IMAGE DEBLURRING BASED ON LIGHTWEIGHT MULTI-INFORMATION FUSION NETWORK

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INTORDUCTION

- We propose a multi-scale hierarchical information fusion scheme (MSHF) to encode the feature of blurred image. MSHF extracts and fuses the image feature in multiple small-scale spaces, which can better eliminate redundant parameters while maintaining the rich image information.
- We employ a very lightweight distillation network to decode the image feature back to a sharp image. To the best of our knowledge, it is the first time that the distillation network is adopted in image deblurring problem.
- Two attention mechanism based modules are also presented in the decoding process of our approach to exploit the interdependency between the layers and feature channels, so that a better information fusion can be achieved.

PROPOSED METHOD

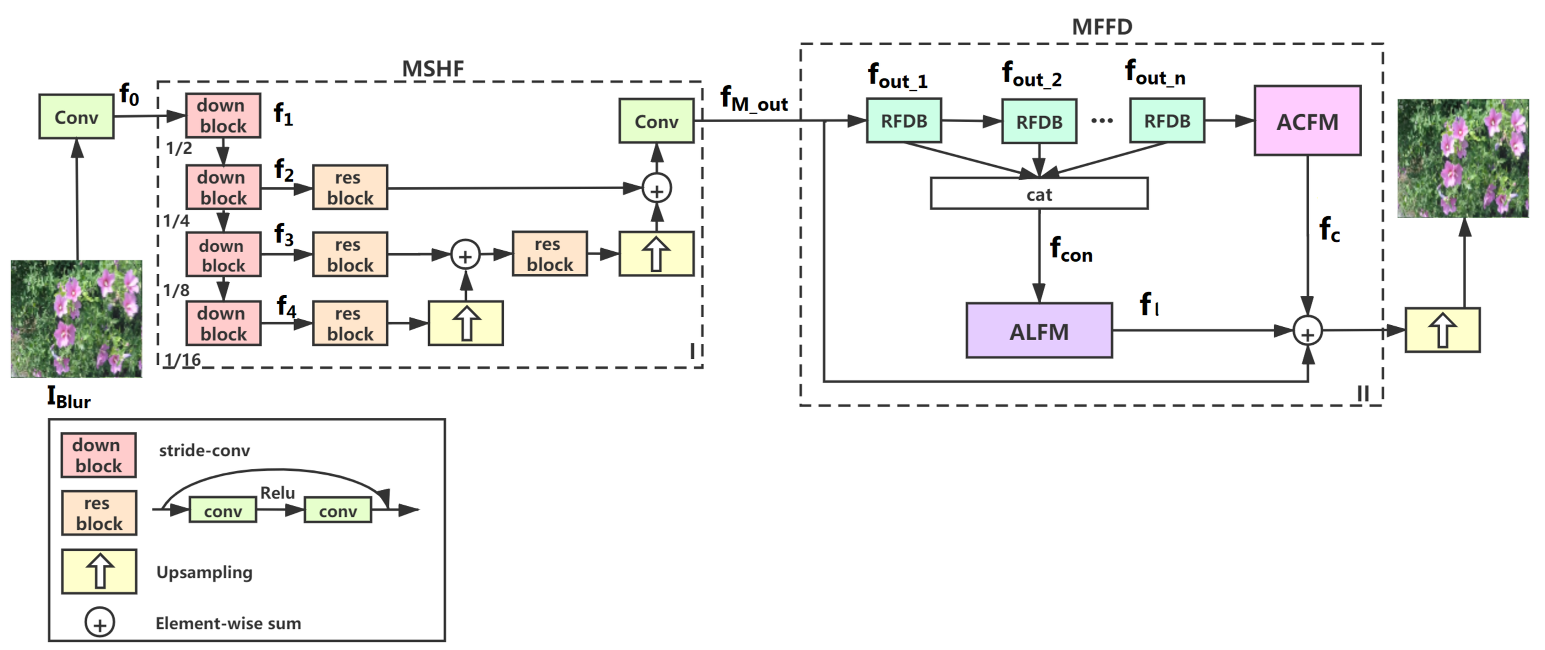

Fig. 1. The architecture of lightweight multi-information fusion network (LMFN).

Multi-scale hierarchical fusion module

MSHF is a down-sampling module which serves as the encoder in our approach. Firstly, the shallow feature f_0 of an input blurred image I_{Blur} is extracted by a convolutional layer with the kernel size of 3×3 and 64 output channels. Then, f_0 is gradually scaled down to four smaller size features f_i (i=1,2,3,4) by using downblock modules. After each downblock for down-sampling, we simply use resblock to realize residual learning. In addition, we fuse different scale features in the small-scale space. The small-scale features after residual learning are up-sampled and then element-wise added with the features of adjacent layers. Finally, the more fine-grained feature f_{M_out} in a small-scale can be obtained.

PROPOSED METHOD

Multi-feature fusion module based on attention mechanism

- ***Distillation block***

For pursuing a light and fast network, the residual feature distillation block (RFDB) is adopted. RFDB makes the network lightweight because it consists of two parts for feature extraction, one is retained and the other is further refined. Furthermore, the shallow residual block in RFDB also makes it benefit from the residual learning.

