CVPR
#1047

CVPR
#1047

CVPR 2017 Submission #1047. CONFIDENTIAL REVIEW COPY. DO NOT DISTRIBUTE.

Rebuttal for Paper ID 1047

We appreciate all the reviewers for their constructive comments, especially R2 for your encouraging comments.

R1's Questions

Q1: Overstatement of claims

A1: The noise in real world images are very complex and cannot be modeled by Poisson or other more complex distribution. Since it is too hard to explicitly model the real noise, we gave up designing good models for real noise. Instead, we turn to model the signals by statistical models such as mixture of Gaussian (MoG). We believe that as long as we model the signals accurately enough, we do not need strong priors for the noise, and hence we employ the ℓ_2 norm for the residual errors. We admit that if we describe the noise with a more suitable model, the performance of our algorithm will be better. But this is not the major point of this paper, as pointed out by the title of this paper.

Q2: There is nothing new in terms of the prior model ...

A2: When taking the MoG model for learning priors from external data, we basically follow the framework of EPLL. However, this is not the exact work we have done in this paper. What we did is to employ the external priors learned from external data to guide the learning of internal priors which are more adaptive to the image being denoised. And we want to argue that this combination makes our model have stronger ability to characterize the signals in real noisy images. We evaluate two algorithms designed for Poisson noise reduction, NLSPCA [3] and [1]. The results are listed in Table 1. Note that we had tune the parameters of these algorithms carefully to achieve their best performance.

R2's Questions

Q1: The number and effect of parameters

A1: The key parameters of our model are the regularization parameter λ and the number of atoms in external sub-dictionary,r. r is very robust as long as it is in a reasonable range as demonstrated in experiments. $\lambda = 0.001$ works well in the experiments. Other parameters are preset by hand and can work well as long as they are set in a reasonable range.

R3's Questions

Q1: hard to believe that it will work for all the cases

A1: We had tested our method on the two datasets which contains a lot of real noisy images for many cases, we will test our method and publish our code in the future for testing on more cases.

Q2: not clear how to choose nonlocal similar patches

A2: Yes, we chose similar patches based on Euclidean distance and we added this detail to our revised paper.

Table 1. Average PSNR(dB) results of different methods on 60 real noisy images cropped from [2].

Methods	NLSPCA	[1]	MLP	CSF
PSNR	24.39	25.67	38.36	38.21
Methods	TNRD	NI	NC	Ours
PSNR	38.32	36.53	37.57	**38.75**

Thanks for pointing it out.

Q3: other noise types

A3: In this paper, we only deal with real noise in real noisy images. Other noise types will be considered in future work.

Q4: the likelihood term is Gaussian denoising

A4: Please kindly refer to the answers **A1** to **Q1** of **R1** and **A3** to **Q3** above for this problem since the space is limited.

Q5: The competing algorithms would also work quite well

A5: We retained the TNRD, CSF or MLP model with the carefully parameter tuning to achieve their corresponding best performance. For example, we retained these models with Gaussian noise levels in $\sigma = 5, 10, 15, 25, 35, 50$. We found that MLP achieves the best PSNR results on the 60 images used in our paper at $\sigma = 10$, which are 38.36dB. But this result is still 0.39dB lower than those of our method. The image qualities of MLP at $\sigma = 10$ are still clearly inferior to those of our method. The new results are listed in Table 1 in which we also evaluated the performance of two algorithms for Poisson noise removal, NLSPCA [3] and [1].

Q6: a single parameter setting for all the cases

A6: The experiments demonstrate that a single parameter can deal with all the cases in the tested datasets. With more flexible parameters setting, the performance would be better and this is the line of our future work.

Q7: why is the image resolution significantly smaller

A7: This is for smaller pdf size of the paper, and down scale the images would not affect much the image quality.

References

[1] M. Makitalo and A. Foi. Optimal inversion of the generalized anscombe transformation for poisson-gaussian noise. *IEEE Transactions on Image Processing*, 22(1):91–103, 2013. 1

[2] S. Nam, Y. Hwang, Y. Matsushita, and S. J. Kim. A holistic approach to cross-channel image noise modeling and its application to image denoising. *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 1683–1691, 2016. 1

[3] J. Salmon, Z. Harmany, C.-A. Deledalle, and R. Willett. Poisson noise reduction with non-local pca. *Journal of Mathematical Imaging and Vision*, 48(2):279–294, 2014. 1

000
001
002
003
004
005
006
007
008
009
010
011
012
013
014
015
016
017
018
019
020
021
022
023
024
025
026
027
028
029
030
031
032
033
034
035
036
037
038
039
040
041
042
043
044
045
046
047
048
049
050
051
052
053
054
055
056
057
058
059
060
061
062
063
064
065
066
067
068
069
070
071
072
073
074
075
076
077
078
079
080
081
082
083
084
085
086
087
088
089
090
091
092
093
094
095
096
097
098
099
100
101
102
103
104
105
106
107