Blur Detection Features

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Digital Image Processing 2015, Vineet Gandhi

June 15, 2017

1 Introduction

Blur is one type of photo degradation that leads to loss of details. In many special cases, it can also be a visual effect purposely generated by photographers to give prominence to foreground persons or other important objects based on out of focus or camera/object motion.
With the fast development of computer vision techniques, it becomes important and practical to understand information immersed in blurred images or regions. We address a central blur detection problem in this area, since quickly and effectively finding blur pixels can naturally benefit many applications including but not restricted to image segmentation, object detection, scene classification, image quality assessment, image restoration, and photo editing, given the fact that many blurred images exist online or are produced from personal cameras. We aim to classify each pixel of the input pixel as blurred or unblurred. We do this by constructing a feature vector for each pixel using five features. These are further discussed in the method. After construction, the pixels are classified using a Bayesian classifier trained with the ground truth values of the image.

2 Related Work

Levin [3] used image statistics to identify partial motion blur. Lin et al. [4] also explored natural image statistics for blur analysis. Liu et al. [7] designed four local blur features for blur confidence and type classification. Chakrabarti et al. [5] analyzed directional blur via local Fourier transform. Dai and Wu [6] developed a two-layer image model on alpha channel to estimate partial blur. Shi et al [1] propose a multi-scale approach with four discriminative blur detection filters. Tong et al [2] proposed wavelet transform based blur extent score based model to determine whether a given image is blurred based on identification of the types of edges in the image.

3 Dataset

The blur detection dataset made in [1] that contains 1000 images. The ground truths are also provided for these images which were obtained with manual labeling. These images are from many field of study, with 500 images having motion blur and 500 images having out of focus blur.

4 Method

To do a pixel by pixel classification of blur, we first construct a feature vector for each pixel of the input image. The features used are described below. All the features extracted are per pixel given a particular patchsize. Once the feature vector is made for multiple scales of the image. We aim to classify each pixel of the input pixel as blurred or unblurred. We do this by constructing a feature vector for each pixel consisting of five features. These are further discussed in the method. After construction, the pixels are classified using a Bayesian classifier trained with the ground truth values of the image.

4.1 Local Kurtosis

We find the logarithm of the Kurtosis of the patches of the image as the blur process widens the distribution. The distribution peak is thus lowered which amounts to the reduction in the Kurtosis value. Kurtosis is given for a distribution a as follows (E is the expectation),

$$K(a) = \frac{E[a^4]}{E^2[a^2]} - 3 \tag{1}$$

To support this claim, [7] have proved the following theorem, stated in verbatim, *Given the local blur model and Kurtosis measure, it is guaranteed to have* $K(B_x) \leq K(I_x)$ *and* $K(B_y) \leq K(I_y)$

4.2 Gradient Histogram Span

The $level of tailedness$ of a distribution is an important property to know in regards to blur detection. Heavy-tailed distributions are those whose tails are not exponentially bounded, and are useful due to the fact that the blur significantly lowers the gradient magnitudes. To find this feature, we fit a Gaussian mixture model for the gradient magnitude ∇_B using two components, G(μ_1,σ_1), and G(μ_2,σ_2). We denote σ_1 as the larger variance between the two. Because the tail distribution variance in the clear patch is much bigger than that of the blur one, the tailedness feature is set as

$$f_2 = \sigma_1 \tag{2}$$

4.3 Local Learned Filter

We initially compute the LDA between the labeled blur patch set (say B) and unblurred patch set (say I), which maximizes the interclass variance and minimizes the interclass variance of the set. We thus get a projection from the eigenvectors of the following equation,

$$S_b W_i = \lambda_i S_w W_i \tag{3}$$

where intraclass and interclass scatters are S_w and S_b respectively. The projection approximates to special kind of high pass filter, however their structures are not intuitive. There is obvious difference from handcrafted gradient and Laplacian filters.

4.4 Average Power Spectrum

Averaged power spectrum, intuitively, represents the strength of change. It is given by the following formulation.

$$J(\omega) = \frac{1}{n} \sum_{\theta} J\omega, \theta \simeq \frac{A}{\omega^2} \tag{4}$$

We know that blur attenuates high frequency components, as it removed details, and therefore makes the power spectra fall off much faster than its sharp counterpart. The $log()log(J())$ curve is stable with respect to high frequency variation. Sharper regions yield larger values.

4.5 Local Blur Extent

The basic idea of the feature is that most natural images contain all types of edges and most Gstep-Structure and Roof-Structure are sharp enough. When blur occurs, no matter whether it is caused by Out-of-focus or Linear motion, both Dirac-Structure and Astep-Structure will disappear. What is more, both Gstep-Structure and Roof-Structure tend to lose their sharpness. The feature, whether a given patch is blurred according to whether it has Dirac-Structure or Astep-Structure, and uses the percentage of Gstep-Structure and Roof-Structure which are more likely to be in a blurred image to determine the blur extent.

