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Detection of Gaussian Noise and Its Level using Deep Convolutional Neural Network

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***Abstract*—This study presents a Convolutional Neural Network (CNN) model to effectively recognize the presence of Gaussian noise and its level in images. The existing denoising approaches are mostly based on an assumption that the images to be processed are corrupted with noises. This work, on the other hand, aims to intelligently evaluate if an image is corrupted, and to which level it is degraded, before applying denoising algorithms. We used 12000 and 3000 standard test images for training and testing purposes, respectively. Different noise levels are introduced to these images. The overall accuracy of 74.7% in classifying 10 classes of noise levels are obtained. Our experiments and results have proven that this model is capable of performing Gaussian noise detection and its noise level classification.**

Keywords—image noise; noise detection; convolutional neural networks; training; Gaussian noise.

I. INTRODUCTION

Image noise is the presence of inaccurate intensity pixel value that does not reflect the true information of the image. In image processing, noise is a major contributor to the loss of useful signal or information in an image data. Therefore, image denoising has been an active research topic in the literature of image processing. The common noise types that may occur in images are Gaussian noise, Impulse noise, Poisson noise, Speckle noise and more [1]. These noises may be added to images during acquisition and transmission [2, 3].

Over the years, noise reduction techniques have been extensively studied. These studies focus on removing mainly the additive white Gaussian noise (AWGN) with standard deviation σ. Image denoising methods transformed from spatial domain filters, to transform domain filters, to learning based denoising methods [4]. Spatial domain filters include local filters [5, 6] and nonlocal mean filters [7, 8] while transform domain filters extend over curvelets [9], wavelets [10], principal components analysis [11] based filters and block matching and 3-D filtering method [12]. Sparse denoising model was proposed in [13] meanwhile [14, 15] applied adaptive learning on image denoising.

It is undeniable that these noise reduction or noise removal techniques are very effective as long as manual image de-noising is concerned. However, they are designed based on one assumption, i.e. they presumed all the images to be processed are corrupted by Gaussian noise without considering that the images might possibly be noise-free. Almost all of them suffer in determining if the images are corrupted and therefore another processing step whereby the noisy images will have to be selected manually in advance. In view of these, an intelligent Gaussian noise and its level detection technique is of our main interest to automatically process the dataset. This is important because once the level of noise is identified from the given image, an appropriate filtering algorithm can then be used to denoise it and therefore a more promising denoising result can be expected. Some researchers have started to focus on high-density impulse noise detection [16] and Gaussian and Poissonian-Gaussian noise level estimation [17].

Recently, many works conducted have proven that deep learning method can perform well in handling images. Among them, convolutional neural network (CNN) has been widely applied in fields like image deconvolution [18], image denoising [19, 20], vehicle type classification [21], face recognition [22] and many more. Researchers have focused CNN in dealing image dataset and [23] has proven to be able to outperform Markov random field (MRF) [24] in denoising natural image with less computational cost. Furthermore, [25] presented a breakthrough in utilizing CNN to classify multiple image noise types. Given sufficiently large volume of data, this deep learning technique is capable of learning the right features by itself [26], circumventing the challenges of feature extraction. Looking at the potential of CNN in processing image data, we are inspired to propose a CNN-based Gaussian noise level classification model that can recognize noise levels in more complicated environment. Therefore, this work targets to work indegraded images of noise levels with very small interval among each other, which makes it very challenging.

II. GAUSSIAN NOISE LEVEL DETECTION

A. Convolutional Neural Networks

CNN is an end-to-end system, in which a digital image is its input and it gives its prediction as output. Mimicking both simple and complex cells in the primary visual cortex of the brain [22], neural network is formed by alternating convolutional and pooling layers, so as to extract features of low to high level.

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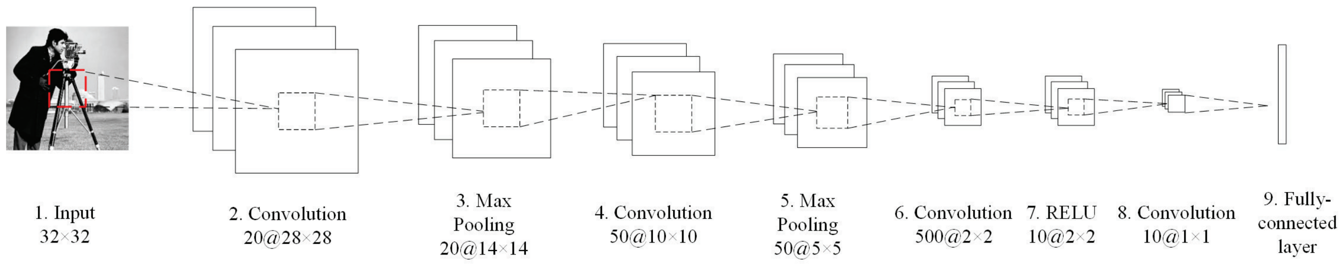

Fig. 1 Architecture of the proposed model.

B. Architecture of the Proposed Model

The architecture of the CNN to carry out Gaussian noise level detection is as shown in Fig. 1. The architecture starts with taking an image degraded with a certain level of Gaussian noise as input. It will then convolve with convolutional filters (or convolutional kernels) in the convolutional layers to obtain low-level features. These filters will be trained repeatedly in the backpropagation process to obtain a set of filters that would result in the best recognition performance. Because the output of a convolutional layer is always many times larger than its input, a pooling layer is often needed to downsample the sample feature map. This is to cut down the computational cost, time and complexity. A set of output feature map is produced at this stage, and will then become the input of the second convolutional and subsampling layers. Note that for both of the downsampling layers, max pooling is implemented so that the maximum feature response of that region is selected [27]. Next, in order to extract higher level features to more precisely represent the image data, two convolution layers are placed. Then, a Rectified Linear Unit (RELU) activation layer is placed between these two convolution layers, contributing to the nonlinearity to speed up training process [28]. The final layer is a fully-connected layer in which softmax classier is utilized to classify the images based on the class that has the maximum response.

