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Image Deblurring Using Convolutional Neural Network

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Abstract: *Images are captured to get useful information or details or keep in record. Due to the problems in the capturing process, the recorded image may be a degraded version of the original one. Blur is a phenomenon caused by camera or object movement, improper focusing, or the use of an aperture. Motion blur can be uniform or non-uniform. Identification of motion blur is a difficult task. Different techniques are available to reconstruct images degraded by motion blur. Most of the techniques were based on estimating motion blur kernels and there by de-convolving the degraded image with the estimated motion blur kernel to obtain the clear image. The kernel estimation process is affected by the presence of significant noise, thereby resulting in a distorted recovered image. It is intended to propose a new method for image deblurring using the advantages of Convolutional Neural Network (CNN), which is also equipped with proper noise handling methods, such that the method can recover a good quality image from a blurry and/or noisy image.*

Keywords: *Image degradation, image deblurring, CNN, PSNR, MSE*

I. Introduction

Digital images are snapshots taken of scene which contains picture elements called pixels. Each pixel in an image carries an intensity value. Images can be obtained from everyday photography to astronomy, remote sensing, medical imaging etc. Images can convey more information than just speaking mere words. While capturing an image, we wish that the captured image is almost the true replica of the original scene. But for the time being, most of the captured images will result more or less blurry or even affected by noise. This will reduce the information which is intended to be conveyed by the image. These distortions occur due to more interference from the surroundings and also from the camera. The blurring of an image occurs mainly due to the movement of the camera or the object during the capture process, using long exposure times and wide angle lens etc.

Image restoration is the method of finding an estimate of an ideal image from its blurred and noisy version. It is one of the essential techniques used in image processing which deals with the recovery of sharp and clear original image from degraded ones. Image blur is difficult to avoid in many situations and can often ruin a photograph.

Basically, blurring means the loss of contrast and sharpness of an image. The solution for this problem is the image restoration techniques such as image deblurring. Image deblurring is the procedures that try to reduce the blur from the degraded set of images. It provides the degraded image a sharp and overall clear appearance. In practical scenario, however it is not possible to obtain the blurriness information directly from the image formation process. By using a mathematical model ie, by using an image degradation model, image deblurring makes the picture sharp and useful. In the image degradation model, the blurred image can be expressed by its degradation function, the noise function and by original image. The degradation process can be expressed using the system shown in Fig.1. Digital image restoration is a process in which we try to obtain an approximation to our original image f(x, y). The input image is introduced into a system with system function h(x,y). This image is then affected by a noise n(x,y) and thereby we obtain the degraded image g(x,y).

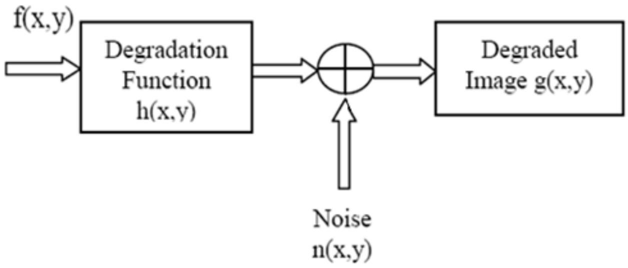

Fig. 1: Image Degradation Model

The blurred image can be expressed with the following equation [2]:

$$g(x,y) = h(x,y) * f(x,y) + n(x,y) \quad (1)$$

Section 2 gives a brief description about image restoration. Detailed explanation of the CNN used in this method is described in section 3. The proposed system is explained in section 4. Experimental result and performance evaluation is performed in section 6.

Image Restoration comprises of a group of techniques that aim to remove or reduce the degradations that have occurred to a digital image while it was being captured. The degradations in an image may occur due to sensor noise, camera misfocus, relative motion between the camera and the object, random atmospheric turbulence or due to some other reasons. The main objective of image restoration includes improving the quality of an image in a predefined manner. It tries to reconstruct an image that has been distorted, by having a priori knowledge about the distortion phenomena that affected the original image. Every captured natural image will have some kind of degradation in it. This degradation may occur during display mode, acquisition mode or during the processing mode.

