

Stroke-based Character Reconstruction

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Abstract

Background elimination for noisy character images or character images from real scene is still a challenging problem, due to the bewildering backgrounds, uneven illumination, low resolution and different distortions. We propose a stroke-based character reconstruction(SCR) method that use a weighted quadratic Bezier curve(WQBC) to represent strokes of a character. Only training on our synthetic data, our stroke extractor can achieve excellent reconstruction effect in real scenes. Meanwhile, It can also help achieve great ability in defending adversarial attacks of character recognizers.

1.Introduction

Deep neural networks(DNN)(Krizhevsky, Sutskever, and Hinton 2012) have already shown great ability in various applications in computer vision, including image classification, object detection, scene understanding etc. Some of the most influential jobs are VGGNet(Simonyan and Zisserman 2014), GoogLeNet(Szegedy et al. 2015) and residual connections(He et al. 2015).

Character recognition is the task that converts the printed or hand-written text into machine-encoded text. This task is usually converted into a multi-category classification task, i.e., one character corresponds to one category. So in recent years, many character recognition models based on DNN have been produced. Since most character recognition methods directly predict the labels based on the character images, no more structure information about characters is considered. If we want to extract the text information of the picture, eliminate the background of the picture, or reconstruct the blurred document, then only the classification information is not enough.

Character recognition of natural images is still a challenging problem to machines. It is because it's tough for machines to extract adequate information while the characters are with a bewildering background, uneven illumination, low resolution and different distortions. It's also shown that the recognition of hand-written digits is easily fooled by adding some noise to the character images(Madry et al. 2017), which is called the adversarial attack. One possible way of increasing

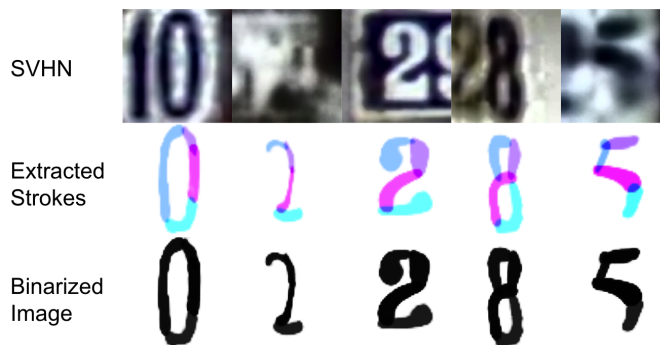


Figure 1: Extracted strokes and reconstructed images for images of SVHN. We only train our model on our synthetic SVHN-like data.

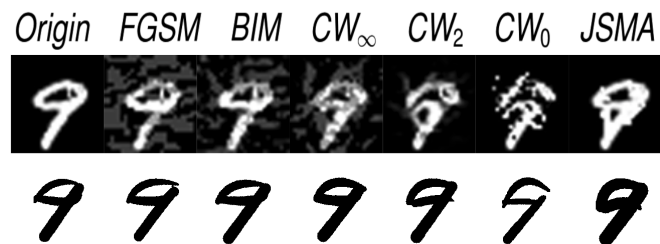


Figure 2: Reconstruction results for adversarial examples of MNIST.

the robustness to noise is extending the training dataset with these noisy character images to train the character recognizer further. But this approach is costly, and it's hard to expose all possible noises to recognizers in training.

Intrinsically, a character is constructed by a sequence of strokes. This property can be used to design a more robust character recognition method. We can extract the strokes first and reconstruct the characters, then further conduct the recognition.