Original	After Blur	Change of sharpness
Dirac-Structure	Roof-Structure	-
Astep-Structure	Gstep-Structure	-
Gstep-Structure	Gstep-Structure	Smaller
Roof-Structure	Roof-Structure	Smaller

For each patch in the image, we find the third level Haar Wavelet decomposition of a given input image. and for each level we find

$$E_{map_i} = \sqrt{LH^2 + HL^2 + HH^2}, i = 1, 2, 3 \tag{5}$$

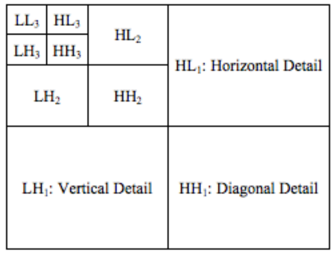


Figure 1: Third level Haar Wavelet decomposition

Then, partition the edge maps into windows of size $8x8$, $4x4$ and $2x2$ for $E_{map_i}, i = 1, 2, 3$ respectively and find local maxima in each window. This is E_{max_i}. Based on the these values, the edges can be classified into the following categories. These can be classified using the following table. For example, if the

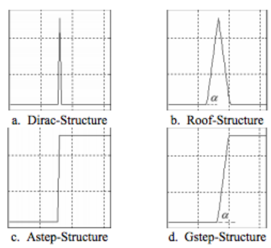


Figure 2: Types of Edges

point(k, l) is an Gstep-structure then for that edge, $E_{max_1} \leq E_{max_2} \leq E_{max_3}$. First, however, we must check if the point is indeed an edge. $E_{max_1} > threshold$ or $E_{max_2} > threshold$ or $E_{max_3} > threshold$. For any Gstep-Structure or Roof-Structure edge point (k, l) , $E_{max_1} < threshold$ (k, l) is more likely to be in a blurred image. [Here the threshold is 35/255]

	E_{max_1}	E_{max_2}	E_{max_3}
Dirac-Structure	Highest	Middle	Lowest
Astep-Structure	Highest	Middle	Lowest
Gstep-Structure	Lowest	Middle	Highest
Roof-Structure	Lowest	Middle	Highest
Roof-Structure	Lowest	Highest	Middle

After identifying the type of each edge point, find

$$Per = \frac{N_{da}}{N_{edge}} \tag{6}$$

$$BlurExtent = \frac{N_{brg}}{N_{rg}} \tag{7}$$

where N_{da} is the number of Dirac and Astep edges, N_{edge} is the total number of edge points, N_{brg} is the number of blurred Roof and Gstep edges, and N_{rg} is the number of Roof and Gstep edges. If $Per > MinZero$, judge that the image is unblurred and vice versa, where $MinZero$ is a positive parameter, ideally $zero$, but here 0.05, and $BlurExtent$ is the blur confident coefficient for the image.

4.6 Gabor Filter

We can also see how spatial filters such as Gabor and Laplacian, can be used in this detection problem. They capture local band-pass or high-pass information that supplements frequency and gradient domain features. The input image, holistically, is convoluted with a Gabor filter, defined below as:

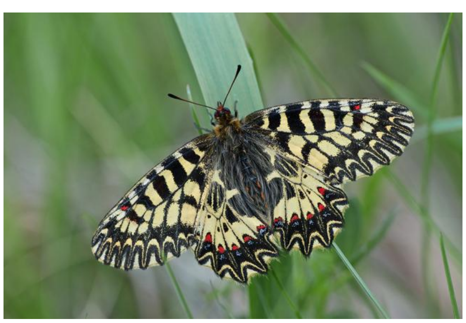
$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = exp(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}) * exp((2\pi \frac{x'}{\gamma})) \tag{8}$$

,where $x' = x * cos(\theta) + y * sin(\theta)$ and $y' = -x * sin(\theta) + y * cos(\theta)$.

The output of the this convolution was passed to a closing operator to make the distribution more even.

5 Results and Observations

The performance of our implementation is comparable to the results of [1] as can be seen here.



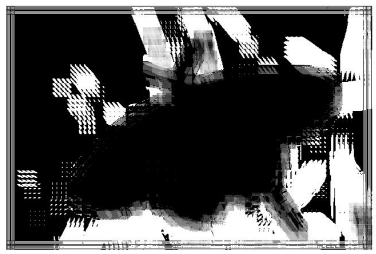
(a) Input Image

(b) Output of Implementation

Also, we tried out the features that we proposed, namely Gabor Filtering and Local Blur Extent using Wavelet Transform and the results are encouraging in nature.

Performing the Local Blur Extent computation over each pixel neighborhood is a very time consuming algorithm, however, it yields good results.

Finding the extent for each block decreases the computation considerably, sacrificing on locality of regions.



(a) LBE over Pixel Neighborhood

(b) LBE over Blocks

Figure 5: Gabor Filter Result

For the second proposed feature, Gabor filtering, we obtained good results after tweaking the parameters, however such tweaks are not applicable for each image. Hence it is important to find a method of parameter estimation for each image.

6 Conclusion

To conclude, we have evaluted the validity of the [1] and [2]. We extended the [2] to a patchwise and blockwise implementation as a new feature. Lastly, we experimented with a Gabor filter to propose a new feature that works well on a case-to-case basis, but can be significantly improved with proper parameter estimation.

References

[1] Jianping Shi, Li Xu, Jiaya Jia *Discriminative Blur Detection Features*, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2014

[2] Hanghang Tong, Mingjing Li, HongJiang Zhang, Changshui Zhang *Blur detection for digital images using wavelet transform*, ICME 2004.

[3] A. Levin. *Blind motion deblurring using image statistics.* NIPS, 19:841, 2007.

[4] H. T. Lin, Y.-W. Tai, and M. S. Brown. *Motion regularization for matting motion blurred objects.* IEEE Transactions on Pattern Analysis and Machine Intelligence, 33(11):2329 2336, 2011.

[5] Chakrabarti, T. Zickler, and W. T. Freeman. *Analyzing spatially-varying blur.* In CVPR, pages 25122519, 2010.

[6] S. Dai and Y. Wu. *Removing partial blur in a single image.* In CVPR, pages 25442551, 2009.

[7] Liu, Z. Li, and J. Jia. *Image partial blur detection and classification.* In CVPR, pages 18, 2008.