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Deep CNN-Blind Image Quality Predictor

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Abstract: This paper outlines Image denoising based on Convolutional Neural Network (CNN). The denoised images occur at smooth edges (missing details) with high noise level. To overcome this problem, we proposed a dual convolutional neural network for image denoising, called as Fusing Edge-information in Image Denoising based on CNN (FEDnets). It consists of two parallel network branches, which retrieve the denoised image and edge details. Also, the edges are fused with the denoised image to get a clearer and more detailed image. Experimental results show that FEDnets can be effectively applied to noise removal tasks and recover clearer images with more edge details and texture features.

Index Terms: Convolution, Denoising, Transparency, Resolution, Fusing and Texture.

I Introduction:

Image denoising is a classical image reconstruction problem in computer vision. It is designed to restore clear images from noisy images. It has been widely applied in many application fields, e.g., camera imaging and medical image processing.

II Existing Work or Literature Survey:

Existing image denoising methods can be categorized into three categories, i.e., filter based methods, sparse representation methods and deep learning based methods. The filter based ones are early traditional denoising methods, and the representative algorithm is Block Matching and 3D Filtering. The sparse representation methods achieve image denoising by constraining the sparsity of the natural image. The deep learning based methods reduce the noisy image by learning a high complexity image restrictor. The deep learning based methods, which can effectively improve the image denoising performance, are currently used. However, most of these methods utilize a single neural network for image denoising, and the denoised image occurs at smooth edges with high noise level.

III Proposed Work:

To overcome this problem, we propose a dual convolutional neural network for image denoising, called FEDnets. It consists of two parallel network branches, which respectively get the denoised image and edge details. Also, the edges are fused with the denoised image to get a clear image with more edge details.

IV Results:

This paper presents an image denoising algorithm (FEDnets) based on convolutional neural network. FEDnets consists of two parallel networks, which are denoising module and edge extraction module. In addition, the edge from the edge extraction module is fused with the denoised image from the denoising module to get a clear image with more edge details.

The proposed method is tested on commonly used image denoising datasets Set5, Kodak and McMaster. The experiments proved that, compared with a single denoising network, the method proposed in this paper has a better denoising effect, and higher PSNRs.

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