Generative Adversarial Classifier for Handwriting Characters Super-Resolution

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Abstract

Generative Adversarial Networks (GAN) receive great attentions recently due to its excellent performance in image generation, transformation, and super-resolution. However, GAN has rarely been studied and trained for classification, leading that the generated images may not be appropriate for classification. In this paper, we propose a novel Generative Adversarial Classifier (GAC) particularly for low-resolution Handwriting Character Recognition. Specifically, involving additionally a classifier in the training process of normal GANs, GAC is calibrated for learning suitable structures and restored characters images that benefits the classification. Experimental results show that our proposed method can achieve remarkable performance in handwriting characters 8× super-resolution, approximately 10% and 20% higher than the present state-of-the-art methods respectively on benchmark data CASIA-HWDB1.1 and MNIST.

Keywords: Super-Resolution, Generative Adversarial Networks (GAN), Handwriting Characters Recognition

1 Introduction.

The super-resolution (SR) which estimates a high-resolution (HR) image from its low-resolution (LR) counterpart is a highly important task in computer vision. SR has attracted much attention from the field of computer vision research and has a wide range of applications [4, 23, 29].

Convolutional neural networks have achieved excellent performance in super-resolution, however there are two main challenges. One is that the high-frequency information lacked in LR image cannot be reconstructed very well. The early neural network can get a good HR image from given an LR image at small scale factors by minimizing the mean squared error (MSE) between the reconstructed image and the ground truth [6, 7, 14, 15, 25]. However, these methods may fail to reconstruct high quality images at large scale factors such as 4×. The deep networks such as DRRN [27], EDSR [19] and MDSR [19] can achieve high PSNR in reconstructed image however the details of the high-frequency information are missing. The other challenge is that reconstructed details of images are fabricated. SRGAN [18] is good at restoring high-frequency information of HR images while the PSNR is relatively low because some of high-frequency information is fabricated and is unfaithful to the ground-truth.

For characters, the details are important, since details often determine whether characters can be recognisable. For example, the characters in the Figure 1(a) are difficult to recognise, and some are misrecognised. The lack of high-frequency information in general deep networks and the fake high-frequency details of the GAN make details become obstacles to recognise for both computer and human. In another word, these networks would not be appropriate for characters super-resolution. Therefore, it is necessary to propose a new network which is suitable for characters super-resolution.

Figure 1: The reconstructed image of 8× scale

In this paper, we propose a novel network based on SRGAN [18], removing the VGG loss while adding a classifier module to classify images reconstructed by...
the generator. There are some reconstructed images given by various methods in Figure 1. We highlight some pixels in the red cycle to show the difference with the results from SRGAN [18] and SRResNet. The proposed method called Generative Adversarial Classifier (GAC) can reconstruct images with more high-frequency information than SRResNet and more faithful to ground-truth than SRGAN [18].

Using the classification loss as additional information so that we can constrain the generator and make the reconstructed images more recognizable. In this sense, our network is similar to Triple-GAN [3]. Triple-GAN also has three parts where the discriminator will decide whether a pair of image and its label \((x, y)\) come from the true distribution \(p(x, y)\). This distribution discrimination model makes Triple-GAN unable to deal with data with large number of classes (e.g., CASIA-HWDB 1.1 containing 3,755 classes [20]), since input image and 3,755 classes label into discriminator will occupy a large amount of memory. In contrast, in our network, the discriminator and classifier are only associated with generator, the discriminator does not distinguish the distribution of images and labels, which makes our network: (1) suitable for the problem with large number of classes in particular for Chinese character recognition, (2) much easier to optimize because the parameter number in our discriminator is far fewer than Triple-GAN’s even if our discriminator is significantly deeper.

The 8x scale reconstructed image recognition rate of our network is 10% higher than SRGAN on CASIA-HWDB1.1 [20] with a 8 upscaling factor. In comparison, the top-1 accuracy is 63.95% and top-3 accuracy is 80.69%, the top-1 accuracy and top-3 accuracy of SRGAN is 55.28% and 69.52% respectively. Besides the CASIA-HWDB 1.1, we also evaluated our proposed methods on benchmark data MNIST [17] and CIFAR-10 [16] and the experimental results show our method can achieve significantly better results than the present state-of-the-art approaches.