In this paper, we propose an encoder-decoder structure based on stroke representation which can deconstruct a character image and encode it into parameters of some strokes, then decode these parameters to an image. The weighted

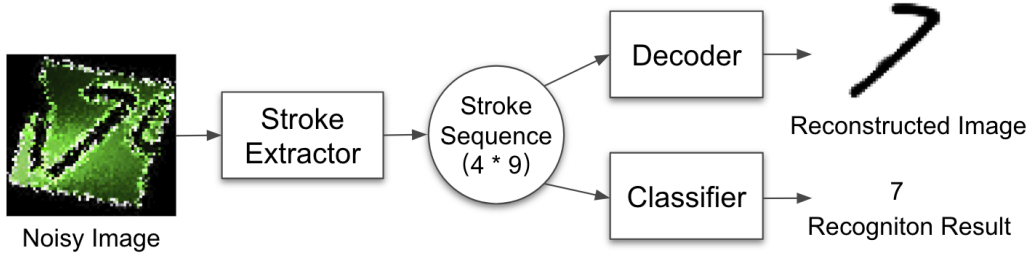


Figure 3: Pipeline of our SCR method. We use four curves to represent a character; each curve has nine parameters.

quadratic Bzier curve(WQBC) is used to simulate the stroke, which is controlled by three weighted points. We pre-train a neural network as the decoder that can embed the WQBC on an image based on the parameters of it. Then we freeze the decoder and train another neural network as an end-to-end stroke extractor, which can be integrated with character recognizers. The extracted strokes can be used in two ways: (1) reconstructing a clean character image for static image-based character recognizer; (2) taking as the input for stroke sequence based character recognizer. The pipeline of our SCR method is illustrated in Fig. 3.

We take the L_2 distance the reconstructed character and the ground truth as the supervised loss and don't expose the strokes sequence of each character to the decoder. Despite all this, we find the decoder still can automatically learn to deconstruct a character into some strokes. And in experiments, we show that the decoder can cope with both the Arabic numerals and English letters well.

Our contributions are as follows:

- We propose to encode character into the meaningful representation to improve the reconstruction ability and robustness of encoder-decoder structure and achieve better reconstruction effect.
- We train a differentiable curve parameter decoder.
- We design an image augmentation process for the training of our stroke extractor. Finally, our SCR method can deal with various image noise and can be well generalized in real scenes. We don't use images of SVHN for supervised training or transfer training but achieve a general reconstruction success rate of 89%.
- Our stroke extractor for scene character images can be integrated with character recognizer to improve the defense against adversarial attacks.

2.Related Work

Character Reconstruction

Some work attempts to improve the performance of character recognition with background image elimination. (Shen and Lei 2015) However, these implementations are usually based on traditional methods of contrast adjustment, sharpening, binarization, etc., and require many manual designs. Among them, only the deblurring of the document is perfect(Chen et al. 2011).

Stroke Extractor

Some works focus on the methods of reinforcement learning(RL) that make the agent have the ability to extract strokes from images. The work of 2013 studied the automatic real-time generation of simple strokes (Xie, Hachiya, and Sugiyama 2013). DeepMind proposed an approach to train agent with reinforced adversarial learning to master synthesizing programs for images and use strokes to reconstruct images (Ganin et al. 2018).

Adversarial Attack and Defense

Robustness is essential to guarantee the security of application of machine intelligence. Unfortunately, many works have confirmed that deep neural networks are susceptible to small perturbations of the input vector (Goodfellow, Shlens, and Szegedy 2014). Current defense method against adversarial examples follows about three approaches: (1) Training to distinguish common and adversarial examples. (2) Training with adversarial examples to improve robustness. (3) Preprocessing input data or some other methods to make it difficult to attack target classifier (Meng and Chen 2017). Both (1) and (2) require many adversarial examples to train the models, but adversarial examples could be generated by unpredictable methods.

3.SCR

Problem Definition

Given a distorted character image I_{dis} , our goal is to reconstruct a clean character image I_{rec} that is close to the ground truth character I_{gt} . We do not intend to crop the character from I_{dis} at a time, because this is quite hard for machines, especially when I_{dis} is with severely distortions. Instead, we deconstruct the character into parameters of strokes and draw strokes on the canvas.

