Image Denoising with CNN-Based Attention

Neval Karaca
Department of Computer Engineering
Harran University
Şanlıurfa, Turkey
nvalkrc.63@gmail.com

Serdar Çiftçi
Department of Computer Engineering
Harran University
Şanlıurfa, Turkey
serdarciftci@harran.edu.tr

***Abstract*— Noise removal is one of the most commonly used processes in computer vision. Noise removal improves the quality of the image, thereby improving the performance of computer vision algorithms and providing user pleasing. In this study, we aim to improve the performance of noise removal by adding an efficient attention module, the Convolutional Block Attention Module (CBAM), to the Fast and Flexible Denoising Network (FFDNet) model with an adjustable noise level map as input. By adding the CBAM module to the convolutions used in FFDNet, the CNN's representational power was increased and successful results were obtained. The proposed method achieved high PSNRs in quantitative experiments on different datasets, and in qualitative experiments we observed that the denoised images are close to the target images.**

Keywords—Image Enhancement, Image Denoising, FFDNet, CBAM

I. Introduction

Image enhancement is one of the most studied topics in terms of increasing the performance of computer vision applications and human visual pleasing [1,2]. Image enhancement is used to make an image clearer, intelligible, sharper, and to restore a degraded or damaged image to its original. The working areas of image enhancement can differ for a number of applications and objectives such as image noise removal, contrast enhancement, resolution enhancement, color preservation, adjusting brightness and correcting exposure settings. Image denoising is an important step in the image enhancement process. Developments in the field of deep learning have disproved the idea that the work on noise removal is complete, and have shown that the improvement studies will continue more successfully [1,3-5]. Noise removal in images with deep learning is performed with different architectures, and Convolutional Neural Network (CNN) is one of these architectures which successfully removes noise in images [6-9]. In noise removal studies, the combination of CNN architectures and attention mechanisms has shown effective results [10-15]. Various studies have been conducted on noise removal and image enhancement area while preserving image features (color, edge, texture, etc.).

Tian et al. [3] presented a comparative study of deep learning techniques for image noise removal. They first used deep CNNs for additive white noise images (AWGN) and then for real noise images. Zhang et al. [6] proposed a CNN based method (RDDCNN) consisting of three blocks: a deformable block (DB), an enhanced block (EB), and a residual block (RB) to overcome the training challenge of varying distributions in the training data. Xue et al. [7] aimed to remove noise in the image by using transformers and convolutions in their architecture, adjusting the feature size through the input adjustment module and extracting low-level features of the image. Chaurasiya et al. [8] presented a study to remove noise in the image using three types of CNNs: CNN with expanded kernels, CNN without expansion but with similar perceived area, and increasing kernel size and CNN without any expansion and without increasing kernel size.

The paper is organized as follows: In Section II, existing literature on image noise removal is reviewed. Section III outlines the proposed approach, while Section IV provides a details of the experimental studies and the obtained results. Finally, Section V draws conclusions regarding the proposed method.

Our main contributions in this study are summarised below:

- Adding CBAM modules to the FFDNET convolution blocks increase CNNs representation power.
- The conducted study shows that the proposed approach increase PSNR values in quantitative experiments, and as a qualitative experiments it is observed that the obtained results are closer to the ground truths.

II. Related Work

Kaur et al. [9] applied a conventional noise removal method to assess the impact of noise removal on CNN performance and to filter noise in the images. Subsequently, they incorporated a noise removal layer into the CNN model. Anwar et al. [10] introduced a blind real image restoration network in a single-stage configuration, employing a modular architecture. Their approach incorporated a residual over residual structure to enhance the flow of low-frequency information, and feature attention was employed to leverage channel dependencies. Wang et al. [11] introduced an innovative neural network known as Channel and Spatial Attention Neural Network (CSANN) designed for noise reduction. In CSANN, they introduced a convolutional network to understand the channel relationships by incorporating input features such as the noise level, along with the average and maximum values of each channel. Han et al. [12] introduced the RSIDNet network, featuring a multi-scale feature extraction module (MFE), multiple locally connected enhanced attention blocks (ECA), a global fusion block (GFF), and a block for reconstructing noisy images (NR). Zhang et al. [13] introduced an enhanced learning module designed to learn and retain detailed information within an image. This was achieved by stacking multiple convolutional layers, batch normalization (BN) layers, and activation function layers to increase the depth of the network. Thakur et al. [14] proposed a blind Gaussian denoising network that uses the features of the input image and its negative to produce a denoised output. Wu et al. [15] proposed a new double convolutional neural network (CNN) with attention to blind denoising, which they called DCANet. Their proposed DCANet combines both binary CNN and attention

