Underwater Image Enhancement with Encoding-Decoding Deep CNN Networks

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♦ Introduction

Serious scattering and absorption make the underwater images have complicated noise distribution. We proposes an underwater image enhancement model based on Encoding-Decoding deep CNN networks. The model achieves the image enhancement in an end-to-end adaptive way rather than considering the physical environment. We provide several comparison experiments with different datasets. Experiments show that it outperforms state-of-the art underwater image restoration methods in underwater image defogging, denoising and color enhancement. Finally, the model is employed to handle the underwater images with the different levels of noise and shows good performance.

♦ Contributions

1. We propose a convolution-deconvolution deep network architecture as the encoding-decoding procedure.
2. To overcome the limitation of insufficient training data, transfer learning is introduced to network training. The fine-tuning process makes the model gradually fit the requirement of the underwater image enhancement.
3. A pixel to pixel (end-to-end) network learning and image enhancement system is achieved without prior knowledge and physical models.
4. Our method shows good performance in underwater image enhancement.

♦ Proposed Model

ED-Alexnet

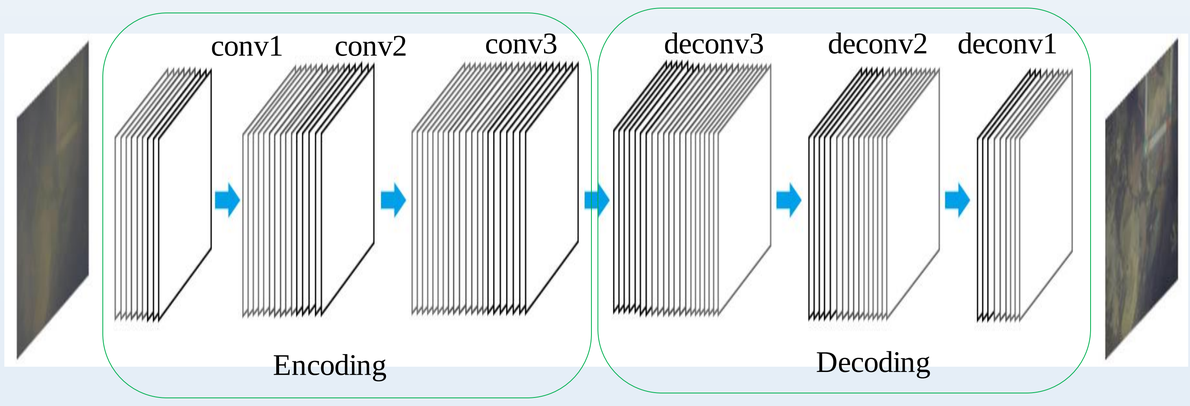

Fig. 1 The ED-Alex network structure.

♦ Network Configuration

Table 1. The configuration of the deep model

ED-Alexnet		
Layer name	**Kernel size**	**Output num**
Conv1	**11**	**96**
Conv2	**5**	**256**
Conv3	**3**	**384**
Deconv1	**3**	**384**
Deconv2	**5**	**256**
Deconv3	**11**	**3**

♦ Training and Testing

The mean square error is used as the loss function：

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n} \|F(Y_i;\theta) - X_i\|^2$$

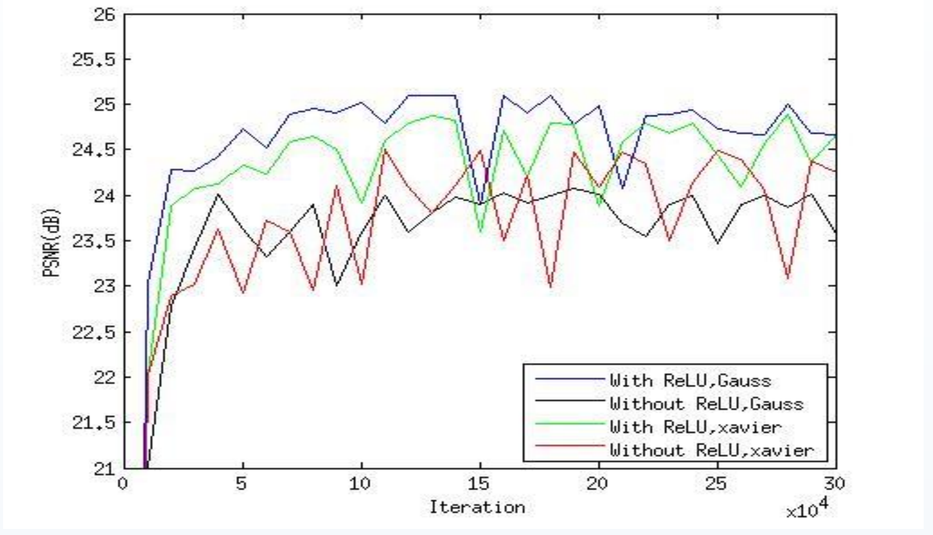

Fig. 2 Comparison of whether use activation function or not and different initialization strategies on enhancement effect.