The information about the degradation or blurriness will be present within the blurred image. But it will be hidden. By knowing about the details of the blurring process, we can recover the hidden information and thereby reconstruct the original image. The main threat in front of image deblurring process is that with a very few prior information about the blurriness, it is required to perform deblurring and reconstruct the clear image. There are different types of blurriness that affect the captured image. Some of them are average blur, motion blur, Gaussian blur etc. Of these all the prior importance is that of motion blur. Motion blur badly affect the quality of an image. Motion blur can be uniform or non-uniform. Identification of motion blur is a difficult task. Different techniques are available to reconstruct images degraded by motion blur. Most of the techniques were based on estimating motion blur kernels and there by de-convolving the degraded image with the estimated motion blur kernel to obtain the clear image. The kernel estimation process is affected by the presence of significant noise, thereby resulting in a distorted recovered image. Different researchers conducted survey on different image deblurring techniques proposed [2, 3]. From the survey they concluded that it is very difficult to remove average blur from an affected image. From the survey it was clear that deblurring using neural networks yielded better PSNR than any other techniques. In [4], image deblurring is approached in a different manner. The estimation of blur kernel is difficult to obtain from a single blurred image. First, both the blurred and noisy images are used to estimate an accurate blur kernel. Then this kernel is used for image deconvolution and there by restoring the clear image. In [6] a blind deconvolution algorithm which performs deblurring without any prior information about the blur kernel is given. [7] gives a new blind deconvolution algorithm for restoration of degraded images without more knowledge about the original image and the blur kernel. [8] defines a new algorithm which uses a combination of blurry sharp images to find the blur kernel and thereby reconstruct the original image. [10] introduces a new deep convolutional neural network that simultaneously identifies multiple motions and motion blur kernels. The drawback of this method is that the blurriness in the boundaries will still remain and also segmentation is not performed in texture less regions. [11] gives a new technique for non-uniform image deblurring using convolutional neural network. This technique uses convolutional neural networks to find the blur kernel and thereby reconstruct the original image. This method is time consuming. In [13], Dilip Krishnan introduces a new blind deconvolution algorithm in which lowest cost is given to true sharp image and thereby find the blur kernel. In [14], Anat Levin described a deconvolution algorithm using MAP estimator.

In this work, it is intended to propose a new algorithm for image deblurring using the advantages of Convolutional Neural Network (CNN), which is also equipped with proper noise handling methods, such that the algorithm can recover a good quality image from a blurry image. We generated a new CNN that performs the entire deblurring process. It is not required to perform deconvolution and all. The CNN itself performs every single operation within its hidden layers and gives out a clear output image. In this work, the performance evaluation is done by comparing the output of the proposed methods with those mentioned in [10], [13] and [14].

There are a lot of threats in front of image deblurring process. Blurring results in imperfect image formation process. Algorithms suitable for deblurring motion blurred images are very rare. Algorithms for deblurring color images are very rare. Method suitable for translational motion is not suited for rotational motion and vice-versa. Method suitable for both translational and rotational motions is concerned with small patch size. Computational complexity and time conception for execution are also a major problem. In order to tackle these issues, in this work a new algorithm using Convolutional Neural Networks is developed which is much better than the existing methods in case of performance.

II. Convolutional Neural Networks

Convolutional neural network (CNN or ConvNet) is a feed-forward artificial neural network. Convolutional Neural Networks (CNNs) consist of multiple layers of small neuron collections that process the receptive fields ie, portions of the input image, when used for image recognition. To obtain a better representation of the original image, outputs of these collections are then tiled so that they overlap and this is repeated for every layer. Major advantages of CNNs are the lack of dependence on prior knowledge and human effort in designing features. CNN architecture is formed by arranging a set of distinct layers that transform the input into an output through a differentiable function. MatConvNet is the toolbox used to build a CNN in this work.

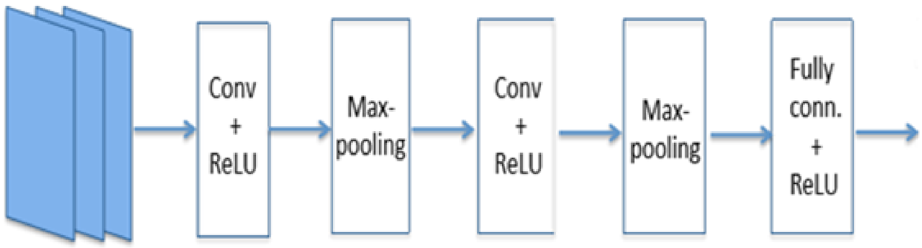

Fig. 2: CNN used in this method

The CNN which is used for image deblurring in this technique is shown in Fig. 2. In this structure of CNN, two convolutional layers along with ReLU layers, two Max-pooling layers and a Fully connected layers are used. So a total of five layers are included in the CNN used here. If we want, we can increase the number of layers in this architecture. The CNN used in this method is designed in such a way that we can directly give image as the input to this system. This is made possible by using the MatConvNet library. The main building block of a CNN is the convolutional layer. The parameters in the layers consist of a set of kernels, which have a small receptive field. The receptive field extends through the full depth of the input. While processing, the dot product between the entries of the filter and the input are computed and is given as the output. Another important part of CNNs is pooling layers. It is a form of non-linear down-sampling. The input image is partitioned into a set of non-overlapping rectangles by pooling and, for each such sub-region, maximum output is obtained. The main function of the pooling layer is to successively reduce the size of the representation. The size is reduced to reduce the amount of parameters and complexity of computation in the network. Always pooling layer is introduced in-between successive convolutional layers in a CNN architecture. In this work, a max-pooling layer is used. ReLU consists of a layer of neurons that applies the non-saturating activation function f(x) = max(0,x). In MatConvNet, ReLU is implemented by the function vl_nnrelu. The high-level reasoning in the neural network is done via fully connected layers finally, after several convolutional and max pooling layers. Neurons in a fully connected layer have full connections to all activation functions of neurons in the previous layer, just like regular Neural Networks. A matrix multiplication followed by a bias offset can compute the activations of this layer.