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mechanism for image denoising. Zhang et al. [16] presented FFDNet (Toward a Fast and Flexible Solution for CNN based Image Denoising), a fast and flexible denoising convolutional neural network with an adjustable noise level map as input. In order to reduce the training cost, the denoising network (FFDNet) used the noisy image in CNN to quickly train the denoising model. FFDNET, like other noise cancellation works in the literature [17-20], assumes that the noise is additive white Gaussian noise (AWGN) and the noise level is given. This study is based on FFDNet, a fast and flexible convolutional neural network for noise cancellation proposed by Zhang et al. [16]. Recognizing the enhanced impact of CNNs on image denoising when combined with attention mechanisms, we incorporated the Convolutional Block Attention Module (CBAM [21]), a straightforward, lightweight, and universal attention module, into the model. The outcomes of this investigation are detailed in Section IV.

III. Proposed Approach

A. *Toward a Fast and Flexible Solution for CNN based Image Denoising (FFDNET)*

Leveraging fast outcomes and superior performance, discriminative learning methods typically entail the learning of a dedicated model for each noise level. Consequently, multiple models might be necessary to denoise images characterized by distinct noise levels. Moreover, these methods exhibit limited adaptability in addressing spatially variant noise, potentially constraining their utility in practical noise removal applications. In response to these challenges, Zhang et al. [16] introduced FFDNET, a convolutional neural network for noise cancellation that is both fast and flexible, utilizing a adjustable noise level map as input. FFDNET operates on downsampled sub-images, achieving a balance between results and image denoising efficacy. The model is trained across a wide noise levels (noise standard deviation [0, 75]) using a single network and employs a non-uniform noise level map to mitigate spatially varying noise. Similar to other noise removal studies in the literature [17-20], the FFDNET study assumes the presence of additive white Gaussian noise (AWGN). The FFDNet model is formulated as follows:

$$\mathbf{x} = \boldsymbol{F}\,(\boldsymbol{M};\boldsymbol{\Theta}) \qquad (1)$$

Here M represents a noise level map. Within the FFDNet model, the noise level map is incorporated as an input, and Θ, denoting the model parameters, is depicted as a consistent map that remains unaltered across different noise levels.

The denoiser can effectively restore the clean image directly under the conditions where the noise level is predetermined or accurately estimated. When faced with scenarios where the noise level is uncertain or challenging to estimate, the denoiser should offer adaptive control over the balance between preserving details and reducing noise [16]. Fig. 1. illustrates the architecture of the FFDNet model.

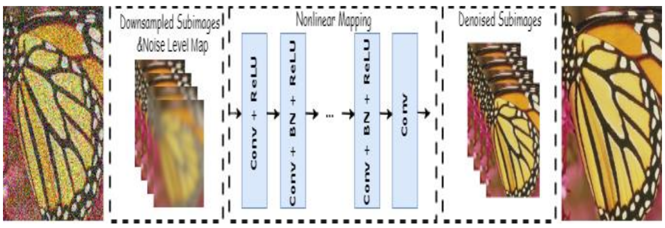

Fig. 1. The FFDNET architecture [16].

B. *Convolutional Block Attention Module (CBAM)*

The Convolutional Block Attention Module (CBAM) is introduced to enhance feed-forward convolutional neural networks through a straightforward yet impactful attention mechanism. When presented with an intermediate feature map, this module generates channel and spatial attention maps in sequence. These attention maps are subsequently applied by element-wise multiplication to the input feature map, resulting in adaptive feature refinement.

