## Non-Local ConvLSTM for Video Compression Artifact Reduction Supplementary File

Yi Xu Longwen Gao Kai Tian Shuigeng Zhou Huyang Sun

## **Qualitative Comparison**

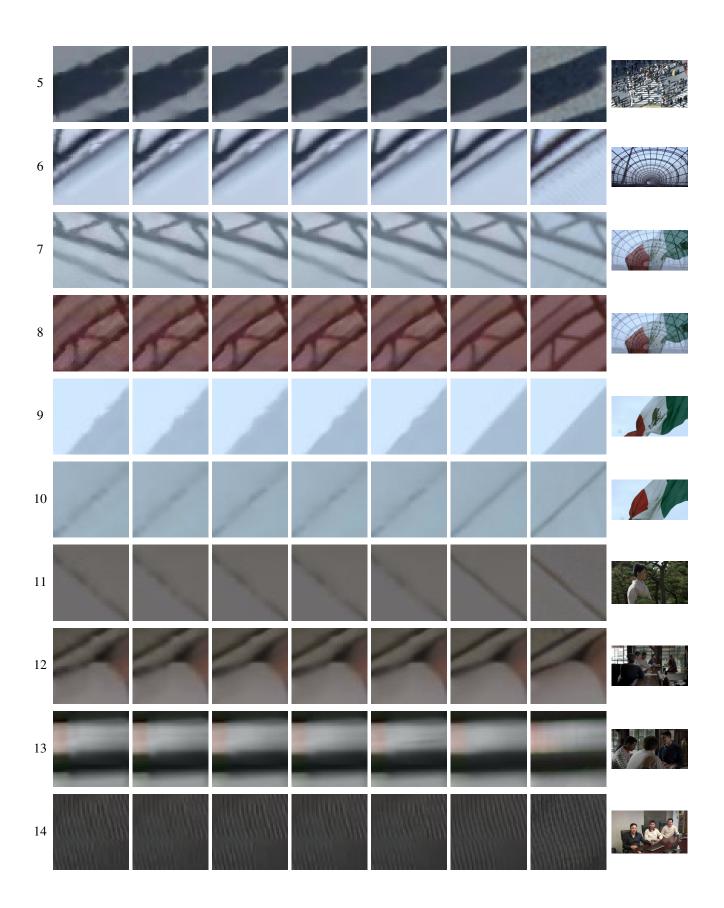
In supplementary material, we show more results of qualitative comparison between our proposed NL-ConvLSTM and other state-of-the-art methods on both Yang *et al.*'s dataset [5] and Vimeo-90K [3]. In each table, the (2nd-8th) columns are cropped patches from the full frame (the 9th column). Patch (in the 2nd column) is compressed from the raw patch (in the 8th column) by HEVC. The (3rd-7th) columns are the enhanced results via ARCNN [1], DnCNN [6], DSCNN [4], MFQE [5](or DKFN [2]), and Ours, respectively. Table 1 are the visual results on Yang *et al.*'s dataset, Table 2 are the frames from Vimeo-90K. Taking some cases for examples:

In Yang *et al.*'s dataset, comparing MFQE and other methods, especially in the 9th, 12th row of Table 1, our proposed method removes the blocking artifact notably. In the 7th, 10th, and 11th row of Table 1, our method recovers the cut lines successfully. In the 1st and 3rd row of Table 1, our method handles the staircase noise better than the other methods. Moreover, our method can recover the missing details caused by some basic mathematical transforms in compression algorithm in the 16th row of Table 1, while other methods can not.

In Vimeo-90K, it is notable that our method performs much better than DKFN and others in blocking removal in the 1st, 7th, and 15th row of Table 2. Moreover, DKFN and other methods have the problem of treating surface roughness textures as artifact and tending to erase them, such as in 8th, 14th, and 18th of Table 2. Meanwhile, our method is capable of reducing distortions while maintaining textures.

Based on these observations, our method achieves the best qualitative performance among existing methods.