III. Proposed System

When we use a camera to capture images, we require that the recorded image should be the faithful representation of the scene that we try to capture. But unfortunately, the captured images end up more or less blurry. Due to this, image deblurring has become a fundamental process in making captured pictures sharp and clear. Deblurring involves the recovery of a sharp and clear image from a corrupted and distorted input image. The application of deblurring comes in the fields of astronomy and medical imaging. In real life scenario, from the given blurred image we have to find the sharp and clear version. There may be different ways by which we can achieve the goal of removing motion blur from a degraded image. In this work, this is achieved by utilizing the adaptive learning ability of a CNN. The proposed system is shown on Fig.3.

Fig. 3: Proposed system block diagram

The detailed block diagram of CNN used in this work is shown in Fig. 2. Here, the input to the CNN is a blurred image and its output intended to be its clear version. First we create a CNN by defining each of the layers, ie, the convolutional, ReLU, pooling and fully connected layers. This is done with the help of the library MatConvNet. Several functions are available for this purpose in the MatConvNet library.

Since CNN is an adaptive network, we have to train it to become adaptive to any of the given inputs. For the training purpose, a set of blurred images and their corresponding ground truth images are collected. In order to give an image as input to this CNN, we have to make this image in a particular image format ie, we have to compress it as a mat file. So first, the blurred and its ground truth images are divided into blocks. Out of these, some blocks are used for training while the rest are used for testing the CNN. The blocks used for training are given a label 1 and those used for testing are given a label 2. The blocks of original image and its blurred version both are converted into a 4D single format. This as a structure is given as the input to the CNN. More number of images used for training, more will be the efficiency of the CNN. After this the CNN is ready for deblurring purpose. Now the blurred image can be given as the input to the CNN and we will get the deblurred clear image as the output.

IV. Experimental Result And Analysis

During image capturing or while taking a photograph, due to a number of reasons like relative motion between the camera and the object, large aperture of the camera lens, atmospheric turbulence etc, the captured image will end up blurry. In this thesis work, a new deblurring technique is introduced which uses the advantages of a Convolutional Neural Network (CNN).The Convolutional Neural Network used here consist of five layers, the layers include convolutional layers, ReLU layers and fully connected layers. The CNN get adapted to each of the input blurred images thereby remove the blurriness. The results obtained using this method is shown in this section.

Fig. 4: First figure in each group represent the blurred image and second image is the deblurred image

The result obtained by using the proposed method is very clear compared to the existing deblurring techniques. This result is compared with the existing techniques performed by Krishnan et. al, Levin et. al and the deblurring using DCNN. The performance evaluation factors used for the comparison are Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) with respect to the ground truth.

Table 1: Comparison between the PSNR of existing techniques and the proposed technique

Images	PSNR (Krishnan)	PSNR (Levin)	PSNR (DCNN)	PSNR (Proposed method)
Image1	7.3702	6.3370	7.5690	12.7375
Image2	10.8856	8.9217	11.3556	14.7702
Image3	8.9270	8.1277	9.4881	14.5135
Image4	5.9557	5.8330	6.4341	12.7715
Image5	10.3725	9.9275	10.9708	13.0442
Image6	8.8540	8.3013	9.5322	10.0090

Table 2: Comparison between them MSE of existing technique DCNN and the proposed technique

Images	MSE (DCNN)	MSE (Proposed method)
Image1	0.2438	0.0532
Image2	0.1151	0.0333
Image3	0.1771	0.0354
Image4	0.3055	0.0528
Image5	0.2004	0.0496
Image6	0.3562	0.0998

(a) (b) (c) (d)

Fig. 10: (a) Input Blurred Image (b) Levin Deblurred Image (c) Krishnan Deblurred Image (d) Proposed System Output

The experimental result shows that, the proposed system yields better PSNR for each of the images which are subjected to image deblurring when compared to its ground truth. The MSE of the images also decreased when compared to the other deblurring technique outputs. This is shown in table 1 and 2. The time taken for the completion of the entire image deblurring process is found to be very low compared to the existing techniques making it more efficient.

V. Conclusion

The photographs taken of scenes will end up blurry due to a number of factors such as atmospheric turbulence, motion between scene and the camera etc. In this method, a new image deblurring technique is introduced which make use of the advantages of Convolutional Neural Networks (CNN). CNN adaptively get adapted to each of the input images and give a clear image in its output. The PSNR and entropy value of the output of the proposed technique improved to a very better extend making the output a perfect one compared to any of the existing technique output. The computational time is also a few milliseconds. As a future work, this can be extended to images blurred by multiple kernels.

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