Stroke Representation

We use the **weighted quadratic Bzier curve** (WQBC) to simulate a stroke. The WQBC is determined by three weighted points P_0 , P_1 and P_2 , either of which is denoted as (x, y, w) , where x and y denote the coordinate and w denotes the radius. Then a WQBC is generated as follows:

$$B(t) = (1-t)^2P_0 + 2(1-t)tP_1 + t^2P_2, 0 \leq t \leq 1$$

We have also tried other curves to simulate strokes. But we find WQBC is simple and flexible enough to simulate the most strokes of common characters. For the WQBC drawing program please refer to **Algorithm 1**. The curve is drawn on a higher resolution canvas (256×256) to eliminate aliasing.

Algorithm 1 Algorithm for drawing a WQBC

Input: Parameters of a WQBC, including $x_0, y_0, w_0, x_1, y_1, w_1, x_2, y_2, w_2$, they range from 0 to 1.
Output: Embedded image, its size is 64×64 .
Initialization: Create a canvas C, which is a full 0 array of 256×256 .

- 1: map $x_0, y_0, x_1, y_1, x_2, y_2$ to $[0, 255]$, map w_0, w_1, w_2 to $[2, 32]$.
- 2: $i = 0$
- 3: **while** $i < T$ **do**
- 4: $t = i * (1/T)$
- 5: $x = (1 - t)^2 * x_0 + 2 * t * (1 - t) * x_1 + t^2 * x_2$
- 6: $y = (1 - t)^2 * y_0 + 2 * t * (1 - t) * y_1 + t^2 * y_2$
- 7: $w = (1 - t)^2 * w_0 + 2 * t * (1 - t) * w_1 + t^2 * w_2$
- 8: draw a circle at (x, y) of C, its radius is w .
- 9: $i = i + 1$
- 10: **end while**
- 11: I = resize C to 64×64
- 12: **return** I

Stroke Extractor

The stroke extractor can deconstruct the character image into parameters of several WQBCs. We find that VGGNet-like architecture has well fitting and generalization capabilities on this task. We use a small size vggnet with halved number of channels as the stroke extractor.

Differentiable Decoder

Embedding the curve based on its parameters requires a method of calculating the distance from a point to a quadratic line segment. Performing such calculations with a differentiable operation is cumbersome, especially since the image is a collection of discrete pixels with size and value limits. When we want to try other different curve representations, we need to re-complete the derivation. One solution is to train an agent with reinforcement learning to implicitly build such a decoding model, but continuous space control is a problem in reinforcement learning. We make some attempts in our earlier version but don't achieve good enough effect.

We train a neural network that combines fully connected layers and upsampling layers. We use supervised learning methods to make the network learn to generate curves like programs. Parameters are uniformly sampled from the range during training. The network structure is shown in the appendix. It can embed WQBCs on a 64×64 image, and the inferred curve is very subtly different from the WQBC drawn by the program.

Training

The implementation of our training is based on the PyTorch v0.4 library (Paszke et al. 2017). We use stochastic gradient

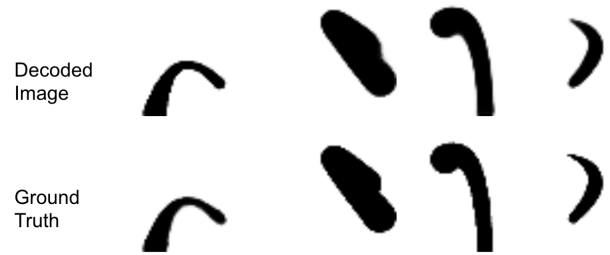


Figure 4: Decoded WQBC and ground truth.

descent(SGD) with momentum (Sutskever et al. 2013) for training the neural network with a learning rate of 3×10^{-2} . For every 1/3 of training, the learning rate is reduced to 1/10.

4. Experiment

Datasets and Noisy Characters Generation

MNIST MNIST (LeCun 1998) contains 70,000 examples of hand-written digits, of which 60,000 are training data and 10,000 are testing data. Each example is a grayscale image with a resolution of 28×28 pixels.