2 Related Work

In this section, we will conduct an overall review of related work, including image super-resolution and Generative Adversarial Nets.

2.1 Image Super-resolution The research of image super-resolution can be divided into two categories: one is based on single image super-resolution (SISR), and the other is based on multiple image super-resolution (MISR) [1]. Our work can be cast into the first category.

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It is not a handwriting dataset
metrics as an intrinsic property of the representations learned by the Generator. Mirza et al. [22] proposed the conditional GAN, the idea is to use labels for some data to help network build salient representations, it can learn the conditional GAN, the idea is to use labels for some.

In single image super-resolution, the aim is to estimate a high-resolution image from a low-resolution input image. Here the high-resolution counterpart is the low-resolution image of its high-resolution counterpart. The proposed overall network can be illustrated in Figure 2. The generator $G$ generates the reconstructed images $I^{SR}$ from given low-resolution images $I^{LR}$, the discriminator $D$ distinguishes the $I^{SR}$ from $I^{HR}$, and the classifier $C$ gives labels for $I^{SR}$. The discriminator $D$ and classifier $C$ are both linked to the generator $G$, trying to guide the generator $G$ for generating more realistic yet recognisable reconstructed $I^{SR}$ images.

Our ultimate goal is to train a generating function $G$ that estimates a reconstructed $I^{SR}$ image as good as possible for a given LR input image. To achieve this, we train a generator network as a CNN $G_{\theta_G}$ parametrized $\theta_G$. For training images $I_n^{HR}$, $n = 1, ..., N$ with corresponding $I_n^{LR}$, $n = 1, ..., N$, the SR-specific problem is formulated as:

$$\hat{\theta_G} = \arg \min_{\theta_G} \frac{1}{N} \sum_{n=1}^{N} I^{SR} \left(G_{\theta_G} \left(I_n^{LR}\right), I_n^{HR}\right)$$

In this work we will specifically design a loss function $I^{SR}$ as a weighted combination of several loss components.

### 3.1 Adversarial Network Architecture

Inspired by Goodfellow et al. [8] and SRGAN [18], we define a discriminator network $D_{\theta_D}$ which we optimize alternately with the generator $G_{\theta_G}$, and the optimized object is to solve the adversarial min-max problem:

$$\min_{G_{\theta_G}} \max_{D_{\theta_D}} E_{I^{LR} \sim P_{GT}(I^{HR})} \left[ \log D_{\theta_D} \left(I^{HR}\right) \right] + E_{I^{LR} \sim P_{GT}(I^{LR})} \left[ \log \left(1 - D_{\theta_D} \left(G_{\theta_G} \left(I^{LR}\right)\right)\right) \right]$$

This formulation follows the basic working principle of GAN. It trains a generator model $G$ to try to fool a discriminator $D$ which is trained to distinguish super-resolved images from real images. With this approach the generator can learn to reconstruct image more realistic and highly similar to real images, even can make discriminator difficult to discriminate true images from reconstructed images. This approach encourages the result of generator perceptually superior in human vision, and it can achieve preferable visual perception, compared to the traditional method obtained by minimizing pixel-level error measurements such as the Mean Square Error (MSE).

For our generator network $G$ and discriminator network $D$, we exploit the SRGAN architecture [18]. The generator network illustrated in Fig. 3(a) are 16 residual blocks with identical layout where the block consists two convolutional layers with small $3 \times 3$ kernels and 64 feature maps followed by batch-normalization layers [12] and Parametric ReLU [10] as the activation function. Before the output layer, We increase the output dimension to the final goal of Triple-GAN is to predict the labels $y$ for unlabeled data as well as to generate new samples $x$ conditioned on $y$.

