Image Blur Classification and Parameter Identification using Two-stage Deep Belief Networks

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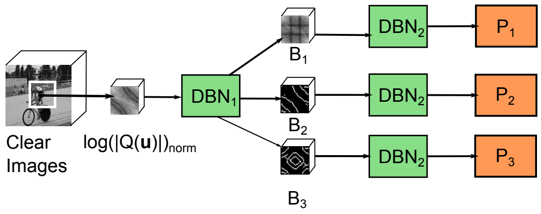

Figure 1: The TDBN architecture: DBN_1 is the first stage for blur type classification, which has 3 output labels. DBN_2 is the blur PSF parameter identification, which has different output labels for each blur type. P_1, P_2, and P_3 are the estimated parameter labels.

Image blur kernel classification and parameter estimation are critical for blind image deblurring. Current dominant approaches use handcrafted blur features [5, 6] that are optimized for a certain type of blur, which is not applicable in real blind deconvolution where the Point Spread Function (PSF) of the blur is unknown. Inspired by the successful applications of deep learning techniques to object recognition and image processing [2, 4], in this paper, a Two-stage system using Deep Belief Networks (TDBN) is proposed to first classify the blur type and then identify its parameters.

In this paper, we intend to design a patch-based blur type classification and parameters identification method to better solve the realistic blur analysis problem. Deep Belief Network (DBN) [3] is chosen for accomplishing the feature extraction and final classification in this system. A two-stage framework is proposed: first, for the input image patches with different blurs, the DBN is used for identifying the blur type; second, different samples with the same blur type will be sent to the corresponding DBN blocks for further parameter estimation. The DBN is trained in a semi-supervised way: the unsupervised training of the DBN is done by a greedy layer-wise pre-training before the supervised backpropagation for the fine-tuning. The unsupervised process helps the feature learning, and the backpropagation helps to construct the discriminative information.

In a word, our contributions are threefold: 1) To the best of our knowledge, this is the first time that deep belief network has been applied to the problem of blur analysis; 2) A discriminative feature, derived from edge extraction on Fourier Transform coefficients, has been proposed to preprocess blurred images before they are fed into the DBN; 3) A two-stage framework is proposed to estimate the blur type and parameters for any given image degraded by spatially invariant blur of an unknown type.

To begin with, for the input blurred patches, the logarithmic spectra are used as a type of feature for the identification of the blur pattern, which is shown in the following Fig. 2. Three types of blur have been considered in our paper, which are the Gaussian blur, the motion blur and the defocus blur. They can be formulated as:

$$q(\mathbf{x},\sigma) = \frac{1}{\sqrt{2\pi}\sigma}\exp(-\frac{x_1^2+x_2^2}{2\sigma^2}), \quad \mathbf{x}\in R \tag{1}$$

where σ is the blur radius to be estimated, and R is the region of support. R is usually set as $[-3\sigma, 3\sigma]$, because it contains 99.7% of the energy in a Gaussian function [1].

$$q(\mathbf{x}) = \begin{cases} \frac{1}{M}, & if(x_1,x_2)\begin{pmatrix} sin(\omega) \\ cos(\omega)\end{pmatrix} = 0 \quad and \quad x_1^2+x_2^2 \le M^2/4 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where M describes the length of motion in pixels and ω is the motion direction with its angle to the x axis.

$$q(\mathbf{x}) = \begin{cases} \frac{1}{\pi R^2}, & \sqrt{x_1^2+x_2^2} \le R \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where the blur radius R is proportional to the extent of defocusing.

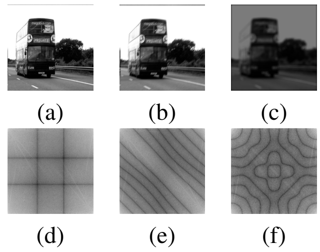

Figure 2: The blur images and their logarithmic spectra. (a) Image with Gaussian blur. (b) Image with motion blur. (c) Image with out-of-focus blur. (d) Logarithmic spectrum of Gaussian blur ($\sigma = 2$). (e) Logarithmic spectrum of motion blur ($M = 9, \omega = 45$). (f) Logarithmic spectrum of out-of-focus blur. ($R = 30$)

In the second stage, an edge detector is applied to the motion blur and defocus blur. Gaussian blur is not affected by this step because its Fourier transform of the PSF barely changes with the blur radius. The processed vectors serve as the input for the individual DBN in the next level.

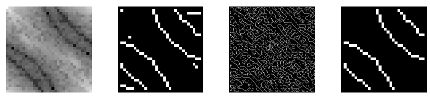

Figure 3: Comparison of the three edge detection methods applied to a training sample. From left to right: (1) the logarithmic power spectrum of a patch; (2) the edge detected by Canny detector (automatic thresholds); (3) the edge detected by the improved Canny detector using scale multiplication; (4) the edge detected by our method.

The final stage is the parameter estimation. For Gaussian blur, we estimate the blur radius of the Gaussian distribution. For motion blur, the length and angle of the motion are estimated. For out-of-focus blur, the blur radius is identified.

Our proposed method has been compared with existing blur classification algorithms based on both handcrafted features and neural networks. It outperforms state-of-the-art approaches significantly (up to 4%) due to the advantages of our selected features and the proposed TDBN structure.

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