DOUBLE CLOSED-LOOP NETWORK FOR IMAGE DEBLURRING

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INTORDUCTION

- We propose a double closed-loop network that can limit the solution space of mapping from blurry to sharp images and provide constraint on the features obtained by the intermedia layers of network.
- Without changing network structure, the loss function of our method can be easily extended to deal with the unpaired samples in the training datasets.
- Both the theoretical analysis and experimental results are provided to demonstrate the effectiveness of our proposed network.

PROPOSED METHOD

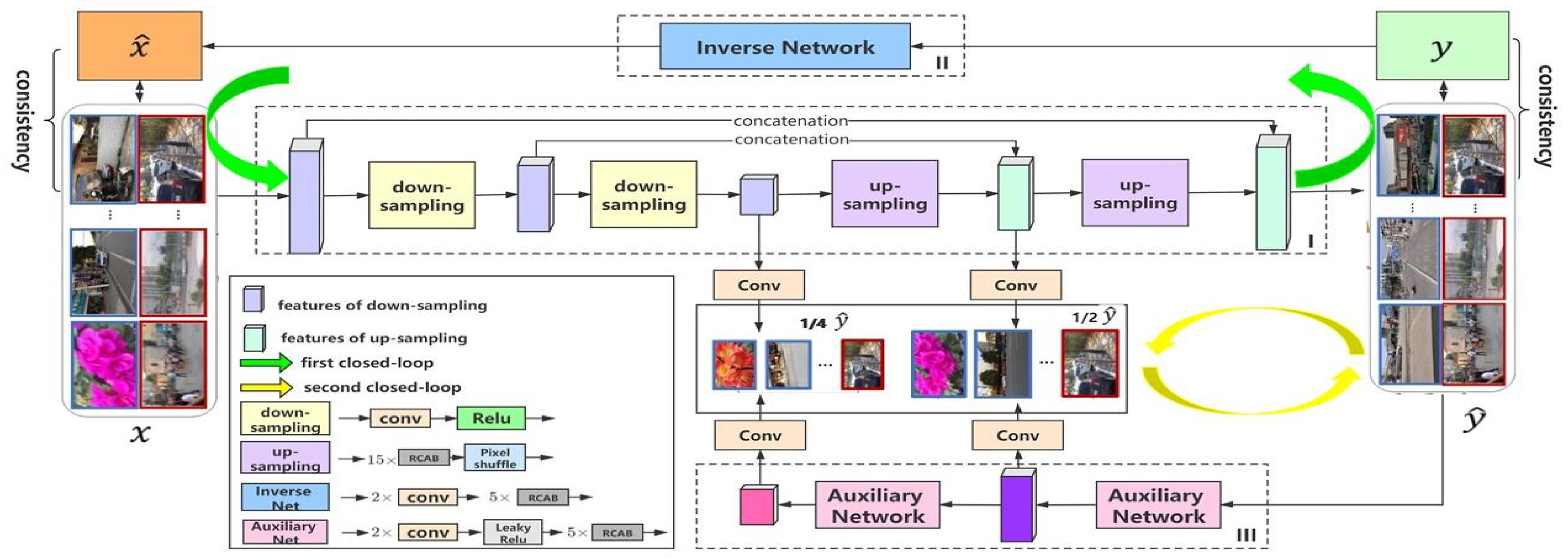

Fig. 1. The structure of the proposed network (DCLNet).

Architecture design of DCLNet

As shown in Fig. 1, the whole network consists of three parts. Part I is the backbone which serves as a generator to recover a sharp image ŷ from the blurry input x. In part II, an inverse network is designed to map the sharp image y to its blurry counterpart $\hat{x}$. This network can be regarded as a model opposite to the backbone network, thus they form the first closed-loop structure to reduce the solution space of our model. Here, it should be noted that since the input of this closed-loop in our proposed DCLNet can be either x or y, we can easily extend our approach to handle the unpaired samples in the training data. The third part is an auxiliary which progressively extracts features of the recovered sharp image ŷ at different scales. Then, additional convolutional layers are added to the features obtained by auxiliary network and decoder of backbone to produce images at corresponding scales (i.e., 1/2 and 1/4). Through designing a loss function to make the images with the same scale supervise each other, the second closed-loop is formed to facilitate the recovery of sharp image.

The Loss Function

The three parts of our network construct three mapping functions between different image domains. Suppose that X is the set of blurry images, Y is the set of sharp images and Y^j is the $1/2^j$ scaled image set obtained by auxiliary network. The three mappings in our model can be denoted as:

$$G=\{X\rightarrow Y\},\ I=\{Y\rightarrow X\},\ Au^j=\{Y\rightarrow Y^j, j=1,2\} \quad (1)$$

● *The Loss function for paired data*

Let $\{x_i, y_i\}$ (i =1,…,N) denotes a set of paired training samples in which x_i and y_i are the i-th pair of blurry and sharp images. The loss function of our DCLNet for paired data training can be defined as:

$$\mathcal{L}_{paired}(X,Y)=\mathcal{L}_G+\lambda_1\mathcal{L}_I+\lambda_2\mathcal{L}_{Au} \quad (2)$$

$\mathcal{L}_G$, $\mathcal{L}_I$, $\mathcal{L}_{Au}$ represent the loss functions corresponding to the three mappings, respectively. $\mathcal{L}_G$ can be represented as follows:

$$\mathcal{L}_G(X,Y)=\sum_{i=1}^{N}\mathcal{L}_1(G(x_i),y_i)+\mathcal{L}_1(I(G(x_i)),x_i) \quad (3)$$

