to 5.
Multi-Scale Perception

• Scale ambiguous
Multi-Scale Perception

• Fuse information in different scales

\[ E(b) = \sum_{s=1}^{3} \sum_{i} |b^s_i - \hat{b}^s_i| + \alpha \sum_{s=1}^{3} \sum_{i} \sum_{j \in N^s_i} |b^s_i - b^s_j| + \beta \sum_{s=1}^{2} \sum_{i} |b^s_i - b^{s+1}_i|, \]

• The input for each layer is the posterior of a naive Bayesian classifier for the set of features.
Multi-Scale Perception

• Fuse information in different scales

Figure. Blur response maps in three layers and our final representation.
Blur Detection Dataset

1000 images with ground-truth
Experiments

• Visual comparisons
• Quantitative comparisons
• Applications enabled by blur detection
Visual Comparison

(a) Input  (b) Chakrabarti et al.  (c) Liu et al.  (d) Su et al.  (e) Ours  (f) Ground truth
Quantitative Comparison
Applications Based on Blur Detection

• Blur Segmentation and Deblurring

Figure. Spatially varying motion deblurring. (a) Input images with blur region masks. (b) Deblurring results.
Blur Magnification

(a) Input image.
(b) Editing result.
Failure Case

(a) Original image  (b) Our result  (c) Ground truth
Conclusion

• We have proposed several effective local blur features
• We have integrated the local blur features into a multi-scale inference framework
• Extensive experiments verified our method