♦ Experimental Results

1. Evaluation on publicly available underwater TURBID datasets：

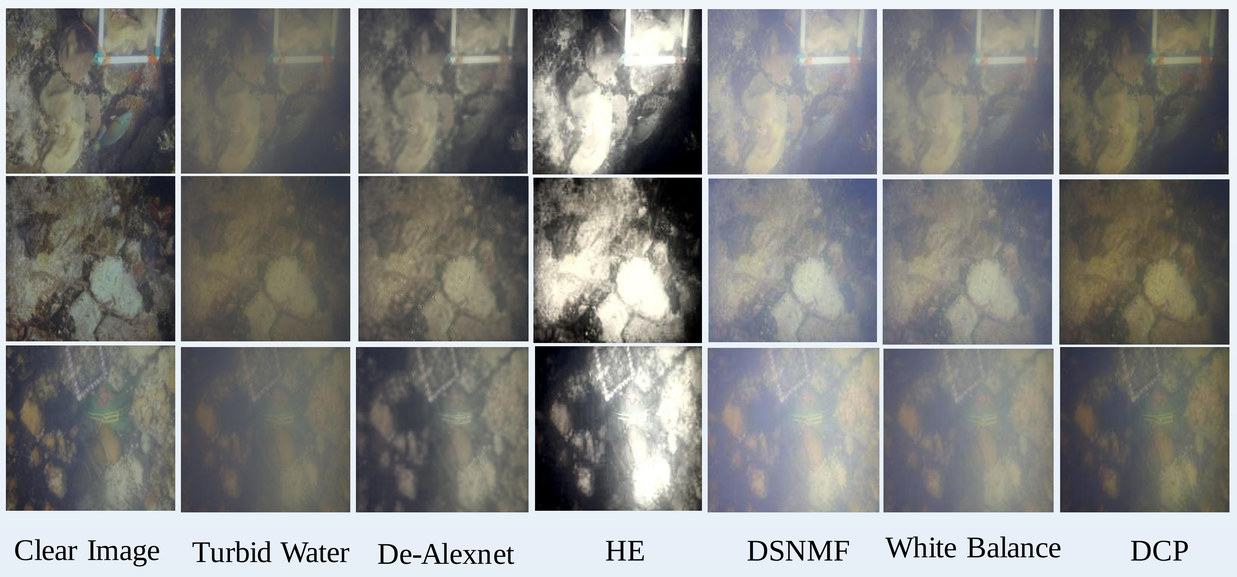

Fig. 3 Comparison enhancement effect among different algorithms underwater TURBID datasets

2.Evaluation on the underwater image collected in our Lab：

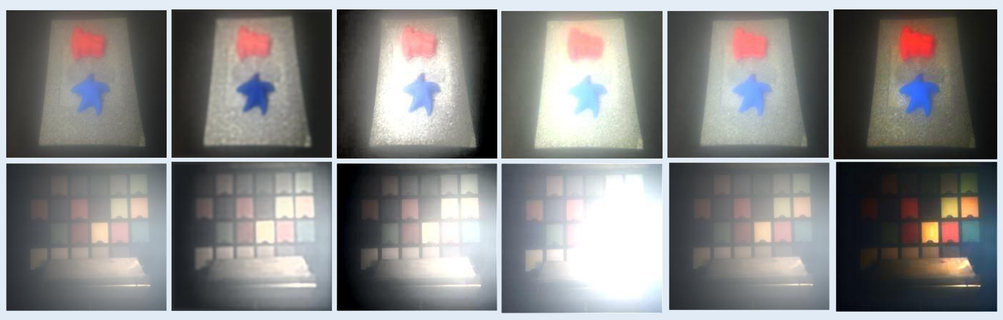

Fig. 4 Effectiveness of the proposed method and comparison methods in underwater image collected in our lab.

♦ Acknowledgements

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