Equation (3) is composed of two terms: the first is used to make the mapping function G generate a sharp image similar to its corresponding ground-truth and the second is a cycle consistency loss to bring x_i back to the original image by the closed-loop structure, so that the solution space can be reduced. $\mathcal{L}_I$ can be represented as follows:

$$\mathcal{L}_I(X,Y)=\sum_{i=1}^{N}\mathcal{L}_1(I(y_i),x_i)+\mathcal{L}_1((G(I(y_i)),y_i) \quad (4)$$

The first term in Equation (4) is adopted to optimize the mapping function I of the inverse network and the second term is also a cycle consistency loss for solution space restriction. The loss function $\mathcal{L}_{Au}$ of auxiliary network is

$$\mathcal{L}_{Au}(X,Y)=\sum_{i=1}^{N}\sum_{j=1}^{2}\mathcal{L}_1\left(Au^j(G(x_i)),D_{out\frac{1}{2^j}}(x_i)\right) \quad (5)$$

● *The Loss function for unpaired data*

In many real-world scenarios, the training dataset for deblurring model may lack of sufficient paired samples. Hence, we also extend the loss function in Equation (2) to deal with the dataset contains both paired and unpaired images. The extension of loss function can be defined as:

$$\mathcal{L}_{ext}(X,Y)=k_1\mathcal{L}_{paired}+k_2(\mathcal{L}'_G+\mathcal{L}_{Au})+k_3(\mathcal{L}'_I+\mathcal{L}'_{Au}) \quad (6)$$

where $\mathcal{L}'_G$ and $\mathcal{L}'_I$ the modified loss functions of $\mathcal{L}_G$ and $\mathcal{L}_I$ which remove the first term and only retain the cycle consistency loss in Equations (3) and (4). $\mathcal{L}'_{Au}$ is defined as:

$$\mathcal{L}'_{Au}=\sum_{i=1}^{N}\sum_{j=1}^{2}\mathcal{L}_1\left(D_{out\frac{1}{2^j}}(I(y_i)),Au^j(y_i)\right) \quad (7)$$

The parameters k_1, k_2 and k_3 are used to make our model adjust to different situations.

EXPERIMENTS

Fig. 2. Visual comparison of the deblurring results on GoPro dataset.

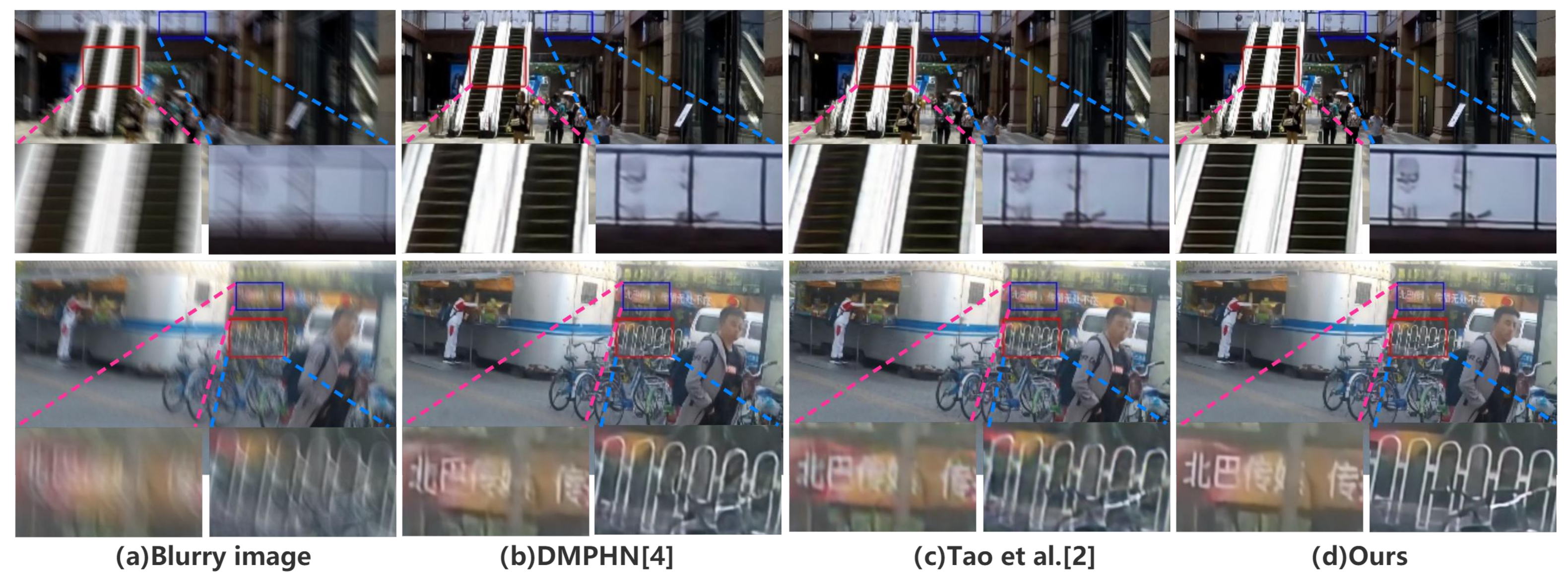

Fig. 3. Visual comparison of the deblurring results on HIDE dataset.

Fig.4. Visual comparison of different training data selection schemes on DCLData dataset.

CONCLUSION

In this paper, a double closed-loop network was proposed for deblurring task. Different from prior work which merely focused on constructing a single network to straightly recover a sharp image from the blurry one, we introduced two closed-loop structures into our model which could effectively improve the deblurring performance. Moreover, we also extended the loss function of our model to deal with the unpaired samples in the dataset. Through extensive experiments on benchmark datasets and a real-world dataset, the advantage of our network over other state-of-the-art methods has been demonstrated.