### 3 Method

In single image super-resolution, the aim is to estimate a high-resolution $I^{SR}$ from a low-resolution input image $I^{LR}$. Here the $I^{LR}$ is the low-resolution image of its high-resolution counterpart $I^{HR}$. In our network, there are labels for $I^{HR}$. The proposed overall network can be illustrated in Figure 2. The generator $G$ generates
resolution of the image with two trained upsampling blocks which contain one convolutional layer with small \(3 \times 3\) kernels followed by one sub-pixel convolution layer \([24]\) with \(scale = 2\) or \(4\) and Parametric ReLU as the activation function.

For the discriminator network \(D\) illustrated in Fig. 3(b) we follow the architectural guidelines summarized by Radford et al. \([24]\). We engage the LeakyReLU activation \((\alpha = 0 : 2)\) and avoid max-pooling throughout the network. The discriminator network is trained to solve the maximization problem in Equation 3.2. It contains eight convolutional layers with an increasing number of \(3 \times 3\) filter kernels, increasing by a factor of 2 from 64 to 512 kernels. Strided convolutions are used to reduce the image resolution each time the number of features is doubled. The resulted 512 feature maps are followed by two dense layers and a final sigmoid activation function.

For the classifier, we simply apply it with 3 convolutional layers with an increasing number of \(3 \times 3\) filter kernels, increasing by a factor of 2 from 64 to 128 kernels followed by 2 two dense layers and a final softmax activation function to obtain a probability for sample classification as illustrated in Figure 3(c).

### 3.2 Loss Function

The definition of loss function \(I^{SR}\) is critical for the performance of our generator network. While \(I^{SR}\) is commonly modeled based on the MSE \([6]\), we design a loss function that assesses a solution with respect to perceptually relevant characteristics. We formulate the loss function as the weighted sum of a content loss and an adversarial loss component and a classification loss component as:

\[
I^{SR} = I^{mse} + 10^{-3} \cdot I^{adv} + \alpha \cdot I^{cla}
\]

#### 3.2.1 Content Foss

We use the pixel-wise MSE loss as our content loss calculated as:

\[
I^{mse} = \frac{1}{rWH} \sum_{x=1}^{rW} \sum_{y=1}^{rH} \left( I^{HR}_{x,y} - G_{\theta_G}(I^{LR})_{x,y} \right)^2
\]

where \(I^{LR}\) and \(I^{HR}\) is the low-resolution image and high-resolution image respectively, \(W, H, C\) and \(r\) is the width, height, channel and scale factor, respectively. We describe \(I^{LR}\) by a real-valued tensor of size \(W \times H \times C\) and \(I^{HR}\), \(I^{SR}\) by \(rW \times rH \times C\) respectively. For character images, \(C\) can be set to 1 or 3 generally.

This is the most widely used optimization target for image super-resolution. However, while achieving particularly high PSNR, solutions of MSE optimization problems often lack high frequency content; this results in perceptually unsatisfying solutions with overly smooth textures.

#### 3.2.2 Adversarial Loss

Following the GAN architecture, we add the adversarial loss to our loss function. This encourages our network to generate images more natural and realistic in vision, by trying to fool the discriminator network. The adversarial loss \(I^{adv}\) is defined based on the probabilities of the discriminator over all training samples as:

\[
I^{adv} = \sum_{n=1}^{N} - \log D_{\theta_D}(G_{\theta_G}(I^{SR}_n))
\]

Here, \(D_{\theta_D}(G_{\theta_G}(I^{SR}))\) is the probability that the reconstructed image \(G_{\theta_G}(I^{SR}_n)\) is judged as a natural image by the discriminator. For better gradient behavior we minimize this equation instead of the original GAN adversarial loss log \([1 - D_{\theta_D}(G_{\theta_G}(I^{SR}_n))])\]

#### 3.2.3 Classification Loss

We introduce the third player, i.e., the classifier, into our proposed GAC model, which can characterize the conditional distribution \(p_c(y|x) \approx p(y|x)\) in general network. In our network, the classifier can label correctly for a given reconstructed image, which can be denoted as \(C_{\theta_C}(I^{SR}_n) \approx y\). We can achieve this simply by minimizing the cross entropy loss as:

\[
I^{cla} = \sum_{n=1}^{N} - y_n \log (C_{\theta_C}(I^{SR}_n))
\]