SVHN SVHN (Netzer et al. 2011) is a real-world image dataset including over 600,000 digit images. The ‘‘Cropped Digits’’ set is similar to MNIST, and each sample is a color image with a resolution of 32×32 pixels.

Synthetic SVHN We collected 250 fonts to generate 2,500 Arabic numerals and 2,500 images from the MNIST training set, using these glyphs to synthesize an SVHN-like data set. We stitch together three digital pictures horizontally each time as ground truth. We randomly set the color of the characters and background then add various types of distortions and noise to ground truth to get the distorted image. We synthesize 200,000 images for training.

Noisy Characters Generation We mainly consider following distortions and use an open source tool named `imgaug`¹ to achieve most image augments. A portion of the augmentation is performed at random each time. Among them, the augmentations involving displacement and deformation are performed on both ground truth and distorted image. Each pixel value of the image is normalized into the range of $[0, 1]$ at first.

- **Random Rotation** The rotation angle is randomly selected from the range of $[-15^\circ, 15^\circ]$.
- **Crop and Pad** The width of the cropped image is between 60% and 90 % of the original image.
- **Gaussian Noise** We add a Gaussian noise ($\sigma \in (0, 0.05)$).
- **Blur** We choose one of the Gaussian blur($\sigma \in [0, 3]$), the median blur($r \in [3, 9]$), and the average blur($r \in [2, 7]$) to act on the image.

¹<https://github.com/aleju/imgaug/>

MNIST Experiments	L_∞ Attacks				L_2 Attacks		L_0 Attacks				All Attacks
	FGSM	BIM	CW_∞		CW_2		CW_0		JSMA		
			Next	LL	Next	LL	Next	LL	Next	LL	
No defense	54%	9%	0%	0%	0%	0%	0%	0%	27%	40%	13.00%
Bit Depth (1-bit)	92%	87%	100%	100%	83%	66%	0%	0%	50%	49%	62.70%
Median Smoothing (3x3)	59%	14%	43%	46%	51%	53%	67%	59%	82%	79%	55.30%
SCR (ours)	94%	86%	97%	92%	94%	83%	86%	79%	91%	84%	88.60%
Human Performance	97%	88%	97%	97%	94%	78%	83%	76%	89%	90%	88.90%

Table 1: Model accuracy against adversarial attack

- **Sharpen and Emboss** We use image sharpen ($alpha \in (0, 1.0)$, $lightness \in (0.75, 1.5)$) and Emboss ($alpha \in (0, 1.0)$, $strength \in (0, 2.0)$) operation.
- **Pepper & Salt Noise** The Signal-to-noise ratio is set to s ($s \in [0.7, 0.97]$).
- **Other distortions** We use perspective transform ($scale \in (0.01, 0.1)$) and piecewise affine ($scale \in (0.01, 0.05)$) operations provided by imgaug.

Defense against Adversarial Attacks on MNIST

Many works show that the written-digit recognizers are easily fooled by existing adversarial attack methods.

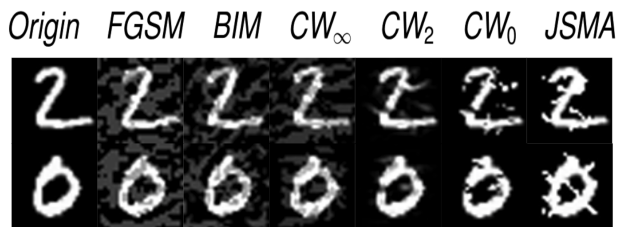


Figure 5: Adversarial examples of MNIST

Based on the MNIST dataset, we make a comparison to an existing defense method, feature squeezing (Xu, Evans, and Qi 2017). As in their paper, we take some adversarial attack methods in our experiments and show some adversary examples in Fig 5.

We take the training set (60,000 images) of MNIST to train the agent. These images are considered as the ground truth. In training, noisy character images are generated following the noisy character generation procedure.

In Table 1, we show the defense results of our method and feature squeezing, including reducing the color bit depth of each pixel and spatial smoothing. It's been demonstrated that our method achieves the best defense results for most adversarial attacks. And the overall performance of our method is significantly better than other methods.

