ON CLASSIFICATION OF DISTORTED IMAGES WITH DEEP CONVOLUTIONAL NEURAL NETWORKS

Yiren Zhou, Sibo Song, Ngai-Man Cheung

Singapore University of Technology and Design

ABSTRACT

Image blur and image noise are common distortions during image acquisition. In this paper, we systematically study the effect of image distortions on the deep neural network (DNN) image classifiers. First, we examine the DNN classifier performance under four types of distortions. Second, we propose two approaches to alleviate the effect of image distortion: re-training and fine-tuning with noisy images. Our results suggest that, under certain conditions, fine-tuning with noisy images can alleviate much effect due to distorted inputs, and is more practical than re-training.

Index Terms— Image blur; image noise; deep convolutional neural networks; re-training; fine-tuning

1. INTRODUCTION

Recently, deep neural networks (DNNs) have achieved superior results on many computer vision tasks [1]. In image classification, DNN approaches such as Alexnet [2] have significantly improved the accuracy compared to previously hand-crafted features. Further works on DNN [3] continue to advance the DNN structures and improve the performance.

In practical applications, various types of distortions may occur in the captured images. For example, images captured with moving cameras may suffer from motion blur. In this paper, we systematically study the effect of image distortion on DNN-based image classifiers. We also examine some strategy to alleviate the impact of image distortion on the classification accuracy.

Two main categories of image distortions are image blur and image noise [5]. They are caused by various issues during image acquisition. For example, defocus blur occurs when the camera is out of focus. Motion blur is caused by relative movement between the camera and the view, which is common for smartphone-based image analysis [6] [7] [8]. Image noise is usually caused by poor illumination and/or high temperature, which degrade the performance of the charge coupled device (CCD) inside the camera.

When we apply a DNN classifier in a practical application, it is possible that some image blur and noise would occur in the input images. These degradations would affect the performance of the DNN classifier. Our work makes several contributions to this problem. First, we study the effect of image distortion on the DNN classifier. We examine the DNN classifier performance under four types of distortions on the input images: motion blur, defocus blur, Gaussian noise and a combination of them. Second, we examine two approaches to alleviate the effect of image distortion. In one approach, we re-train the whole network with the noisy images. We find that this approach can improve the accuracy when classifying distorted images. However, re-training requires large training datasets for very deep networks. Inspired by [9], in another approach, we fine-tune the first few layers of the network with distorted images. Essentially, we adjust the low-level filters of the DNN to match the characteristics of the distorted images.

Some previous works have studied the effect of image distortion [10]. Focusing on DNN, Basu et al. [11] proposed a new model modified from deep belief nets to deal with noisy inputs. They reported good results on a noisy dataset called n-MNIST, which contains Gaussian noise, motion blur, and reduced contrast compared to original MNIST dataset. Recently, Dodge and Karam [12] reported the degradation due to various image distortions in several DNN. Compared to these works, we perform a unified study to investigate effect of image distortion on (i) hand-written digit classification and (ii) natural image classification. Moreover, we examine using re-training and fine-tuning with noisy images to alleviate the effect.

In classification of “clean” images (i.e., without distortion), some previous work has attempted to introduce noise to the training data [13] [14]. In these works, their purpose is to use noise to regularize the model in order to prevent overfitting during training. On the contrary, our goal is to understand the benefits of using noisy training data in classification of distorted images. Our results also suggest that, under certain conditions, fine-tuning using noisy images can be an effective and practical approach.

2. DEEP ARCHITECTURE

In this section, we briefly introduce the idea of deep neural network (DNN). There are many types of DNN, here we mainly introduce deep convolutional neural network (DCNN), a detailed introduction for DNN can be found in [15].

DNN is a machine learning architecture that is inspired by humans’ central nervous systems. The basic element in DNN is neuron. In DNN, neighborhood layers are fully connected by neurons, and one DNN can have multiple concatenated layers. Those layers together form a DNN.

DNN has achieved great performance for problems on small images [16]. However, for problems with large images, conventional DNN need to use all the nodes in the previous layer as inputs to the next layer, and this lead to a model with a very large number of parameters, and impossible to train with a limited dataset and computation sources. The idea of convolutional neural network (CNN) is to make use of the local connectivity of images as prior knowledge, that a node is only connected to its neighborhood nodes in the previous layer. This constraint significantly reduces the size of the model, while preserving the necessary information from an image.