No.	Compressed	ARCNN [1]	DnCNN [6]	DSCNN [4]	MFQE [5]	Ours	Raw	Full Raw
1	Í		Í		Í			
2	2	2	0	2	2	2	2	
3	Ž	Ż	ý	Š	>	>	5	
4							1	



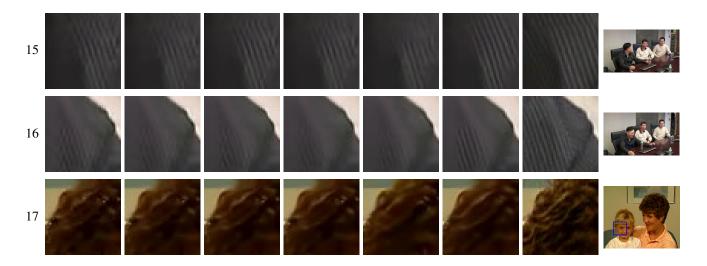


Table 1: More Visual Results on Yang et al.'s dataset

No.	Compressed	ARCNN [1]	DnCNN [6]	DSCNN [4]	DKFN [2]	Ours	Raw	Full Raw
1								A S
2								
3								
4	X	R	X	R	X	X	X	
5								
6		H.		4		24		
7	1	1	1	1	1	1		
8								
9		y 1	<b>y</b>	y 1		7		
10								

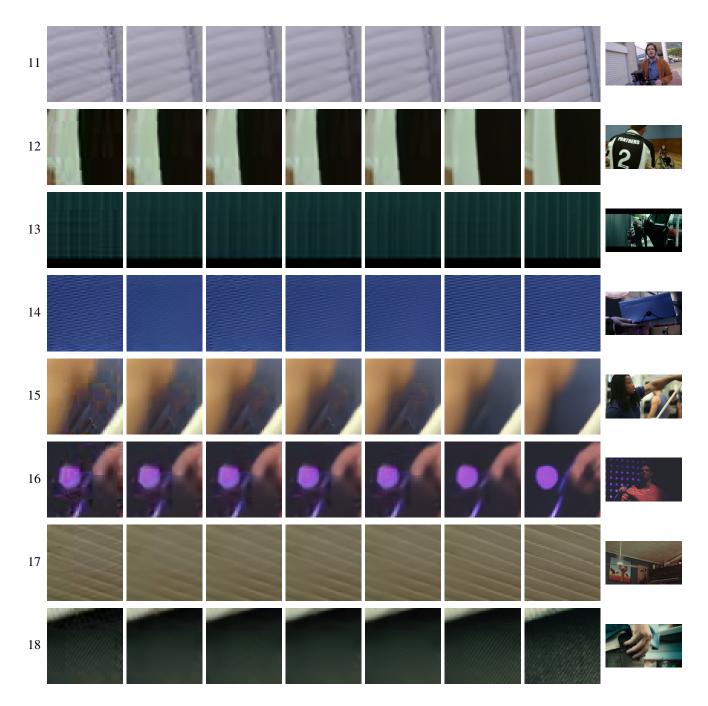


Table 2: More Visual Results on Vimeo-90K

## References

- Chao Dong, Yubin Deng, Chen Change Loy, and Xiaoou Tang. Compression artifacts reduction by a deep convolutional network. In ICCV, pages 576–584, 2015.
- [2] Guo Lu, Wanli Ouyang, Dong Xu, Xiaoyun Zhang, Zhiyong Gao, and Ming-Ting Sun. Deep kalman filtering network for video compression artifact reduction. In *ECCV*, pages 568–584, 2018.
- [3] Tianfan Xue, Baian Chen, Jiajun Wu, Donglai Wei, and William T Freeman. Video enhancement with task-oriented flow. *IJCV*, 127(8):1106–1125, 2019.
- [4] Ren Yang, Mai Xu, and Zulin Wang. Decoder-side heve quality enhancement with scalable convolutional neural network. In ICME, pages 817–822. IEEE, 2017.
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- [6] Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. *IEEE TIP*, 26(7):3142–3155, 2017.