In order to make sure that the distribution \((I^{SR}, Y)\) be as close as possible to the true data distribution \((I^{HR}, Y')\), we need another one loss \(R_c\) as:

\[
R_c = \sum_{n=1}^{N} - y_n \log (C_{\theta_C}(I^{HR}_n))
\]

Consequently, we define the overall loss function as:

\[
I^{SR} = I^{mse} + 10^{-3} \cdot I^{adv} + \alpha \cdot I^{cla} + R_c
\]

The detailed algorithm to minimize the overall loss function is given in Algorithm 1.

### 4 Experiments

#### 4.1 Experimental Set-up

We perform experiments on the widely used handwriting Chinese characters dataset CASIA-HWDB1.1 \([20]\), handwriting digits dataset MNIST \([17]\). In addition, to further check if our method could work well in non-text data, we also evaluate our methods on CIFAR-10 \([10]\).

CASIA-HWDB1.1 consists of 897,758 training samples, and 223,991 testing samples for 3,755 classes. On CASIA-HWDB1.1 and CIFAR-10 datasets, experiments
are performed with a scale factor of $8 \times$ between low- and high-resolution images from $8 \times 8$ to $64 \times 64$. On MNIST, we set that scale factor is $7 \times$ from $4 \times 4$ to $28 \times 28$. We also implemented other super-resolution methods include bicubic, SRResNet [11], SRGAN [18] and Triple-GAN [2] and compared them on the three benchmark datasets. Our code will be uploaded to GitHub once this paper is published.

We obtained the LR images by downsampling the HR images using bicubic kernel with downsampling scale factor $r = 8$ on CASIA-HWDB1.1 and CIFAR-10, and $r = 7$ on MNIST. For each mini-batch we pick 128 random HR images of distinct training images. Note that we can apply the generator model to images of arbitrary size as it is fully convolutional. The MSE loss was thus calculated on images of intensity range $[-1; 1]$. We employed the trained MSE-based SRResNet network as initialization for the generator when training the actual GAN to avoid undesired local optima.

As we mentioned above, the performance of the network is not easily measured by the human eyes. For character recognition, the simplest performance test method is to recognise the reconstructed character image with to the classifier and exploit the recognition accuracy as the evaluation standard. We train a simple classifier $C_0$ for measurement, which contains 3 Convolutional Layers and 2 dense layers. $C_0$ can achieve the 89.29% in top 1 accuracy on CASIA-HWDB1.1.

For the SRResNet and SRGAN, we first train these two networks on CASIA-HWDB1.1 training set by using the $64 \times 64$ images as HR images and downsampling $8 \times$ these images to $8 \times 8$ as input. Then we get the test reconstructed images by downsampling CASIA-HWDB1.1 test set to $8 \times 8$ as input. Finally, we can use the $C_0$ to recognise the reconstructed test images.

For our proposed GAC model, we use two strategies to train it. The first strategy is to initialize $C$ to $C_0$, then freeze $C$ network so that its parameters are not updated. In this way, $C$ plays the same role in the network as VGG used in SRGAN, restricting the distribution $(I^{SR}, Y)$ trending to the ground-truth distribution $(I^{HR}, Y^r)$. The second strategy is to initialize $C$ to $C_0$, and $C$ network updated its parameters during training. In this strategy, it makes the distribution $(I^{SR}, Y)$ deviate from the ground-truth distribution $(I^{HR}, Y^r)$, but $C$ becomes more suitable for generator. The hyper-parameter $\alpha$ in Equation 3.8 was tuned empirically and we choose the best one on a validation set.

4.2 Experimental Results We report the experimental results on CASIA-HWDB1.1. As clearly observed, our proposed GAC model achieves significantly better performance than all the comparison algorithms. In particular, the GAC model without fixing $C$ achieves the top-1 accuracy of 63.95%, around 10.7% higher than SRGAN, the best of the other competitive algorithms. On the other hand, a simplified version of GAC with fixed $C$ also leads to significant improvement over SRGAN. Note that, on CASIA-HWDB1.1, we did not report the performance of Triple-GAN since it is intractable to be trained on the large category data CASIA-HWDB1.1 with 3,755 classes due to its inherit nature.