CBAM stands out for its straightforward design, serving as a versatile module that effortlessly integrates into various Convolutional Neural Network (CNN) architectures. Its lightweight nature allows seamless end-to-end training with standard CNNs, incurring negligible additional costs.

The CBAM module comprises two successive submodules: the Channel Attention Module and the Spatial Attention Module. In each convolutional block of deep networks, the CBAM module dynamically refines the intermediate feature map.

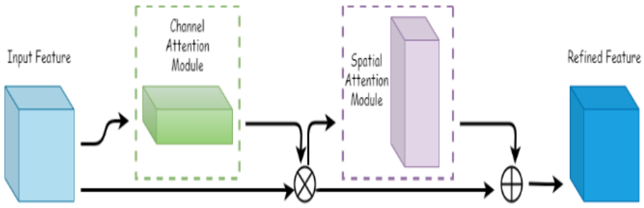

Fig. 2. The architecture of the Convolutional Block Attention Module (CBAM) [21].

Provided with an intermediate feature map, $\mathbf{F} \in \mathbb{R}^{CxHxW}$, as input, CBAM systematically generates a one-dimensional channel attention map $\boldsymbol{Mc} \in \mathbb{R}^{Cx1x1}$ a two-dimensional spatial attention map $\boldsymbol{Ms} \in \mathbb{R}^{1xHxW}$ as shown in Fig. 2.

General attention operations can be summarised as in Eq. 2 and Eq. 3:

$$\boldsymbol{F'} = \boldsymbol{Mc}(\boldsymbol{F}) \otimes \boldsymbol{F}\,, \qquad (2)$$

$$\boldsymbol{F''} = \boldsymbol{Ms}(\boldsymbol{F'}) \otimes \boldsymbol{F'} \qquad (3)$$

Here, $\otimes$ denotes element-wise multiplication. $\boldsymbol{F''}$denotes the ultimately refined and cleaned output. The computation process for each attention map is depicted in Fig. 3 and Fig. 4. The specifics of each attention module are detailed below.

1. *Channel Attention Module*

Channel attention maps are constructed by utilising channel relationships between features. As each channel is regarded as a feature detector [14] within a feature map, channel attention directs attention to what is meaningful in the input image. The efficiency of channel attention is achieved by compressing the spatial dimension of the input feature map. For the collection of spatial information, the average pooling method is usually preferred [22]. However, in the CBAM module, it is observed that maximum pooling provides a better channel-wise attention inference and collects another important clue about distinctive object features. Hence, a combination of average pooling and maximum pooling is employed, and it has been demonstrated that this fusion enhances the representativeness of the network more effectively than using the features independently. In this phase, the spatial information of a feature map is gathered through the integration of average pooling and maximum pooling operations, resulting in the generation of two distinct spatial context descriptors: average-pooled features $\boldsymbol{F}^{c}_{avg}$ and maximum-pooled features $\boldsymbol{F}^{c}_{max}$. Then, $\boldsymbol{Mc} \in \mathbb{R}^{Cx1x1}$ conveys both descriptors to a shared network (Shared MLP) for the construction of the channel attention map. This shared network employs a hidden layer, which incorporates a multilayer perceptron (MLP). To minimize the parameter overhead, the hidden activation size is adjusted to $\mathbb{R}^{C/rx1x1}$, where r represents the reduction ratio. Once the shared network is applied to each descriptor, the output feature vectors are combined through element-wise aggregation. In summary, the channel attention is computed as follows:

$$\begin{aligned} \boldsymbol{Mc}\,(\boldsymbol{F}) &= \left(MLP\big(AvgPool(\boldsymbol{F})\big) + MLP\,\big(MaxPool(\boldsymbol{F})\big)\right) \\ &= \sigma\,(\boldsymbol{W_1}\left(\boldsymbol{W_0}(\boldsymbol{F}^{c}_{avg})\right)) + (\boldsymbol{W_1}(\boldsymbol{W_0}(\boldsymbol{F}^{c}_{max}))) \end{aligned} \quad (4)$$

In this context, σ, represents the sigmoid function, where $\boldsymbol{W_0} \in \mathbb{R}^{C/r \times C}$ and $\boldsymbol{W_1} \in \mathbb{R}^{C \times C/r}$. The MLP weights, denoted as $\boldsymbol{W_0}$, are common to both inputs, and the ReLU activation function follows $\boldsymbol{W_0}$.