For a convolutional layer, each node is connected to a local region in the input layer, which is called receptive field. All these nodes form an output layer. For all these nodes in the output layer, they have different kernels, but they share the same weights when calculating activation function.

Fig. 1 shows the architecture of LeNet-5, which is used for digit image classification on MNIST dataset [17]. From the figure we can see that the model has two convolutional layers and their corresponding pooling layers. This is the convolutional part for the model. The following two layers are flatten and fully connected layers, these lay-
We consider two approaches to deal with distorted images: fine-tuning and re-training with noisy images. All the parameters to train: the first two convolutional layers, flatten and fully connected layers.

**Deep architectures and datasets:** In this evaluation we consider three well-known datasets: MNIST [17], CIFAR-10 [18], and ImageNet [19].

MNIST is a handwritten digits dataset with 60000 training images and 10000 test images. Each image is a $28 \times 28$ greyscale image, belonging to one digit class from '0' to '9'. For MNIST, we use LeNet-5 [17] for classification. The structure of LeNet-5 we use is shown in Fig. 1. This network has 6 layers and 4 of them have parameters to train: the first two convolutional layers, flatten and fully connected layers.

We consider two approaches to deal with distorted images: fine-tuning and re-training with noisy images:

In fine-tuning, we start from the pre-trained model trained with the original dataset (i.e., images without distortion). We fine-tune the first N layers of the model on a distorted dataset while fixing the parameters in the remaining layers. The reason to fix parameters in the last layers is that image blur and noise are considered to have more effect on low-level features in images, such as color, edge, and texture features. However, these distortions have little effect on high-level information, such as the semantic meanings of an image [21]. Therefore, in fine-tuning, we focus on the starting layers of a DNN, which contain more low-level information. As an example, for LeNet-5 we have 4 layers with parameters, that means N is ranging from 1 to 4. We denote fine-tuning methods as first-1 to first-4.

In re-training, we train the whole network with the distorted dataset from scratch and do not use the pre-trained model. We denote the re-training method as re-training.

For re-training LeNet-5, we set the learning rate to $10^{-3}$, and the number of epochs to 20. For fine-tuning, we set learning rate to $10^{-7}$ (1% of the re-training learning rate), and number of epochs to 15. Each epoch takes about 1 minute, so the training procedure takes about 20 minutes for re-training, and 15 minutes for fine-tuning. CIFAR-10 dataset consists of 60000 $32 \times 32$ color images in 10 classes, with 6000 images per class. 50000 are training images, and 10000 are test images. To make the training faster, we use a fast model provided in MatConvNet [20]. The structure of CIFAR10-quick model is shown in Fig. 2.

Similar to previous approaches for MNIST, we use fine-tuning and re-training for CIFAR distorted dataset. There are 5 layers with parameters in CIFAR10-quick model, so we have first-1 to first-5 as fine-tuning methods. The re-training method is denoted as re-training.

For re-training CIFAR10-quick, we set the number of epochs to 45. Learning rate is set to $5 \times 10^{-2}$ for first 30 epochs, $5 \times 10^{-3}$ for the following 10 epochs, and $5 \times 10^{-4}$ for the last 5 epochs. For fine-tuning, we set the number of epochs to 30. Learning rate is $5 \times 10^{-4}$ for first 25 epochs, and $5 \times 10^{-5}$ for last 5 epochs. Each epoch takes about 3 minutes, so the training procedure takes about 135 minutes for re-training, and 90 minutes for fine-tuning.

**3. EXPERIMENTAL SETTINGS**

We conduct experiment on both relatively small datasets [17, 18] and a large image dataset, ImageNet [19]. We examine different full training / fine-tuning configurations on some small datasets to gain insight into their effectiveness. We then examine and validate our approach on ImageNet dataset.

We conduct the experiment using MatConvNet [20], a MATLAB toolbox which can run and learn convolutional neural networks. All the experiments are conducted on a Dell T5610 WorkStation with Intel Xeon E5-2630 CPU.
more than one million images in 1000 categories. The images and
categories are selected from ImageNet [19]. To understand the effect
of limited data in many applications, we randomly choose 50000
images from training dataset for training, and use validation set of
ILSVRC2012, which contains 50000 images, for testing.