Experiments on SVHN

The character images of SVHN are cropped from real-scene street view images, and they are with rich noises in nature. Since it's hard for us to obtain the ground truth images (clean and without noise) for SVHN, we take a special strategy to

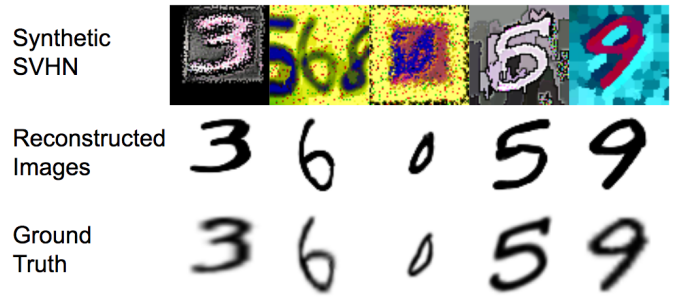


Figure 6: Reconstructed images for images of synthetic SVHN.

train the stroke inference agent. We synthesize noisy character images based on MNIST and character images generated by system fonts as shown in Fig 6. Then take them to train our networks. When testing, we use the trained agent to infer stroke for SVHN. The agent still achieves a higher than 89% recognition rate on SVHN.

Experiments on synthetic English letters

Training on synthetic English letters is similar to the training on MNIST. We use the same noisy character generation procedure to generate noisy character images in training and testing.

Some stroke inference results are shown in Fig 7.



Figure 7: Reconstructed images for images of synthetic English letters

5. Discussion

The core part proposed SCR method is the stroke inference module, which is implemented as a stroke extractor and a

differentiable decoder. The experiments show that the stroke extractor robust to the noise on characters. And this SCR method shows excellent ability in defending adversarial attacks of the hand-written digits.

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Appendix

Network structure

The network structure diagram is shown in Figure 8 and Figure 9, where FC refers to a fully-connected layer, Conv is a 3×3 convolution layer. The shape representation format of the output of the convolutional layer is [H, W, C]. All ReLU(Nair and Hinton 2010) activations between the layers have been omitted for brevity. The activation function after stroke extractor and decoder is a sigmoid function in order to map the output into range [0, 1].

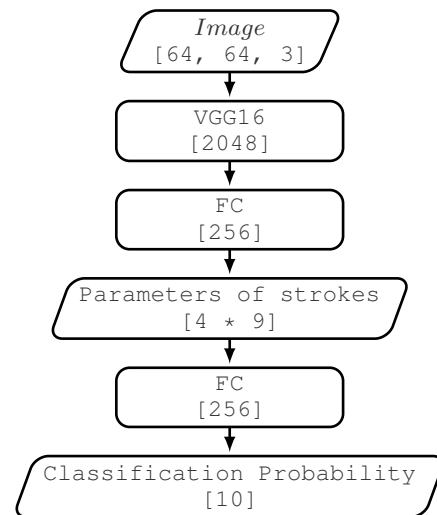


Figure 8: The architecture of the **stroke extractor** and **classifier**.

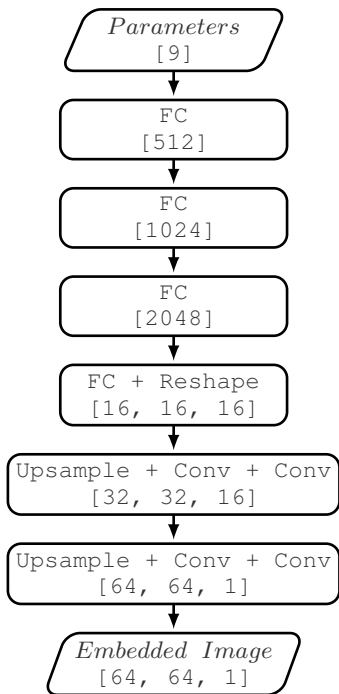


Figure 9: The architecture of the **decoder**.