Review: Coarse-to-fine blind image deblurring based on K-means clustering

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1 Summary

The aim of this paper is to address the challenging problem of blind image deblurring, where both the sharp image and blur kernel are unknown. Traditional methods place substantial limitations on the problem[13] and deep learning approaches have typically relied on extensive training data, resulting in slow processing and dependency on training sets[14].

The proposed method introduces a multiscale coarse-to-fine approach based on a maximum a posteriori estimation for blur kernel deblurring, at each scale using K-means clustering for image segmentation in order to isolate and preserve salient edges of the latent image. The method is consistent with the aims of the research and is concisely explained in several sections. Diagrams and pseudo code algorithms are accompanied by relevant equations, and reference to related techniques implemented to accelerate innate debluring optimisation problems[4][6].

Results shared in the paper come in several metrics including; PSNR, SSIM, RMSE, and Error ratio. The results are consistent with the aims of the research. It is shown that the proposed method outperforms some existing approaches in terms of runtime whilst having either comparable or outperforming in several error metrics. Results are served in visualisations and graphs, the paper also makes a brief but valid point that in blind image and real world deblurring, the blur kernel isn't known so the optimal sharp image can be subjective.

The novel aspect of this paper and its contribution to the field is the applied combination of a coarse-to-fine multiscale MAP based approach with K-means clustering for image segmentation. Specifically the use of K-means to segment the latent image, which was shown to improve estimation of the blur kernel. The paper concludes that unlike other methods which make assumptions about the blur kernel, they estimate the blur kernel at each point in the image pyramid iteratively offering a way to deblur images without needing to make assumptions about blur kernel priors.

2 Related Work

Foundational work for the presented paper can be found in "Removing Camera Shake from a Single Photograph"[7], they adopt a coarse-to-fine multiscale approach but make use of Bayesian statistics for blur kernel estimation. Later approaches attempt to reconstruct an intermediate sharp image from the blurred image but require complex prior knowledge to effectively estimate the blur kernel[14].

Image smoothing techniques have been used to improve latent image quality for blur kernel estimation[3]. K-means has also been previously used with deep learning models to aid in feature selection in image deblurring[1]. Deep learning approaches have been conducted with CNNs and GNNs [17][8], in work conducted by Pan et al, they trained a CNN and only needed 2500 sharp images to generate a training set[14]. Recent state of the art statistical approaches have used extreme channel priors[18], which built on the dark channel prior make the assumption that, bright pixels in the clear images are not likely to be bright after the blur process.It has been shown that true state of the art image deblurring comes from the deep learning approaches [21].

The work outlined in this paper approaches the problem differently as its explicit focus is on the blind aspect of image deblurring, this paper contributes a way to deblur images whilst making very few prior assumptions, this can be useful where you don't know what the properties of the blind image are, hence this work has been cited in for its K-means approach[20].

3 Strengths of the paper

The strength of the paper lies in its clear presentation of results and comprehensive evaluation using multiple error metrics supported by diagrams and graphs. Particularly noteworthy is the inclusion of overlaid synthetic and estimated blur kernels in the figures, offering a visual comparison that enhances understanding. Moreover, the authors acknowledge the subjectivity of deblurring outcomes in certain contexts. The discussion effectively links key findings in prior research, the K-means algorithm is well-explained and proven to be a well performing method for image segmentation, the novel proposal of using it is well suited to enhance blur kernel estimation. The proposed method avoids complex assumptions and achieves fast execution in line with the aims of the research. The authors make appropriate use of related work[6][4], as they leverage Fourier space to directly estimate the blur kernel and employ the ADMM method for optimization, contributing to algorithm efficiency. One notable strength of the K-means approach is its interpretability, as demonstrated in Figure 3, where the segmentation of the latent image is visually interpretable even with a lower number of clusters. The clarity in segmentation enhances the understanding of the deblurring process and the effectiveness of the proposed method.

4 Weaknesses of the paper

While the use of K-means clustering for image segmentation has been established, the paper lacks a clear justification for that clustering method over other methods for example K-harmonic means[10]. The implementation of K-means lacks details for optimal parameters, the dataset used to conduct the analysis was limited and the non-deterministic allocation of cluster centroids introduces variability in the results, raising questions about the reliability of the proposed approach.

It might have been helpful for the authors to provide more detail on how they decided on the chosen testing dataset; the sample size of the data set seems fairly small in view of available datasets[11], The total synthetic test data is 132 blurred images generated from 29 sharp images and 12 blur kernels from 2 data sets. The paper doesn't present all synthetic blur kernels. However, considering other blur kernels presented in related work, the kernels used in this paper appear to have comparatively less variance and complexity[12]. The limitations of testing on a synthetically blurred data set are not presented, synthetic data isn't representative of real data [16], the Levin data used was generated by convolution of a blur kernel which assumes uniform motion[9]. No explanation is provided as to why the results are only compared against traditional techniques and no deep learning approaches. The paper criticizes deep learning approaches for their reliance on extensive training data and the dependence between training data and results. However, it should be noted that current deep learning approaches have been proven to be state-of-the-art in blind image deblurring, and ample data is available[21][11]. It might have been useful for the authors to provide more details of the intended use case for the algorithm and its limitations.

5 Potential advancement

The strength of this paper and where it contributes is its ability to make no prior assumptions about the image or blur kernel, it might be useful to expand on that arm of research. Because there's only one blur kernel estimated at each level of the image pyramid it assumes that the blurring is uniform and the same across all parts of the image. This might not necessarily be the case, I propose an algorithm which would split up the latent image and try to learn a blur kernel for each sub image, by learning multiple kernels, we can compare them and learn about local properties of image. This idea comes from "Edge-based Blur Kernel Estimation Using Patch Priors" [15] where they use a 'trusted' subset of the image to learn a blur kernel and apply it to the whole image. The strength of this new approach is that it may be able to account for types of blurring not associated with motion and would behave more like the state of the art techniques such as a CNN which learns localised parts of the image.

