A Novel Multi-Connected Convolutional Network for Super-Resolution

ABSTRACT

Convolutional neural networks (CNNs) exhibit superior performance for single image super-resolution (SISR) tasks. However, as the network grows deeper, features from the earlier layers are impeded or less used in later layers. In SISR, the earlier layers are mainly composed of local features that are essential to the task. In this letter, we present a novel multi-connected convolutional network for SISR tasks by enhancing the combination of both low- and high-level features. We design a structure built on multi-connected blocks to extract diversified and complicated features via the concatenation of low-level features to high-level features. In addition to stacking multi-connected blocks, a long skip-connection is implemented to further aggregate features of the first layer and a specific later layer. Furthermore, we employ a flexible two-parameter loss function to optimize the training process. The proposed method yields state-of-the-art performance both in terms of quantitative metrics and visual quality. The method also outperforms existing methods on datasets via unknown degrading operators, indicating an excellent generalization ability.

EXISTING SYSTEM

- In existing system, the VDSR adopts a 20-layer convolutional network with residual learning.
- Thus, deep networks use more contextual information and model complex functions with more nonlinear layers, which are necessary steps for SISR tasks.
- SRResNet and EDSR are motivated by ResNet and employ residual blocks to achieve state-of-the-art performance.

PROPOSED SYSTEM

- We propose a multi-connected convolutional network to solve the aforementioned problems.
- The proposed method implements a structure built on multi-connected blocks to combine low- and high-level features via an operator of concatenation, which extract diverse and complex features simultaneously.
- The features are further aggregated via a long skip-connection. Furthermore, we adopt a robust and flexible two-parameter loss function to optimize training and improve restoration quality.

SYSTEM REQUIREMENTS

HARDWARE REQUIREMENTS:

- Processor - intel core i3
- RAM - 2GB
- Hard Disk - 20 GB

SOFTWARE REQUIREMENTS:

- Tool - MATLAB R2016
- Operating system - Windows 7,8

REFERENCE

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