III. EXPERIMENTS & RESULTS

A. Experiments

Standard test images such as Barbara, Cameraman, House, Lena, Mandril and Monarch which are used in this model are as shown in Fig. 2. The images are added with different levels of Gaussian noise using the method from LPG-PCA [11]. Each level of noise is considered as a class, from noise-free, to σ of 10, 20, 30, 40, 50, 60, 70, 80 and 90. There are a total of 12000 training images being used to train the model by understanding the characteristics of noise level while 3000 testing images to validate the model. To increase the learning efficiency, all training and testing sets are formed by six different standard testing images. The learning rate of the model is 0.01. From Fig. 3, it can be seen that the degree of images being corrupted by Gaussian noise is affected by the σ of the noise. The noise added from class to class is insignificant that even it is hard to distinguish visually. In our work, we implement our CNN by using MatConvNet [29]. The specified parameters of each CNN network layer are explained in detail in Table I.

Fig. 2 Standard test images for training and testing purposes.

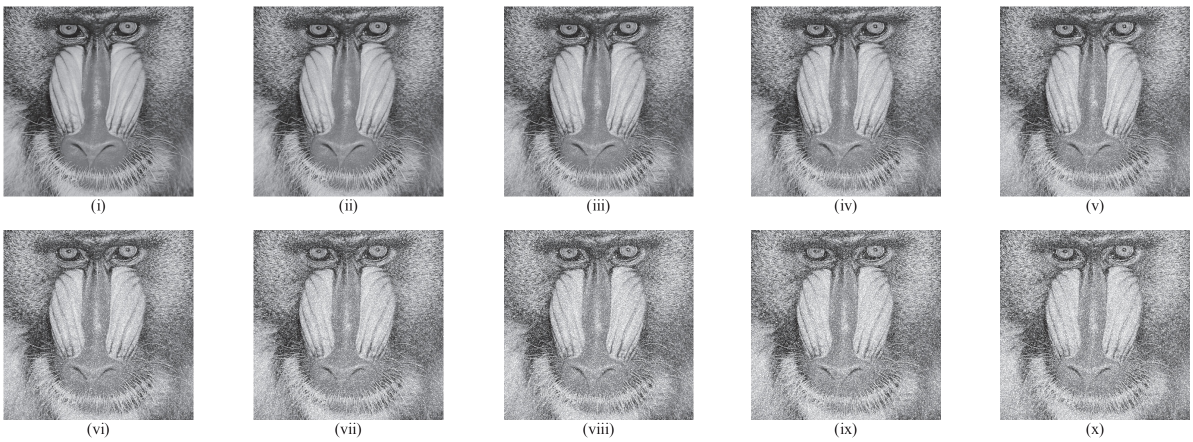

Fig. 3 Mandril images of (i) noise free, and corrupted by Gaussian level with σ of (ii) 10, (iii) 20, (iv) 30, (v) 40, (vi) 50, (vii) 60, (viii) 70, (ix) 80, (x) 90.

TABLE I PARAMETERS OF EACH CNN NETWORK LAYER.

Layer	Operation	Stride	Kernel Size
1.	Input	-	-
2.	Convolution	1	5×5×20
3.	Max Pooling	2	2×2
4.	Convolution	1	5×5×50
5.	Max Pooling	2	2×2
6.	Convolution	1	4×4×500
7.	RELU Activation	-	-
8.	Convolution	1	2×2×10
9.	Softmax Loss	-	-

B. Results and Analysis

We used 100 epochs and minibatch size of 100 images to train the model. To speed up the training process, we employ graphic processing unit (GPU) and it is able to complete a training cycle within 15 minutes. As illustrated in Fig. 4, two validation parameters are utilized i.e. top1err and top5err in both training and validation process. top1err is the error in misclassifying test images into the actual one label whereas top5err is the error when the predicted class does not fall among the top five labels that would most probably be the actual class. It is noticeable that both errors are lower in training than that in testing. These classification errors decrease across the training epochs, especially in the first 25. The testing error for top1err and top5err are 25.3% and 0%, respectively, showing that the overall accuracy is 74.7%.

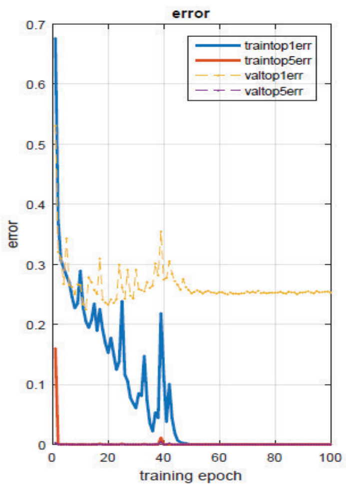

Fig. 4 Training curve for noise level detection.

IV. CONCLUSION

In this work, we present a method for detecting Gaussian noise and classifying its level using CNN. From the experimental results, it is feasible to implement the approach to detect the level of Gaussian noise, if there is any, present in the images so as to further apply suitable filters to the images. In view of the fast development of multimedia technology, this model is important as massive images need to be processed rapidly and intelligently. The implementation of the method eliminates the needs to have human handpicking the data that does not require further processing. The future work will include statistical technique optimization using data adapting filters generation in solving multiple noise types classification and noise level detection. It is feasible to design a model that could accurately identify multiple classes form by Gaussian noise, Impulse noise, Periodic noise, Speckle noise and Poisson noise.

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