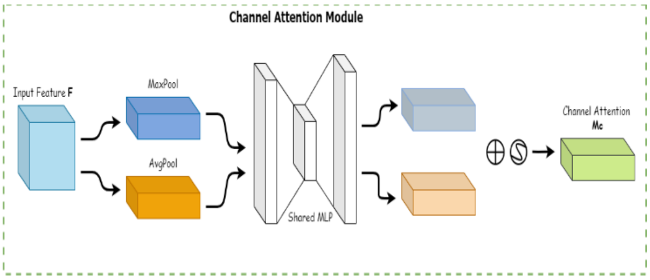

Fig. 3. The architecture of Channel Attention Module [21].

2. Spatial Attention Module

The formation of the spatial attention map involves leveraging the inter-location relationships among features. In contrast to channel attention, spatial attention directs its focus to the location of information, constituting a complementary and informative aspect. The computation of spatial attention entails the initial application of average pooling and max pooling operations along the channel axis, followed by their integration to create an impactful feature descriptor. Furthermore, a prior investigation [23] demonstrated the effectiveness of applying pooling operations along the channel axis to accentuate informative regions that warrant emphasis. The spatial attention map, denoted as $\boldsymbol{M}_s(\boldsymbol{F}) \in \boldsymbol{\mathcal{R}}^{H\times W}$, is designed from the combined feature descriptor through the application of a convolution layer. This map encompasses the regions to be highlighted or suppressed, again focusing on the spatial aspect of the information. The channel information of a feature map is synthesized by generating a two-dimensional map via binary pooling processes, represented as $\boldsymbol{F}^{s}_{avg} \in \mathbb{R}^{1\times H\times W}$ and $\boldsymbol{F}^{s}_{max} \in \mathbb{R}^{1\times H\times W}$. These operations represent the average pooled features and maximum pooled features across the channels, respectively. Subsequently, these maps are integrated and subjected to further processing with a convolutional layer, concluding in the creation of a two-dimensional spatial attention map.

The detailed steps involved in the processing of spatial attention are described below:

$$\begin{aligned} \boldsymbol{M}_s(\boldsymbol{F}) &= \sigma(f^{7\times7}([AvgPool(\boldsymbol{F}); MaxPool(\boldsymbol{F})])) \\ &= \sigma\left(f^{7\times7}\left([\,\boldsymbol{F}^{s}_{avg}\,;\ \boldsymbol{F}^{s}_{max}\,]\right)\right) \end{aligned} \quad (5)$$

Here σ, symbolizes the sigmoid function, and $f^{7\times7}$ signifies a convolution operation employing a filter size of 7×7.

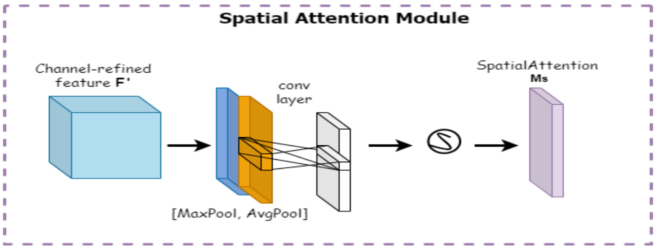

Fig. 4. The architecture of the Spatial Attention Module [21].

In general, when an input image is given in the attention modules, complementary attention is calculated by focusing on 'what' information in the Channel Attention Module and 'where' information in the Spatial Attention Module. As a result, the design of the CBAM module is divided into three parts: First, channel attention is computed, then spatial attention is computed, and finally, it is shown how both channel and spatial attention modules can be combined.