- ***Fusion mechanism***

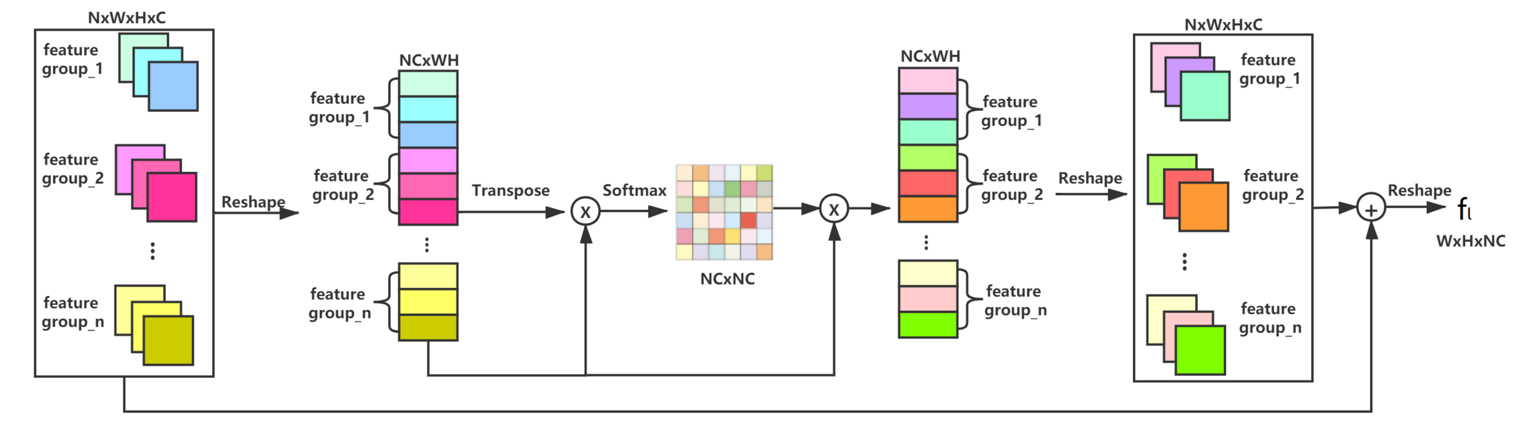

Fig. 2. ALFM: the architecture of attention layer fusion module.

The attention layer fusion module (ALFM) is employed to learn the correlation between feature channels obtained by multiple RFDB layers.

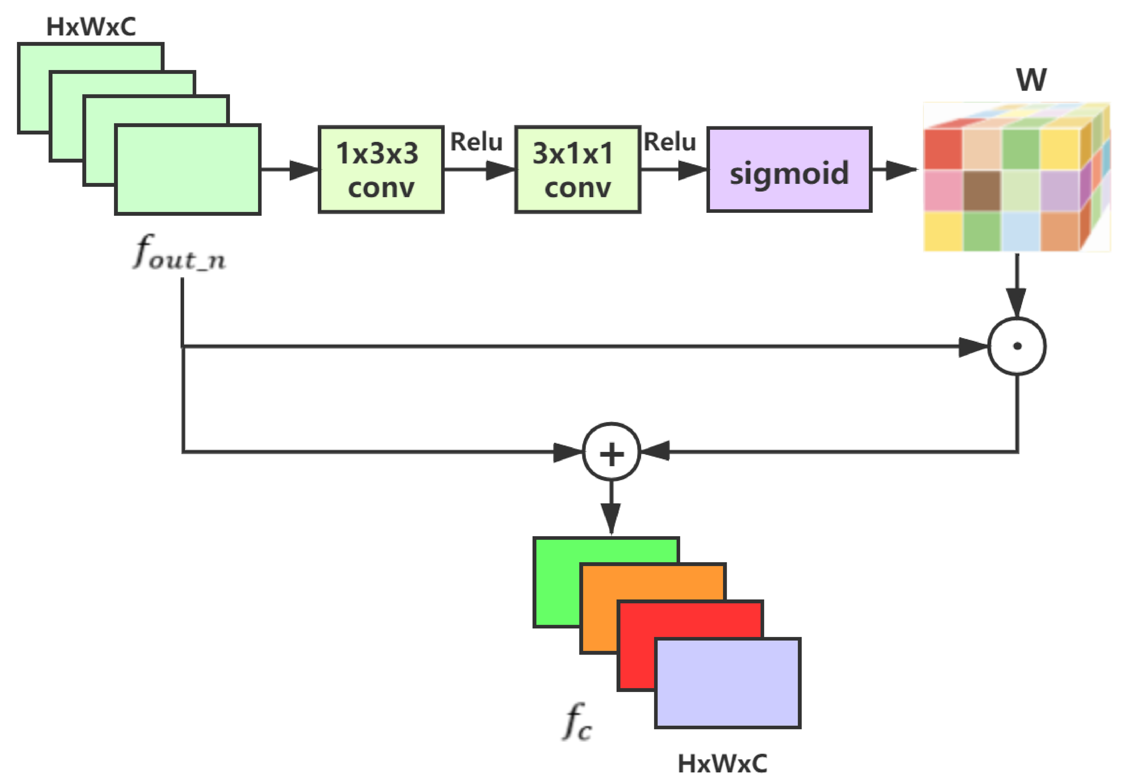

Fig. 3. ACFM: the architecture of attention channel fusion module.