We use fine-tuning method for ILSVRC2012 validation set with a
pre-trained Alexnet model [2]. We do not use re-training method
here, because re-training Alexnet using only small part of the train-
ing set of ILSVRC2012 would cause overfitting. We fine-tune the
first 3 layers of Alexnet, while fixing the remaining layers. For fine-
tuning process, the number of epochs is set to 20. The learning rate
is set to $10^{-8}$ to $10^{-10}$ from epoch 1 to epoch 20, decreases by log
space. We also use a weight decay of $5 \times 10^{-4}$. Approximate train-
ing time is 90 minutes for each epoch, and 30 hours for total process.

Regarding the computation time, fine-tuning takes less time than
re-training on the MNIST and CIFAR-10 dataset. For ILSVRC2012
validation set, we also need to use fine-tuning method in order to
prevent overfitting.

Fig. 5. Example images from ImageNet validation set. (a) is the
original image. (b) is the distorted image.

**Types of blur and noise:** In this experiment, we consider two
types of blur: motion blur and defocus blur, and one type of noise:
Gaussian noise.

Motion blur is a typical type of blur usually caused by camera
shaking and/or fast-moving of the photographed objects. We gener-
ate the motion blur kernel using random walk [23]. For each step
size, we move the motion blur kernel in a random direction by 1-
pixel. The size of the motion blur kernel is sampled from $[0, 4]$.

Defocus blur happens when the camera loses focus of an im-
age. We generate the defocus blur by uniform anti-aliased disc. The
radius of the disc is sampled from $[0, 4]$.

After generating a motion or a defocus blur kernel for one image,
we use this kernel for convolution operation on the whole image to
generate a blurred image.

Gaussian noise is caused by poor illumination and/or high tem-
perature, which prevents CCD in a camera from getting correct pixel
values. We choose Gaussian noise with zero means, and with stan-
dard deviation $\sigma$ sampled from $[0, 4]$ on a color image with an integer
value in $[0, 255]$.

Finally, we consider a combination of all the above three types of
distortions. The value of each noise is sampled from $[0, 4]$, re-
spectively.

Fig. 5(a) and 5(b) show the example images of blur and noise effects in
MNIST and CIFAR-10, respectively. Each row of images represents
one type of distortion. For the first 3 rows, only one type of distortion
is applied, and for the last row, we apply all 3 types of distortion
on one single image. As we see each row from left to right, the
distortion level increases from 0 to 4.

Fig. 5(c) shows an example in ILSVRC2012 validation set. When
we generate the distorted dataset, each image in training and testing
set has random distortion values sampled from $[0, 4]$ for all 3 types of
distortion.

4. EXPERIMENTAL RESULTS AND ANALYSIS

Fig. 6 and 7 show the results of our experiment. We compare 3 meth-
ods: no train means that the model is trained on the clean dataset,
while tested on the noisy dataset. first-N means that we fine-tuning
the first N layers while fixing the remaining layers in the network.
For LeNet-5 network, there are 4 trainable layers, so we have first-1
to first-4, for CIFAR10-quick network, we have first-1 to first-5.

**Results on MNIST:** Fig. 6 shows the results on MNIST dataset.
For motion blur and Gaussian noise, the effect of distortion is rela-
tively small (note that the scales of different plots are different). De-
focus blur and combined noise have more effect on error rate. This
result is consistent with the observation on Fig. 3 that the motion
blur and Gaussian noise images are more recognizable than defocus
blur and combined noise. MNIST dataset contains greyscale images
with handwritten strokes, so edges along the strokes are important
features. In our experiment, the stroke after defocus blur covers a
wider area, while weakens the edge information. The motion blur
also weakens edge information, but not as severe as defocus blur.
This is because, under the same parameter, the area of motion blur is
smaller than the defocus blur. Gaussian noise has limited effect on
the edge information, so the error rate has little increase. Combined
noise have much impact on the error rate.

Both fine-tuning and re-training methods can significantly re-
duce error rate. first-3 and first-4 have very similar results, indicat-
ing that distortion has little effect on the last several layers. When
the distortion is small, fine-tuning by first-3 and first-4 achieve com-
parable results with re-training. When the distortion level increases,
re-training achieves a better result.