C. Proposed Method

This study is presented to add an innovation to the existing FFDNET study and to obtain better results than FFDNET in terms of visual and numerical results. The model employed a sequence of 3×3 convolution layers as input in the FFDNet investigation. Each layer encompassed three operations: Conv (Convolution), ReLu (Rectified Linear Unit), and BN (Batch Normalisation). To elaborate, "Conv+ReLu" was applied to the initial convolution layer, "Conv+BN+ReLu" for the intermediate layers, and "Conv" for the ultimate convolution layer. Subsequently, following the application of "Conv" in the last layer, an architecture was devised wherein the output of this layer serves as the input for the CBAM module—an uncomplicated and lightweight attention module. As CBAM lightweight and versatile module, its impact on the overall overhead is considered negligible. As a result, the CBAM module integrates easily with the CNN architecture used in the current study. The CNNs used in the model demonstrated effective noise cancellation based on the model's capacity and advances in network architecture. The model is adaptable to a given noise level. Similar to FFDNet and many recent works [24-26], this work treats the noise as additive white Gaussian noise (AWGN). AWGN is conceptualised as a noise source that introduces random and unwanted excess information into any image. Specifically, the FFDNet study uses only a few image. (Convolutional Block Attention Module) stands as a

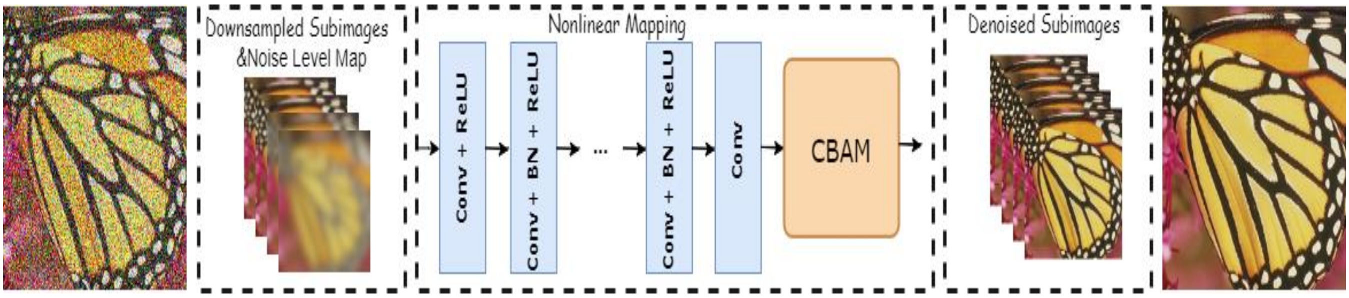

Fig. 5. The proposed architecture modified from FFDNet [16].

convolutional neural network layers to remove noise from the In this study, in addition to the convolutional neural network layers used in FFDNet, the CBAM is included to provide more interpretable and clearer results. Fig. 6 illustrates the architectural configuration of the proposed method, derived from the existing FFDNet study, with the CBAM module integrated into the FFDNet model.

IV. Experiments

A. Dataset

In this study, CBSD68 [27], Kodak24 [28], General100 [29], McMaster [30], Set5 [31], Waterloo Exploration [32] datasets were used. During the model training phase, a set of 1500 randomly chosen sample images from the Waterloo Exploration dataset, which comprises a total of 4744 images, along with 400 images from the ImageNet [33] dataset, were utilized for validation purposes. The remaining 300 images from the Waterloo Exploration dataset, not included in the training process, were specifically reserved for testing. The trained model underwent testing on the test sets of additional datasets, including 68 images from the CBSD68 dataset, 5 images from the Set5 dataset, 24 images from the Kodak24 dataset, 100 images from the General100 dataset, and 18 images from the McMaster dataset.

B. Configurations

This study was carried out in Google Colab (Colaboratory) environment, a cloud-based Python coding environment provided by Google. In the implementation process, the experiments were performed using Python programming language and Pytorch library. For optimisation, the learning rate was set to 0.001 and the Adam optimisation algorithm was used. In the training phase of the study, 1500 training images were used and the model was trained by setting 80 epochs and batch-size 24. To substantiate the performance superiority of this study through quantitative analysis, the PSNR (Peak Signal-to-Noise Ratio) metric was employed. The loss function utilized in this study is depicted in Eq. 6.

$$L(\theta) = \frac{1}{2N} \sum_{i=1}^{N} \| F(y_i, \boldsymbol{M}_i; \theta) - x_i \|^2 \quad (6)$$

Here F is the image generated by the model and x is the target image.