The attention channel fusion module (ACFM) is used to describe the dependency between the inter-channel and intra-channel information in adjacent feature channels of the last layer.

EXPERIMENTS

Fig. 4. Visual comparison of the deblurring results obtained by some methods on GoPro dataset.

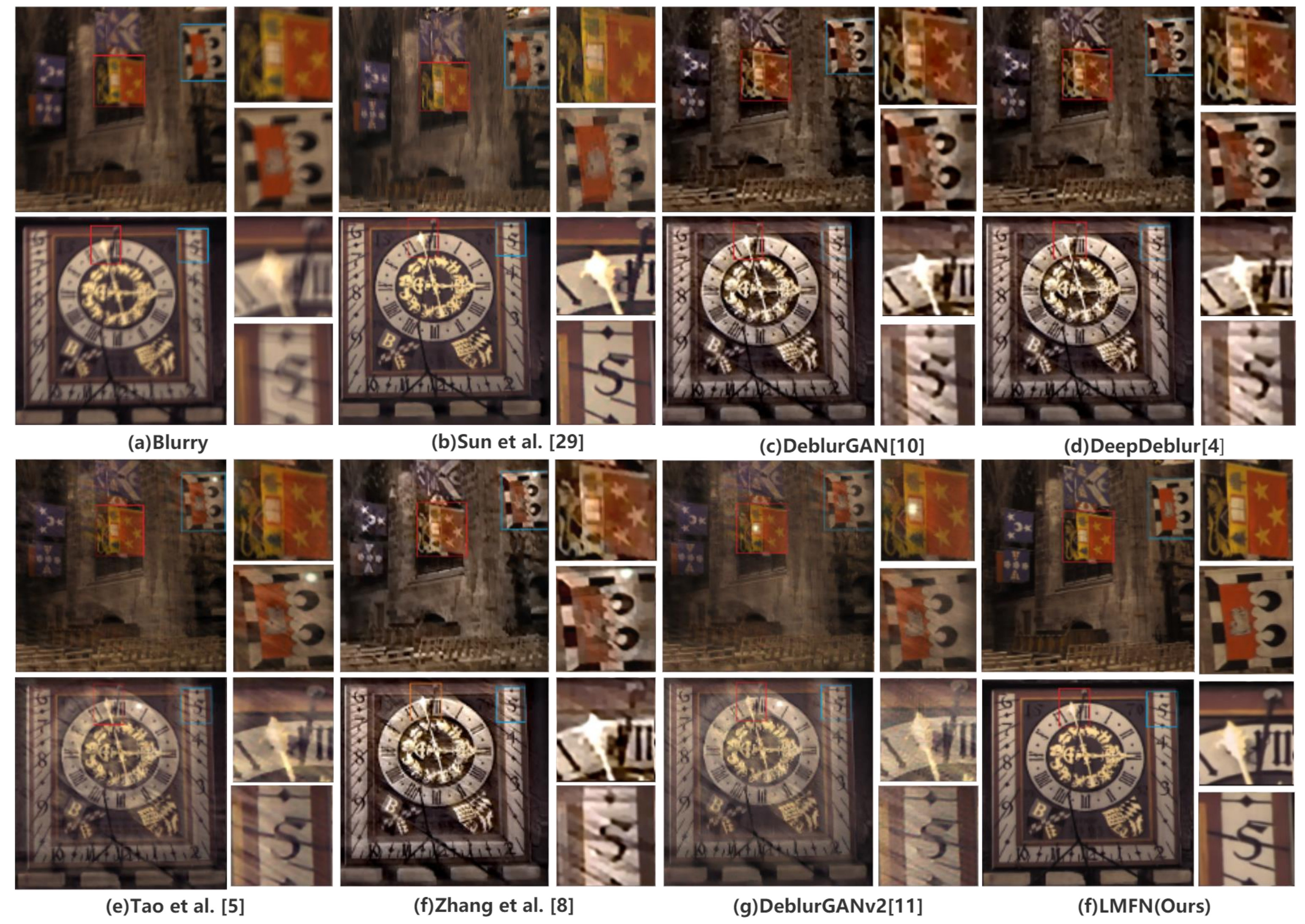

Fig. 5. Some visual comparison examples on Kohler dataset.

CONCLUSION

In this work, we propose a lightweight multi-information fusion network (LMFN) for image deblurring tasks. In order to make the network have fewer parameters and faster speed, the multi-scale hierarchical fusion module and residual feature distillation block are adopted in the encoding and decoding stages respectively. Moreover, two attention based modules are also proposed to improve the feature representation power in our approach. A large number of experiments on two datasets show that the LMFN achieves good results in both image deblurring quality and model complexity.