I also propose a more comprehensive investigation into image segmentation and sharpening techniques used to improve salient edges in the latent image for blur kernel estimation, K-means is a centroid based approach, and other methods such as fuzzy or harmonic K-means might yield different results, there's also density based clustering options I would consider useful for latent image segmentation as they can serve to smooth weak edges[19][5].

Limitations with the method proposed in the paper is that it works with grey level images, hence it fails to properly deblur the texture images with low intensity variation, it might be useful to consider an additional step before the latent image segmentation, where we stretch the image histogram, making full use of the range of intensity values available, or using equalization to redistributes the intensity values in the image to enhance the contrast[2] and sharpen salient edges to improve blur kernel estimation.

References

[1] Sanaz Aliyan and Ali Broumandnia. “A New Machine Learning Approach to Deblurring License Plate Using K-Means Clustering Method”. In: *International Journal of Advanced Research in Artificial Intelligence* 1.2 (2012). DOI: 10.14569/IJARAI.2012.010202. URL: http://dx.doi.org/10.14569/IJARAI.2012.010202.

[2] Tarik Arici, Salih Dikbas, and Yucel Altunbasak. “A histogram modification framework and its application for image contrast enhancement”. In: *IEEE Transactions on image processing* 18.9 (2009), pp. 1921–1935.

[3] Yuanchao Bai et al. “Graph-Based Blind Image Deblurring From a Single Photograph”. In: *IEEE Transactions on Image Processing* 28.3 (2019), pp. 1404–1418. DOI: 10.1109/TIP.2018.2874290.

[4] Stephen Boyd et al. “Distributed Optimization and Statistical Learning via the Alternating Direction Method of Multipliers”. In: *Foundations and Trends® in Machine Learning* 3.1 (2011), pp. 1–122. ISSN: 1935-8237. DOI: 10.1561/2200000016. URL: http://dx.doi.org/10.1561/2200000016.

[5] Jinyin Chen et al. “A novel image segmentation method based on fast density clustering algorithm”. In: *Engineering Applications of Artificial Intelligence* 73 (2018), pp. 92–110.

[6] Sunghyun Cho and Seungyong Lee. “Fast motion deblurring”. In: *ACM Trans. Graph.* 28.5 (Dec. 2009), pp. 1–8. ISSN: 0730-0301. DOI: 10.1145/1618452.1618491. URL: https://doi.org/10.1145/1618452.1618491.

[7] Rob Fergus et al. “Removing camera shake from a single photograph”. In: *Acm Siggraph 2006 Papers*. 2006, pp. 787–794.

[8] Orest Kupyn et al. “Deblurgan: Blind motion deblurring using conditional adversarial networks”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018, pp. 8183–8192.

[9] Anat Levin et al. “Understanding and evaluating blind deconvolution algorithms”. In: *2009 IEEE Conference on Computer Vision and Pattern Recognition*. 2009, pp. 1964–1971. DOI: 10.1109/CVPR.2009.5206815.

[10] Qi Li, Nikolaos Mitianoudis, and Tania Stathaki. “Spatial kernel K-harmonic means clustering for multi-spectral image segmentation”. In: *IET Image Processing* 1.2 (2007), pp. 156–167.

[11] Seungjun Nah, Tae Hyun Kim, and Kyoung Mu Lee. “Deep multi-scale convolutional neural network for dynamic scene deblurring”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017, pp. 3883–3891.

[12] Jinshan Pan et al. “L_0 -Regularized Intensity and Gradient Prior for Deblurring Text Images and Beyond”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 39.2 (2017), pp. 342–355. DOI: 10.1109/TPAMI.2016.2551244.

[13] Jinshan Pan et al. “Blind Image Deblurring Using Dark Channel Prior”. In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. 2016, pp. 1628–1636. DOI: 10.1109/CVPR.2016.180.

[14] Jinshan Pan et al. “Learning to Deblur Images with Exemplars”. In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 41.6 (2019), pp. 1412–1425. DOI: 10.1109/TPAMI.2018.2832125.

[15] Libin Sun et al. “Edge-based blur kernel estimation using patch priors”. In: *IEEE international conference on computational photography (ICCP)*. IEEE. 2013, pp. 1–8.

[16] Hao Wei et al. “Rethinking blur synthesis for deep real-world image deblurring”. In: *arXiv preprint arXiv:2209.13866* (2022).

[17] Zhengrong Xue. “Blind image deblurring: a review”. In: *arXiv preprint arXiv:2201.10522* (2022).

[18] Yanyang Yan et al. "Image deblurring via extreme channels prior". In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2017, pp. 4003–4011.

[19] Qixiang Ye, Wen Gao, and Wei Zeng. "Color image segmentation using density-based clustering". In: *2003 International Conference on Multimedia and Expo. ICME'03. Proceedings (Cat. No. 03TH8698)*. Vol. 2. IEEE. 2003, pp. II–401.

[20] GS Yogananda and J Ananda Babu. "Multiobjective Reptile Search Algorithm Based Effective Image Deblurring and Restoration". In: *Journal of Artificial Intelligence and Technology* 3.4 (2023), pp. 154–161.

[21] Kaihao Zhang et al. "Deep image deblurring: A survey". In: *International Journal of Computer Vision* 130.9 (2022), pp. 2103–2130.