To further check the sensitivity of the proposed GAC on the hyper-parameter $\alpha$ as defined in Equation 3.8, we also report the recognition performance against different $\alpha$ on CASIA-HWDB1.1. These results can be seen in Figure 4. We can observe that, though the proposed GAC network is insensitive to the hyper-parameter $\alpha$ in general, smaller values may usually lead to better performance. In contrast, GAC (fixed $C$) is

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**Algorithm 1** Minibatch stochastic gradient descent training method of Classified-GAN in SSL

```plaintext
for number of training iterations do
  • Sample a batch of pairs $(I^{LR}; I^{HR}; Y)$ of size $N$
  • Update $D$ by ascending along its stochastic gradient:
    $$\hat{\theta}_D \left[ \frac{1}{N} \left( \sum_{n} \log D(I^{HR}_n) - \log D(G_{\theta_G}(I^{SR}_n)) \right) \right]$$
  • Update $C$ by descending along $R_c$ stochastic gradient:
    $$\hat{\theta}_C \left[ \frac{1}{N} \left( \sum_{n} -y_n \log (C_{\theta_C}(I^{HR}_n)) \right) \right]$$
  • Update $G$ by descending along its stochastic gradient:
    $$\hat{\theta}_G \left[ \frac{1}{N} \left( \sum_{n} (I^{HR}_n - G_{\theta_G}(I^{LR}_n))^2 \right) \right]
    - \log D(G_{\theta_G}(I^{SR}_n)) - y_n \log (C_{\theta_C}(I^{SR}_n)) \right]$$
end for
```
Table 1: Recognition accuracy of reconstructed test images on CASIA-HWDB1.1

| Method           | top-1(%) | top-3(%) |
|------------------|----------|----------|
| bicubic          | 2.24     | 4.04     |
| SRResNet         | 36.33    | 50.73    |
| SRGAN            | 53.28    | 69.52    |
| Triple-GAN       |          |          |
| GAC(fixed C, α=0.001) | 58.24   | 74.03    |
| GAC(α=0.0005)    | 63.95    | 80.69    |
| HR               | 89.29    | 95.86    |

Table 2: Recognition accuracy of reconstructed test images on MNIST and CIFAR-10

| Dataset | MNIST(%) | CIFAR-10(%) |
|---------|----------|-------------|
| bicubic | 12.17    | 10.00       |
| SRResNet| 36.75    | 10.66       |
| SRGAN   | 42.99    | 11.06       |
| Triple-GAN | 74.07  | 37.28       |
| GAC(fixed C, α=0.001) | 93.50  | 42.68       |
| GAC(α=0.001)    | 93.69    | 53.61       |
| HR               | 98.91    | 62.14       |

Figure 4: The top-1 accuracy of different α in CASIA-HWDB1.1.

5 Conclusion

We propose a new three-player generative adversarial classifier (GAC) with three components, a generator, a discriminator and a classifier, particularly for the purpose of character super-resolution. Specifically, involving additionally a classifier in the training process of normal GANs, GAC is calibrated for learning suitable structures and restored characters images that benefits the classification. Our empirical results on CASIA-HWDB1.1, MNIST, CIFAR-10 datasets demonstrate that GAC can achieve the state-of-the-art classification results for character super-resolution.

Acknowledgement

The work was partially supported by the following: National Natural Science Foundation of China under no. 61473236 and 61876155; The Natural Science Foundation of the Jiangsu Higher Education Institutions of China under no. 17KJD520010; Suzhou Science and Technology Program under no. SYG201712, SZZS201613; Natural Science Foundation of Jiangsu Province BK20181189, 17KJB520041; Key Program Special Fund in XJTLU under no. KSF-A-01, KSF-A-10, KSF-P-02.

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