**Results on CIFAR-10:** From Fig. 7 we can see the distortions in
CIFAR-10 not only affect the edge information, but also have effect
on color and texture information. Therefore, all 3 types of distortion
can make the images difficult to recognize. This is consistent with
the results shown in Fig. 7. Different from the results on MNIST
dataset, all 3 types of distortion significantly worsen the error rate
on no train result.

Using both fine-tuning and re-training methods can significantly
reduce the error rate. first-3 to first-5 give very similar results, indicat-
ing that the distortion mainly affects the first 3 layers. When the
distortion level is low, fine-tuning and re-training have similar results.
However, when the distortion level is high or under combined noise,
re-training has better results than fine-tuning.

From both figures we can observe that when we fine-tune the
first 3 layers, the results are very similar to fine-tuning the whole
networks. This result indicates that image distortion has more effect
on the low-level information of the image, while it has little effect
on high-level information.

**Analysis:** To gain some insight into the effectiveness of fine-
tuning and re-training on distorted data, we look into the statistics
of the feature map inside the model. Inspired by [24], we find the
mean variance of image gradient magnitude to be a useful feature.
Instead of calculating the image gradient, we calculate the feature
map gradient. Then, we calculate the mean variance of feature map
gradient magnitude.

Given a feature map $f(m, n)$ as input, we first calculate gradient
along horizontal $(x)$ and vertical directions using Sobel filters
$$s_x = \frac{1}{4} \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix},
    s_y = \frac{1}{4} \begin{bmatrix} 1 & 2 & 1 \\ -1 & 0 & -1 \end{bmatrix}$$  (1)

Then we have gradient magnitude of $f$ at location $(m, n)$ as
$$g_{fm}(m, n) = \sqrt{(f m \otimes s_x)^2(m, n) + (f m \otimes s_y)^2(m, n)}$$  (2)
After we have the gradient magnitude $g_{fm}$ for feature map $fm$, we calculate the variance of gradient magnitude: $v_{fm} = \text{var}(g_{fm})$.

When we apply defocus blur or motion blur on an image, the clear edges are smeared out into smooth edges, thus the gradient magnitude map becomes smooth, and has lower variance. Feature maps with higher gradient variance value $v_{fm}$ are considered to have more edge and texture information, thus more helpful for image representation. While lower $v_{fm}$ value indicates that the information inside the feature map is limited, thus not sufficient for image representation.

Fig. 8 shows the mean variance of feature map gradient magnitude for conv layer 3 of CIFAR10-quick model. (a): motion-blur. (b): defocus blur.

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Results on Imagenet: We also examine the efficiency of fine-tuning on a large dataset and a very deep network. For experiment on the training and validation set of ILSVRC2012, we generated the distorted data by combining all 3 types of blur/noise. For each image, and for each type of distortion, the distortion level is uniformly sampled from $[0, 4]$. After obtaining the distorted data, we fine-tune the first 3 layers of a pre-trained Alexnet model [2]. Table 1 shows the accuracy comparison between the original pre-trained Alexnet model and the fine-tuned model. Compared with the original pre-trained model, the fine-tuned model increases the performance on distorted data, while keeping the performance on clean data. When we want to use a large DNN model like Alexnet on a limited and distorted dataset, fine-tuning on first few layers can increase model accuracy on distorted data, while maintaining the accuracy of clean data.

### Table 1. Accuracy comparison between pre-trained Alexnet model and fine-tuned model on ImageNet validation set.

| Error rate (%) | Clean data | Distorted data | Clean data | Distorted data |
|---------------|------------|---------------|------------|---------------|
| Top-1 error   | Original model | Fine-tuned model |
| 30.1          | 28.2       | 20.4          | 23.6       |
| Top-5 error   | 53.1       | 47.7          | 42.9       |

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5. CONCLUSIONS

Fine-tuning and re-training the model using noisy data can increase the model performance on distorted data, and re-training method usually achieves comparable or better accuracy than fine-tuning. However, there are issues we need to consider:

- The size of the distorted dataset: If the model is very deep and the size of distorted dataset is small, training the model on the limited dataset would lead to overfitting. In this case, we can fine-tune the model by first N layers while fixing the remaining layers to prevent overfitting.
- The distortion level of noise: When the distortion level is high, re-training on distorted data has better results. When
the distortion level is low, both re-training and fine-tuning can achieve good results. And in this case, fine-tuning is preferable because it converges faster, which means less computation time, and is applicable to limited size distorted datasets.

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