C. Results

In this section, using various datasets (Set5, General100, Waterloo Exploration), visual comparisons between the FFDNET study and the proposed method adapted from the FFDNET study are presented. In these comparisons, some sections are shown where the best improvement is observed on the noisy input images. When we look at the visual results obtained by using different types of data sets and based on the ground truth image equivalents of the images in these data sets, it is observed that the proposed method exhibits more successful results compared to the visual results obtained from the existing FFDNET model.

Fig. 6. Visual comparison of an image from the Set5 data set.

Fig. 7. Visual comparison of an image from the Waterloo Exploration dataset.

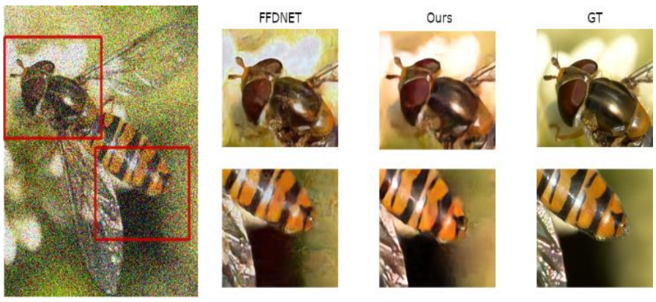

Fig. 8. Visual comparison of an image from the General100 dataset.

To assess the numerical performance, the PSNR (Peak Signal-to-Noise Ratio) metric was employed as an evalution metric. Table 1 presents the numerical results of the FFDNET model and the proposed method under specified parameters. The table displays the average PSNR values for both the existing FFDNET model and the model augmented with the CBAM module in diverse datasets (CSBD68, Kodak24, McMaster, Set5, and Waterloo Exploration) across different noise levels (15, 25, 35, 50, 75). Specifically, looking at the experimental results in Table 1, the PSNR value that provides the best increase compared to FFDNet is obtained with the images in the General100 dataset. The highest PSNR value shown by the proposed method was obtained with the Waterloo Exploration dataset with 11.83.

Table 1. Quantitative experiment results.

Dataset	***Method***	***σ=15***	***σ=25***	***σ=35***	***σ=50***	***σ=75***
CBSD68	FFDNET FFDNET+CBAM	11.23 11.45	11.18 11.20	11.10 11.13	11.06 11.08	10.66 10.72
KODAK24	FFDNET FFDNET+CBAM	11.02 11.13	11.00 11.10	10.99 11.08	10.89 11.01	10.87 11.01
McMaster	FFDNET FFDNET+CBAM	11.03 11.39	11.00 11.02	10.87 11.00	10.85 10.89	10.82 10.85
SET5	FFDNET FFDNET+CBAM	11.29 11.67	11.25 11.30	11.19 11.23	11.10 11.20	10.98 11.17
General100	FFDNET FFDNET+CBAM	10.93 11.13	10.91 11.12	10.91 11.10	10.90 11.09	10.88 11.09
Waterloo Exploration	FFDNET FFDNET+CBAM	11.59 11.83	11.54 11.77	11.50 11.76	11.46 11.69	11.46 11.69

V. CONCLUSION

In this study, the FFDNET model was enhanced by incorporating the CBAM module, resulting in an augmented success based on both visual and numerical outcomes. Given that the Convolutional Block Attention Module (CBAM) is a straightforward and versatile module, its seamless integration into the Convolutional Neural Network (CNN) architecture is effortlessly achieved in the proposed approach. For the noise removal task, attention helped to emphasise the important information and helped the model to produce more meaningful and informative outputs. Besides, it was concluded that the use of attention in combination with CNN was more effective and successful than the use of CNN alone. Both visual and numerical evaluations using various and comprehensive data sets confirm this success. In future studies, in addition to increasing the number of data to be used for training the model, it is planned to expand the network structure by adding new attention modules to the CBAM module, which is the attention module used in the proposed study.

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